

Three Essays in Fund Management

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The President:

Prof. Dr. Bernhard Ehrenzeller

To Mum and Dad

Summary

The study of networks pervades all of science. In this spirit, the first and the third paper of my doctoral thesis tackle questions of how information disseminates through agents in financial markets and into security prices. This work is further contrasted by the second paper of my doctoral thesis, which strikes at the root of seemingly irrational investment behavior.

The thesis was written during my time as a PhD student and research assistant at the Chair of Finance of Manuel Ammann at University of St. Gallen from November 2017 to December 2021, and was further developed during my research stay at Harvard Business School under the supervision of Lauren Cohen starting in November 2021. My sincere gratitude goes to my supervisor Manuel Ammann and my fellow doctoral students for igniting my passion for financial research and for the many inspiring discussions.

In the first paper, “Hidden Alpha,” using the setting of financial agents, we explore the importance of hidden connections relative to all other network connections. We find that hidden connections are those associated with the largest and most significant abnormal returns accruing to fund managers. This is relative to insignificant abnormal returns accruing to all other trades, including to trades of publicly observable connections in the fund manager–firm officer network. The hidden connection premium does not appear to be driven by endogenous selection or familiarity, as fund managers seem to be correctly timing when to hold and when to avoid their friends’ stocks. Further, the more hidden the connection is, the more valuable the information that appears to be associated with the trading across it. More broadly, our findings highlight the importance of missing nodes and hidden edges when attempting to understand the true nature of shock propagation in complex network systems.

In the second paper, “In Military We Trust: The Effect of Managers’ Military Background on Mutual Fund Flows,” we take a mutual fund investor’s point of view. We address the question why investors continue to pay such high fees to fund managers and advisers, although actively managed funds have long been shown to underperform passive investments. The paper reveals that trust-building characteristics of fund managers affect purchase decisions of mutual fund investors. We exploit variation in fund managers’ prior affiliations with the U.S. military, a well-trusted institution, and relate it to fund flows. We find that funds with ex-military managers have significantly higher flows relative to other funds.

In the third paper, “The Social Side of Investing: Fund Manager Networks and Portfolio Choice,” I reveal private social networks among U.S. mutual fund managers and examine how network characteristics affect portfolio choice. I find that managers who are socially connected have more similar holdings and trades even after controlling for their location and employer. Stocks purchased together and simultaneously by managers within a network exhibit positive risk-adjusted returns suggesting that valuable information is shared through social interactions. Managers who are more central in a network tend to have higher risk-adjusted returns.

Zusammenfassung

Diese Dissertation besteht aus drei Aufsätzen, die sich in ihren empirischen Analysen mit Forschungsfragen aus dem Gebiet des Fondsmanagements befassen und die Fondsmanagementbranche dabei gleichsam als wissenschaftliches Labor nutzen. Der erste und der dritte Aufsatz gehen der Frage nach, wie Informationen sich über auf dem Finanzmarkt agierende Akteure verbreiten und in Aktienpreise einfließen. Im Kontrast hierzu widmet sich der zweite Aufsatz irrationalem Investitionsverhalten aus dem Blickwinkel der Behavioral Finance.

Das vorgelegte Werk ist während meiner Zeit als Doktorand und wissenschaftlicher Mitarbeiter am Lehrstuhl für Finance von Manuel Ammann an der Universität St. Gallen zwischen November 2017 und Dezember 2021 entstanden, und wurde während meines Forschungsaufenthaltes an der Harvard University ab November 2021 unter Betreuung von Lauren Cohen weiterentwickelt. Ich danke herzlich meinem Doktorvater Manuel Ammann und meinen Mitdoktoranden an der School Finance für die Unterstützung und die vielen inspirierenden Diskussionen.

Das erste Papier, “Hidden Alpha”, befasst sich mit verborgenen Verbindungen zwischen zentralen Akteuren am Finanzmarkt. Es beleuchtet die Bedeutung dieser Verbindungen für die Verbreitung und Weitergabe von Informationen und untersucht ihren Einfluss auf die Bepreisung von Wertpapieren. Wir stellen fest, dass stärker verborgene Verbindungen zwischen Fondsmanagern und Unternehmensleitern mit grösseren abnormalen Renditen in den zugehörigen Aktien einhergehen. Neben einer theoretischen Bedeutung für ein besseres finanzwissenschaftliches Verständnis von Netzwerkstrukturen entfaltet das Papier seine praktische Relevanz insbesondere in Gestalt quantitativer Anlagestrategien für das Portfoliomanagement.

In der Studie “In Military We Trust: The Effect of Managers’ Military Background on Mutual Fund Flows” nehmen wir die Sichtweise eines Fondsanlegers ein und gehen der Frage nach, warum Anleger weiterhin hohe Gebühren für Fondsmanager bezahlen, obwohl aktiv verwaltete Fonds regelmässig schlechter abschneiden als passive Anlagen. Wir können zeigen, dass vertrauensbildende Eigenschaften von Fondsmanagern die Kaufentscheidungen der Anleger beeinflussen, indem wir die frühere Zugehörigkeit der Manager zu dem von Anlegern als besonders vertrauenswürdig eingestuften US-Militär mit Fondsströmen in Beziehung setzen. Wir finden, dass von Ex-Militärs geführte Fonds deutlich höhere Fondsströme aufweisen. Dieser Effekt ist grösser, wenn das Engagement des Fondsmanagers im Militär stärker vermarktet wird.

In der dritten Studie “The Social Side of Investing: Fondsmanager Networks and Portfolio Choice” befasse ich mich mit Verbindungen zwischen Fondsmanagern und deren Einfluss auf Investitionsentscheidungen. Hier stelle ich fest, dass sich Anlagen und Investitionen miteinander verbundener Fondsmanager stärker überlappen. Zentralere Manager im Netzwerk haben tendenziell höhere risikobereinigte Renditen. Die von verbundenen Managern gemeinsam gekauften Aktien weisen positive risikobereinigte Renditen auf, was darauf hindeutet, dass über soziale Kanäle werthaltige Informationen ausgetauscht werden.

Hidden Alpha^{*}

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ABSTRACT

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

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

In this paper, we provide novel evidence on the powerful impact of such hidden connections among influential agents in financial markets. In particular, we explore hidden connections between mutual fund managers and firm executives of the publicly traded companies whose stocks the funds invest in. To address our research question, we make use of social connection data from the world’s largest social networking platform—Facebook (facebook.com)—at the time of writing the third-most visited website in the United States numbering more than 200 million monthly active users. Specifically, we assemble a data set of 71,000 manually identified Facebook profiles of fund managers and firm officers active in the period 1984–2020. Using data on their connections and interactions on Facebook, we classify friendship ties that are public versus those that are hidden by one (or even both) sides of a connected pair.

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

To better understand our approach, consider the following examples from our sample.¹ The first example involves Ms. Ananke, the CEO and a subsequent board member of a large healthcare-related firm. Among her many activities, Ananke had maintained an active and lively social network on Facebook. Her friends on the platform included Mr. Bergelmir, a fund manager of a large active mutual fund. Interestingly, there were no documented meetings, mentions, or interactions between Ananke and Bergelmir precipitating their connection, nor any other observable or detectable common network ties (i.e., no common school networks, work networks, location networks, common friends, etc.).

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

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

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

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

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

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

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

In contrast, a more convincing version of the argument includes selection. Selection might be able to drive both the dispersion in average performance between returns earned on connected relative to nonconnected stocks and the dispersion in average performance earned on stocks associated with more-hidden relative to less-hidden connections. First, high type individuals may select to or be more likely to jointly match (i.e., the more successful the fund manager, the more likely the firm officer to match with the fund manager, if the firm officer too is successful). Second, unobserved characteristics (e.g., skill or ability) may simultaneously affect both the likelihood of a connection to be hidden and the likelihood of a connection to be

associated with performance. In both these scenarios—that is, if our story is either one of a correlation between mutual success and the likelihood of forming friendship ties, or if it is one of an unobserved characteristic which causes hidden connections to select on better quality fund-stock pairs—we would expect to find identical returns on both the (hiddenly) connected stocks that the fund managers invest in and the (hiddenly) connected stocks that the fund managers choose to avoid, because these two groups sort on the same (hidden-connection) characteristics. Having said that, we find holdings of hiddenly-connected stocks to outperform significantly in times when they are held by the fund managers relative to times when they are not held—by 119 basis points in abnormal returns per month (t -stat = 2.59), or 14% per year. This finding is more consistent with hidden connections being valuable sources for fund managers, and it is less consistent with a familiarity heuristic or selection explanation.

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

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

Our paper connects to the growing literature concerned with the role of social ties in the transfer of information in financial markets. Papers in this spirit include Cohen, Frazzini, and Malloy (2008), who find that mutual fund managers place larger bets and make more profitable trades on firms run by management personnel with whom they share educational commonalities. Engelberg, Gao, and Parsons (2012) provide evidence that firms that have social ties with their

banks obtain loans with lower interest rates and fewer covenants. Hochberg, Ljungqvist, and Lu (2007) show that better-networked venture capital investors exhibit higher fund performance. Findings from Cai and Sevilir (2012) suggest that target–acquirer board connections lead to better merger performance. Finally, Engelberg, Gao, and Parsons (2013) find that CEOs with social connections to outsiders bring more valuable information into the firm and receive higher compensation.

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

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

I. Data and Sample Construction

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

A. Facebook Profiles

In this study, we explore the personal relationships between individuals based on their social ties to one another. To uncover these ties, we use Facebook friendships as our laboratory network metric. A central measure of interest in the paper is an indicator variable for whether a fund manager and a firm officer are connected via a friendship relation on Facebook. To

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

establish whether such a relation exists between any two sample individuals, we must identify their Facebook profiles. These are personal user pages created upon joining the platform and typically comprise a user’s name, profile picture, friends list, timeline, photos tab, and an “about” section. The latter includes biographical, demographic, and other types of descriptive information on the user, such as work experience, educational background, places lived, family members, and relationship status.

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

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

B. Matching of Facebook Profiles

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

³In response to several controversies (e.g., Cambridge Analytica), Meta Platforms has severely restricted Facebook’s main API (“Graph API”) in April 2018 by deprecating its major endpoints. Further restrictions were imposed in June 2019 when Facebook’s 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.

In the first step of the identification procedure, for each target in our sample, we populate a list of candidates that we retrieve from different sources. We start by querying each target using Facebook’s internal search engine, which takes a name and 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 several limitations arising from the search engine’s web interface, we prepare customized query strings in which we embed the search parameters’ internal identifiers.⁴ Appending these query strings to the search engine’s base URL allows us to execute a large number of search queries. We provide details on the procedure in Appendix B.

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

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

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

tion pertaining to the user’s connections, such as the most frequently appearing attribute value among those connections. Specifically, for some measures, we retrieve the plurality of users connected to the candidate (i.e., friends) and determine the number of friends who share a certain attribute. For example, 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. Further, we weight certain measures with a confidence factor that indicates the likelihood of the measure being accurate. For example, if the alma mater of a candidate is inferred based on a large number of the user’s friends having attended this institution, the confidence factor attached to the inferred attribute is determined to be high; otherwise, it is low. Some measures, depending on the dynamics of the values they generate, are set to be complementary to the match probability, so that they reflect the rarity of a positive match. For example, if we find the alma mater value “Coe College” of a candidate with the common name “James Miller” to match the alma mater of its target, we denominate the probability of the match by the number of Coe College graduates in our sample by the name of James Miller. Lastly, for every target whose portrait we observe during the data collection process (e.g., on the company website or on their LinkedIn profile), we 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.

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

⁶We 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).

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

C. Facebook Friendship Ties

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

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

Second, we disclose connections between users by examining their interactions on the platform. On Facebook, one way for users to interact with one another is through likes, comments, and tags that can be given to other users’ content (e.g., posts, photos). Users may limit the audience that is allowed to see their content, engage with it, or see who has engaged with it to a selected few (e.g., only the user’s friends). While such content will be hidden from the public eye, the visibility of a limited number of profile items—content that Facebook classifies as “public information”—cannot be restricted. In addition to the user’s screen name and gender, these items include the user’s current profile picture and current cover photo. Notably, while the above-stated items remain visible even to non-friends, the audience of users that can engage with them (i.e., by liking, commenting, or tagging) is by default still limited to the user’s friends. This unique constellation allows us to disclose connections between users even if both sides hide their friends by examining user reactions received by these items—if certain additional conditions are met. These conditions include, for example, that a photo cannot be considered for evaluation if users other than the profile holder are tagged in it because its audience (i.e., users that can engage with it) will automatically expand to also include the friends of the user that is tagged in it.

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

D. Mutual Fund Sample

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

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

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

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

E. Fund Manager Sample

The 5,119 mutual funds that pass our initial filters are managed by the 10,029 fund managers.⁸ Before matching the fund managers' Facebook profiles in line with the matching procedure outlined in Section I.B, we compile data on their biographical characteristics. We start by determining the fund managers' most complete names (i.e., middle names, nicknames, birth names, family names adopted upon marriage, and suffixes) by searching the Financial Industry Regulatory Authority's (FINRA's) BrokerCheck database, the Securities and Exchange Commission's (SEC's) Investment Adviser Public Disclosure database, and the CFA Institute's member directory. Next, we gather data on educational degrees, graduation years, work history, birthday, residence, portrait, and family members by conducting a cross-database search across multiple sources including LinkedIn profiles, Bloomberg executive profiles, profiles on The Wall Street Transcript, biographies published by fund firms, filings with the SEC, obituaries on legacy.com, alumni publications on ancestry.com, and newspaper articles on newspapers.com.

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

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

⁸The reported number of fund managers in our sample is subject to two adjustments: (1) We identify and resolve 251 cases in which different identifiers reference the same individual. The majority of these duplicates are attributable to name changes (e.g., Katherine Lieberman (née Buck) is referred to as both "Katherine Buck" and "Katherine Lieberman") or pseudonyms (e.g., Langton C. "Tony" Garvin is referred to as both "Langton C. Garvin" and "Tony Garvin"). (2) We exclude 36 fund managers who we find to have died before Facebook's launch in February 2004. We retain individuals who have died after this date as they may have created Facebook profiles which might be active to the present day (either as memorialized profiles or because Facebook has not been notified about their passing).

F. Firm Officer Sample

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

With these data at hand, we successfully match the Facebook profiles of 67,162 (or 25.1%) of the 267,106 firm officers in our sample.

G. Descriptive Statistics

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

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

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

Panel B further reports statistics on photos (i.e., profile pictures, cover photos, and miscellaneous photos) and reactions (i.e., likes, comments, and tags) received by and collected from these photos. From each profile, we collect all photos uploaded to its various photo albums along with all user reactions received by these photos. Taken together, we collect and evaluate a total of 2.2 million photos and 17.8 million reactions.

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

The bottom part of Panel B presents statistics on the sample individuals’ family member profiles. We manually identify family member profiles during the preliminary data collection process to support the evaluation of candidate profiles or to rule out the existence of an individual’s Facebook membership.¹⁰ Additional family member profiles stem from the sample individuals’ family member profile section. In total, we collect at least one family member for 35% of the fund managers (N=1,383) and for 33% of the firm officers (N=22,396).

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

Table III reports details on the Facebook friendships that we observe between fund managers and firm officers in our sample. We disclose a total of 15,242 fund manager–firm officer connections involving 2,653 unique fund managers and 9,135 unique firm officers. We classify a total of 10,520 connections (or 70%) as “visible,” 3,609 connections (or 24%) as “invisible,” and 1,113 connections (or 6%) as doubly invisible (in accordance with the definition of visibility in Section I.C). Moreover, from the 15,242 disclosed connections, we classify 7,476 (or 49%) as potentially “tradable.” We call a friendship “tradable” if the fund manager’s tenure at the fund overlaps with the firm officer’s tenure at the firm, and the firm’s stock in the same month is held by at least one fund within the same Morningstar category. Of the 7,476 connections that we classify as tradable, we find 2,415 (or 32%) actually to be “traded,” that is, the fund manager’s holdings of the stock overlap with the firm officer’s tenure at the firm. Interestingly,

¹⁰If we are able to identify the Facebook profile of a sample individual’s immediate family member (i.e., spouse, parent, or child) and determine that the sample individual is not among this profile’s friends, we assume that the sample individual is not holder of a Facebook account and no more matching is performed.

while roughly 30% of all visible friendships are traded, the share of these traded connections increases to 36% and 45% when looking at invisible and doubly invisible friendships, respectively, suggesting that the more-hidden connections in our sample have a higher tendency to be activated.

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

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

II. Main Results

A. Portfolio Weights

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

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

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

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

These results are economically important. In summary, the different specifications tell a consistent story: Fund managers place larger bets on their friends’ securities, and these allocations seem to be highly dependent on the particular connection’s visibility.¹¹

B. Performance Tests

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

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

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

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

and

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

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

¹¹In untabulated tests, we also control for industry fixed effects (based on the 48-industry classification used in Fama and French (1997)) and fund fixed effects (using the fund’s Morningstar categories), both leading to more pronounced results than the specification in column 9.

greater weight to funds with relatively large dollar values of investments, and effectively corresponds to a simple investment strategy of investing in the entirety of connected and nonconnected stocks in proportion to the amounts held by our sample of funds. We obtain slightly more pronounced results when applying equal-weighting schemes.

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

Table V illustrates our main results. The table reports the average monthly performance of the funds’ portfolio of Facebook-connected stocks and the portfolio of nonconnected stocks as well as returns yielded by a long-short (LS) portfolio strategy. We first note that the funds’ connected portfolio performs significantly better relative to the nonconnected portfolio across all three performance metrics. From column 4 of the table we see that the connected portfolio earns, on average, a monthly four-factor alpha of 45 basis points compared with zero basis points for the nonconnected portfolio in column 5. Moreover, columns 7 and 8 of the table indicate that the connected portfolio outperforms its size, book-to-market, and momentum benchmark portfolio significantly by an average of 56 basis points per month, whereas the nonconnected portfolio exhibits no such outperformance.

This first set of numbers strongly suggests that fund managers with network ties to the firm officers heading the stocks that they invest in are better informed. At the same time, the evidence on the average return of the nonconnected portfolio indicates that the sample of Facebook-identified fund managers does not generally outperform.

Most interestingly, when forming connected portfolios sorted by fund manager–firm officer friendship visibility, we find that the outperformance increases with the connection’s hiddenness across all performance measures, and that the most-hidden connections (*DoublyInvisible*) are those associated with the largest and most significant abnormal returns accruing to fund managers—on average 135 basis points per month (over 16% alpha per year, t -stat = 3.54). Column 6 indicates that buying doubly invisible-connected holdings and selling short nonconnected holdings delivers a monthly four-factor alpha of 136 basis points on average (significant at the 1% level). The same long-short investment strategy involving invisibly connected stocks exhibits an alpha of 56 basis points per month (significant at the 10% level). In contrast, trad-

ing visibly connected stocks provides a positive but insignificant four-factor alpha of 17 basis points per month. Results are similar in magnitude when looking at DGTW-adjusted returns. Overall, our tests suggest that hidden connections on average are the most valuable connections in the fund manager–firm officer network.

To examine whether the managerial information that we seem to capture has implications for the stocks’ fundamental values, we explore the evolution of the connected portfolios using event-time returns. Specifically, we compute value-weighted cumulative abnormal returns for the first 18 months following a fund’s purchase of a connected stock, sorted by friendship visibility. Consistent with the results in Table V, we find abnormal returns to increase with the level of connection hiddenness—we report these findings in Figure 5. Over the course of 18 months, the portfolio of stocks formed based on doubly invisible connections does not fall below the portfolio formed based on invisible connections, which in turn does not fall below portfolio of visibly connected stocks. The figure further indicates that the returns accrue gradually over the course of the subsequent months. The information that we seem to capture eventually goes into the stock prices and then never reverses.

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

By incorporating tie strength into the equation, we take into account that online social networks allow users to keep many different friends, some of which might be closer friends, while others might be more casual friends or acquaintances. From there on, given our data, many paths open up to measure tie strength. Drawing on a substantial body of research on social networks indicating that online interactions between individuals are diagnostic of stronger real world ties,¹² we here choose to assess tie strength by examining the subset of fund manager–firm officer pairs from our sample that interact with each other on the Facebook platform. We explore alternative measures of tie strength in the robustness section.

Note that the prevalent interaction modes on Facebook are likes, tags, and comments that users give to other users’ profile content or that users receive on their own profile content (hereafter, reactions). For the 1,927 fund managers and 5,152 firm officers that form the 7,476 connections in our sample that we classify as tradable (see Table III), we collect 3.97 million reactions given to 309 thousand photos (including to posts with photographic elements) uploaded by these particular individuals. Of these 3.97 million reactions, we find 10,318 to have

¹²One might as well argue that strongly tied friends could be less likely to interact on Facebook, because strong ties often lead to other means of interaction (e.g., in-person, phone calls, texting). However, a substantial body of research on social networks suggests that more closely tied individuals use a greater variety of media to interact with each other online and offline rather than substituting these instruments (e.g., Haythornthwaite (2005)), further evidenced by findings that Facebook interactions serve as an accurate proxy for real world friendship tie strength (Jones, Settle, Bond, Fariss, Marlow, and Fowler (2013)).

been exchanged between the particular fund manager–firm officers pairs. Taking a crude first look at the data, when we decompose the 7,476 tradable fund manager–firm officer connections into 2,415 traded and 5,061 nontraded pairs, we note that 29% of all traded pairs have mutually interacted with the other’s profile content at least once, compared to 21% of the nontraded pairs. An example of the data on interactions between a fund manager and his set of firm officer friends is presented in Appendix D.

In Table VI, we adjust our above performance analysis and construct portfolios sorted by friendship visibility and a reaction dummy. The “Reaction” portfolio includes the set of connected fund-month-stock observations for which we find the associated fund manager–firm officer pair to have mutually interacted with the other’s profile content at least once. The “No Reaction” portfolio consists of the fund’s connected stocks for which no interaction takes place between the particular fund manager–firm officer pair. Note that doubly invisible connections are excluded from the No Reaction assessment, as these, by construction, are identified based on the sample individuals’ interactions on the platform (see Section I.C).

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

Before moving to the next section, we examine a further opportunity that our data offer to explore whether some fund manager–firm officer connections might be more important than others. Although unsubstantiated by theoretical predictions, we consider the question whether the performance of connected holdings may also depend on the respective firm officer’s seniority level. For this empirical exercise we use BoardEx’s categorization of role seniority, that is, the subdivision of roles occupied by management personnel into senior managers, executive directors, and supervisory directors (refer to Section I.F for the definitions of those roles). We then

allocate fund holdings into portfolios based on whether any of the fund’s current fund managers and a current firm officer of the given firm are friends on the Facebook platform (*AllSeniorities*); and whether the connected firm officer is a senior manager (*SM*); an executive director (*ED*); or a supervisory director (*SD*).

The results are summarized in Table VII. The table indicates that fund managers seem to possess more information about firms when they are friends with the firms’ executive directors and supervisory directors, as opposed to when they are friends with the firms’ senior managers. Trading fund managers’ executive director and supervisory director connections yields an average monthly four-factor alpha of 80 and 102 basis points, respectively (significant at the 5% and 1% levels). More broadly, our results suggest that friendship ties with c-suite executives and board members are the most advantageous to financial agents.

C. Connected Not Held Portfolios

Since we are generally interested in testing the hypothesis of whether or not connected fund managers are better informed, and since mutual funds are restricted from short selling, the funds’ active portfolio allocations may not reflect the funds’ full information advantage. Given that our previous findings suggest that the funds’ portfolio allocations reflect positive information about the fund managers’ connected securities, we would expect that negative information should manifest itself in the performance of the fund managers’ connected stocks that are not held by the funds. To gain further insights into this hypothesis, using a similar portfolio construction approach as in the prior subsection, we next investigate returns on connected stocks that fund managers choose not to hold. Specifically, for each fund-period observation, the stocks in each fund portfolio are sorted into Connected Held (CH) and Connected Not Held (CNH) portfolios. We define Connected Not Held stocks as stocks that are not held by the particular fund and are headed by a fund manager’s then-active firm officer Facebook friend while in the same month being held by at least one other fund from the same Morningstar category. Based on the assumption that funds did not change their holdings between two reporting dates, we construct monthly portfolios by keeping non held stocks in the portfolio until the next reporting date, when the actual portfolios are rebalanced to reflect changes in holdings. Within a given portfolio, we weight the non held stocks’ returns by the stock’s respective market capitalization. We then compute value-weighted returns by averaging across funds, weighting each fund portfolio return by the fund’s total net assets value. The resulting sample includes 2,613 distinct funds and 177,156 fund-month observations covering the period from January 1984 through December 2020. The average monthly observation of a fund’s Connected Not Held portfolio consists of 2.96 stocks pertaining to the fund managers’ 2.25 connected firm officer friends.

Table VIII compares the average performance of the Connected Held and the Connected Not Held portfolios. The Connected Not Held portfolio exhibits no significant outperformance (columns 5 and 6). As shown in columns 8 and 9, the portfolio of connected stocks held by the fund managers tends to outperform the portfolio of connected stocks that fund managers choose not to hold. For invisible and doubly invisible connections, this outperformance amounts to a statistically significant monthly four-factor alpha of 57 and 119 basis points per month, respectively, with DGTW-adjusted returns being of a similar magnitude.

The results in Table VIII suggest that fund managers do not simply weight all connected stocks at all times, as a familiarity explanation might suggest, but instead actively decide which connected stocks to hold and which not to hold. Moreover, note that these results also provide strong evidence against potential endogeneity concerns.

D. Returns Around Corporate News

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

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

To obtain information on firm-specific news events, we use data available via the RavenPack Analytics database (RavenPack). The service provides real-time collection and analysis of entity-related news using natural language processing and machine learning techniques. The RavenPack data is extracted from Dow Jones Newswires, The Wall Street Journal, FactSet, and tens of thousands of other traditional and social media sources. To ensure that the news items that we use for our test actually convey material information about the firms rather than information about market movements, we follow Weller (2018) in excluding news reports on trading or prices (technical analysis signals, stock price movements, order imbalance reports)

and news reports on investor relations themes (typically announcements of future information revelation dates). We filter the data down further to only include news in which RavenPack considers the related firm to be playing a key role (i.e., news items with an “event relevance” score of 100). To remove duplicated news reports, we isolate the first news item in chains of items that relate to the same subject (using RavenPack’s “event similarity days” analytic). Following these preliminary data cleaning steps, we use the CUSIP bridge provided by RavenPack’s entity mapping file to merge RavenPack’s firm identifier (rp entity id) with CRSP’s firm identifier (permco) and map the firms’ news items to their stock returns. We align news items and stock returns using the New York Stock Exchange trading calendar. In this procedure, we follow a close-to-close rationale in accordance with CRSP’s return formula.¹³ 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, Nonconnected Held, and Connected Not Held portfolios on days with and without news announcements. At first we note that the Connected Held portfolio earns significantly positive returns around news announcements across all measures of visibility, which are most pronounced in the *DoublyInvisible* specification with a daily four-factor alpha of 6 basis points (significant at the 1% level). By contrast, the returns of the Connected Held portfolio on days without news announcements are small and statistically indistinguishable from zero. These findings suggests that most of the observed return premium is generated on days with news headlines. The same pattern holds true for stocks in the Nonconnected Held portfolio, but importantly, a long-short strategy that buys connected stocks on news days and sells short nonconnected stocks on news days yields a daily four-factor alpha of 2.2 basis points (significant at the 10% level). This outperformance almost doubles to 4 basis points (significant at the 1% level) in the *DoublyInvisible* specification. A similar picture emerges when looking at the Connected Not Held portfolio: Again we find positive returns that are concentrated around news announcements, however, the average return of a long-short portfolio that buys the portfolio of connected stocks and sells short the portfolio of connected not held stocks reveals that the Connected Held portfolio experiences news returns significantly greater on average than those of the Connected Not Held portfolio, corroborating the evidence presented in section Section II.C.

¹³For 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 using multivariate cross-sectional Fama-MacBeth regressions (Fama and MacBeth (1973)) to check for the persistence of returns earned on the fund managers' hiddenly connected stocks. This allows us to control for several other firm- and stock-level characteristics that have been found to contain relevant pricing information and are commonly used in the literature. These control variables include firm size (ME), book-to-market ratio (BM), momentum (MOM), short-term reversal (STR), industry momentum ($IMOM$), and standardized unexpected earnings (SUE). The dependent variable in the Fama-MacBeth regressions is next month's stock excess returns. We calculate the main regressor of interest, $DiffWeight_{k,t}$, for each month t and stock k as the difference between the average weight that Facebook-connected funds invest in the stock and the average weight that all other funds invest in the stock. To make results comparable across all models, we standardize $DiffWeight_{k,t}$ by dividing it by its cross-sectional standard deviation each month.

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

B. *Potential Selection Bias Concerns*

By selecting only fund managers who we find to have a Facebook account, we are likely introducing aspects of selection. For fund-month observations prior to Facebook's widespread adoption in the 2005–2010 period, the fund managers whose Facebook profiles we are able to identify must have been comparatively young at their time of active management. Here, a possible concern is that the Facebook-identified fund managers who have managed money in the early years are ex post successful by design, have a lot of connections, and may therefore dominate our identification of connected versus nonconnected stock holdings. These fund managers

may have a large high-profile network because they were successful, not because the network helped them to be successful. This is true for every time period (including today), but it might be expected to have the largest impact in the earlier sample observations (as the more sparser Facebook sample might be more dominated by these selected fund managers).

Indeed, when comparing the characteristics of Facebook-identified and non-identified fund managers, we find the Facebook-identified fund managers to be significantly younger on average in the earlier years of our sample.¹⁴ These data are presented in Figure 6, which compares the average age of all fund managers in the universe of domestic actively managed U.S. equity mutual funds across our sample period (solid line) to both the average age of Facebook-identified fund managers (dotted line) and the average age of non-identified fund managers (dashed line).

Although Facebook-identified fund managers on average are up to eight years younger in the earlier years of our sample, we note that the age gap converges to become statistically indistinguishable from zero in the later years of our sample (post-2010). However, by selecting on age, we may also select on sophistication. This may even hold true for the post-2010 period (in a time when there was widespread adoption of Facebook by the demographic of the average fund manager in our sample) and up to the present day because our study selects on fund managers who choose to have a Facebook account. It could be that the choice not to join Facebook is deliberate; that is, these fund managers may have the scope or ability to have a Facebook account, but deliberately choose not to. Or, some fund managers may not be interested in using Facebook because they have different ways of connecting to others (e.g., they substitute Facebook usage with a more exclusive network tool or different technology for connecting with the people they find it optimal to stay connected to). However, when comparing the performance of Facebook-identified and non-identified funds, we do not find any statistical differences between the two groups of funds, suggesting that our Facebook matching does not introduce a selection bias toward more sophisticated fund managers. Figure 7 illustrates the fund performance of Facebook-identified (dashed line) and non-identified funds (solid line) across our sample period. For this comparison, fund performance is calculated as annualized four-factor alpha using funds' monthly net returns.

C. Additional Tests

Having already examined the persistence of returns earned on hidden connections in a multivariate regression framework in Section III, we now turn to a battery of additional robustness exercises to examine the general consistency of returns earned on connected stocks across different subsamples. To this end, we rerun the analysis of fund managers' holdings of connected stocks as in the first row of Table V. We report results in Table XI, measured as average

¹⁴Interestingly, when comparing other characteristics of Facebook-identified and non-identified fund managers, we find no systematic differences neither in gender nor in dimensions that have been shown to be negatively (or positively) related to fund performance, including MBA degrees, Ivy League enrollments, CFA certifications, and college SAT percentile ranks.

monthly four-factor alphas. In Panel A we use alternative approaches to assessing tie strength of fund manager–firm officer connections. In Panel B we examine the robustness of our analyses across various subperiods of our initial sample. In Panel C we investigate robustness to including additional fund characteristics. In Panel D we undertake tests to further abate potential reverse causality concerns. The starting point to building subsamples are the 2,415 traded fund manager–firm officers pairs reported in Table III for which we find a fund manager’s holdings of the stock to overlap with the firm officer’s tenure at the firm.

The specifications (1) through (3) in Panel A assess tie strengths of the observed fund manager–firm officer connections by exploring each particular individual’s friendship ties with the other’s family members. These specifications are motivated by the assumption that connected individuals that are acquainted with members of each other’s family may be more closely tied. To disclose such connections, we use data collected from the roughly 59 thousand Facebook profiles belonging to our sample individuals’ family members.¹⁵ Specification (1) indicates a connection premium of 84 basis points (significant at the 5% level) for the subsample of pairs for which we find one or both individuals in a connected pair also to be connected to at least one member of the other’s family. In specification (2), we find trades pertaining to the subsample of connected pairs for which we find one or both individuals in a pair to be connected to the other’s spouse to yield a return of 93 basis points (significant at the 5% level). Interestingly, the subsample of connected pairs in specification (3) for which we find the pair’s respective spouses to be connected to one another yields a premium of 128 basis points (significant at the 1% level). The three remaining specifications in Panel A proxy crudely for physical propinquity, which is classically regarded as a necessary condition for a friendship tie to form (e.g., Festinger, Schachter, and Back (1950)). For instance, subsamples formed for the connected fund manager–firm officer pairs that were either classmates in high school (specification (4)) or attended the same college (specification (5))¹⁶ both produce large and significant results (at the 5% level). The connection premium is smaller in magnitude for a subsample of connected pairs with matching hometowns (that also are in the same age group by no more than a one year difference), but loses significance. Overall, these results in Panel A corroborate our findings in Table VI.

¹⁵Refer to Panel B of Table I for a more detailed breakdown of the data collected on family members. Family member profiles undergo the same treatment as the profiles of the main protagonists.

¹⁶The following data-cleaning steps are applied: First, in dealing with universities with multiple campuses, we treat each satellite campus as a separate institution (e.g., we treat the University of Texas campuses at Austin and Arlington as separate institutions). Second, we assign all business schools to their corresponding universities or hosting institutions (e.g., we treat the McCombs School of Business and the University of Texas at Austin as the same institution). Third, if no campus can be determined for an individual’s degree from an institution with multiple campuses, we assign the observation to the university system’s main campus (e.g., we assign graduates of Texas A&M University to the school’s main campus located in College Station).

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

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

The non-positive outperformance of nonconnected stocks held (reported in Table V) and the returns of connected stocks not held (reported in Table VIII) are hard to reconcile with a reverse causality story. It is conceivable but unlikely that fund managers’ past outperformance in specific stocks and time periods is related to forming subsequent Facebook connections with the respective firm officers but no connections with other firm officers. However, to ensure with a fair degree of certainty that tie formation is independent of later success in the professional career, in Panel D, we form two more subsamples. In specification (13), in order to limit the sample of fund-month observations to investment decisions that occurred after the friendship tie was most likely formed, we restrict it to observations pertaining to all fund manager–firm officer pairs that meet the criteria of specifications (4) through (6), i.e., pairs that were high school classmates, overlapped in the pursuit of their degrees while attending the same college, or that come from both the same hometown and age bucket. In addition, in specification (14), we build a subsample of fund-month observations following the earliest Facebook connection date that we are able to identify.¹⁷ We find the outperformance of connected pairs in both subsamples to remain large and statistically significant (at the 5% level), suggesting that most of the correlation that we uncover between fund manager–firm officer connections and stock performance is driven by network effects, rather than the other way around.

IV. Conclusion

This paper explores hidden connections based on a sample of 71,000 fund managers and firm officers using data from Facebook, the world’s largest social networking platform. Making use of unique aspects of Facebook’s functionality, we are able to measure the extent to which the network ties among fund managers and firm officers are visible versus hidden. We find

¹⁷To identify a pair’s earliest connection date we proceed in two ways. First, we determine the timestamp associated with the earliest interaction between the particular pair of individuals on the Facebook platform. Second, we resort to the date when the friendships was first observed in a friends list.

that the more hidden a network tie is, the more valuable the information that appears to be associated with the trading across it. The premium on hidden connections remains strong and significant through the present day. It seems to be neither driven by a familiarity or selection story—as fund managers seem to be correctly timing when to hold (and when to avoid) stocks of the firms to which they are hiddenly tied to—nor by any industry, firm type, time period, or style criteria.

Stepping back from our setting, the costs of establishing and maintaining connections across network structures continue to decrease. As they do, we are observing that networks across all aspects of behavior, influence, and information transfer are largely becoming richer and more complex, heightening the need to understand their hidden aspects. Future research should explore the impact of these nodes in greater depth, potentially even estimating the impact of biased inference based on failing to account for hidden ties. This could be done, for instance, by identifying a small subsample of a network in which all nodes are “fully revealed,” comparing it to the remainder of the network, comprising both transparent and shrouded nodes, and estimating the different dynamics therein. Richer inferences derived from these types of comparisons have the potential to alter optimal responses in complex networked system dynamics and the understanding of economy-wide shock propagation.

Appendix A. Variable Definitions

Table A.I. Descriptions of Main Variables and Sources

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

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

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Table A.I – continued from previous page.

Variables	Description	Source
Reaction	A fund-month-stock observation is added to the Reaction portfolio if any of fund i 's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform, and the individuals mutually react to the other's content on the Facebook platform; otherwise, it is added to the No Reaction portfolio.	MS, CRSP, FB
AllSeniorities	A fund-month-stock observation is added to the AllSeniorities portfolio if any of fund i 's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform—irrespective of the firm officer's role.	MS, CRSP, FB, BO
SM	A fund-month-stock observation is added to the SM (Senior Manager) portfolio if any of fund i 's fund managers in period t and a firm officer of stock k in period t in the role of a senior manager are friends on the Facebook platform.	MS, CRSP, FB, BO
ED	A fund-month-stock observation is added to the ED (Executive Director) portfolio if any of fund i 's fund managers in period t and a firm officer of stock k in period t in the role of an executive director are friends on the Facebook platform.	MS, CRSP, FB, BO
SD	A fund-month-stock observation is added to the SD (Supervisory Director) portfolio if any of fund i 's fund managers in period t and a firm officer of stock k in period t in the role of a supervisory director are friends on the Facebook platform.	MS, CRSP, FB, BO
Connected Not Held	A fund-month-stock observation is created and added to the Connected Not Held portfolio if any of fund i 's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform, and stock k is not held by the fund i in period t , while stock k is held by at least one other fund from fund i 's Morningstar category.	MS, CRSP, FB
News	A fund-day-stock observation is added to the News portfolio if any of fund i 's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform, and stock k was the subject of a news announcement on day t ; otherwise, it is added to the No News portfolio.	MS, CRSP, FB, RP
Panel B: Weight Regressions		
Stock Weight $w_{f,s,t}$	Fund i 's net assets invested in stock k at time t divided by the total net assets of fund i 's equity portfolio at time t .	MS, CRSP, CS

Continued on next page.

Table A.I – continued from previous page.

Variables	Description	Source
$Style_{i,k,t}$	Percentage of net assets that fund i invests in period t in stock k 's 5x5x5 portfolio bucket, determined as in Daniel et al. (1997).	MS, CRSP, CS
$pME_{i,k,t}$	Market value of equity of stock k , held by fund i , in time t .	CRSP, CS
$pBM_{i,k,t}$	Book value of stock k relative to market value of stock k , held by fund i , in time t .	CRSP, CS
$R12_{i,k,t}$	Stock k 's return from the end of month $t-12$ to the end of month t .	CRSP
Panel C: Fama-Macbeth Regressions		
$ExcessRet_{k,t}$	Stock k 's excess return in period t . $ExcessRet_{k,t}$ is stock k 's raw return in period t obtained from CRSP. $RiskFree_t$ is the U.S. risk free rate in period t obtained from Kenneth R. French's website.	CRSP, KF, AE
$DiffWeight_{k,t}$	The difference between the average weight that FB-connected or FB-interacted funds in period t simultaneously invest in stock k (i.e., stock buys) and the average weight that all other funds invest in stock k in period t .	MS, FB, AE
$ME_{k,t}$	Stock k 's market equity in month t , calculated as stock k 's price at the end of month t times its shares outstanding at the end of month t . If $ME_{k,t}$ is non-positive, the observation is considered to be missing. The variable is log-transformed.	CRSP, AE
$BM_{k,t}$	Stock k 's log-transformed book-to-market ratio at the end of month t , calculated as the firm's book equity from the last fiscal year (ending at least six months and less than 18 months ago) divided by stock k 's ME at the end of the month of the last fiscal year ending. If book equity or ME are non-positive, the observation is considered missing.	CRSP, CS, AE
$MOM_{k,t}$	Stock k 's momentum at the end of month t , calculated as stock k 's return from the end of month $t-12$ to the end of month $t-1$.	CRSP, AE
$STR_{k,t}$	Stock k 's short-term reversal at the end of month t , calculated as stock k 's return from the end of month $t-1$ to the end of month t .	CRSP, AE
$IMOM_{k,t}$	Stock k 's industry momentum at the end of month t , calculated as the value-weighted return of stock k 's Fama-French-48 industry from the end of month $t-1$ to the end of month t .	CRSP, CS, KF, AE
$SUE_{k,t}$	Stock k 's standardized unexpected earnings measure at the end of month t , calculated as in Livnat and Mendenhall (2006).	CRSP, CS, AE

Appendix B. Facebook Search Query Strings

Here we describe our approach to issuing queries to the Facebook search engine (SE). Note that organizations can set up “pages” on Facebook to share content, engage with their audience, or link with their customers. This in turn enables Facebook users to signal their association with these organizations on their profiles (e.g., attendance of a college, affiliation with a firm). If the audience with whom this association is shared is not restricted, the SE will return the particular user’s profile when queried for the specific parameter. Each Facebook page is automatically assigned a numeric identifier (PageID) upon registration, which is present in the page’s source code. We embed these PageIDs into customized Base64-encoded JSON strings and append them to the SE’s URL as part of a query string. This allows us to automatically assign desired parameters to the SE’s filters when passing the URL to the server. A JSON string may be composed of up to three nested name-argument pairs which correspond to the SE’s search filters (city, education, work). For illustration, suppose that we want to search for “James Smith,” educated at Harvard University (fb.com/Harvard, PageID 105930651606) and working at Citigroup (fb.com/citi, PageID 152431441489088). In conformity with Facebook’s JSON syntax, we write:

```
{ "school": "{ \"name\": \"users_school\", \"args\": \"105930651606\" }", 1
  "employer": "{ \"name\": \"users_employer\", \"args\": \"152431441489088\" }" } 2
```

We next convert this JSON string into the Base64 format:

```
eyJzY2hvb2w6MCI6IntcIm5hbWVcIjpcInVzZXJzX3NjaG9vbFwiLFwiYXJnc1wiOlw 1
iMTA1OTMwNjUxNjA2XCJ9IiwKImVtcGxveWVyOjAiOiJ7XCJyZW1lXCI6XCJ1c2Vyc1 2
9lbXBsb3llclwiLFwiYXJnc1wiOlwiMTUyNDMxNDQxNDg5MDg4XCJ9fQ== 3
```

Paired with a parameter q that takes the name of the individual separated by the percent-encoded value for the space character (“%20”), the Base64-encoded JSON string can then be used as a *filter* parameter in a query string that may be appended to the SE’s URL:

Base URL	SE’s path	Query string with q and filter parameter
https://facebook.com/search/people?q=James%20Smith&filters=eyJzY2hvb2w6MCI6IntcIm5hbWVcIjpcInVzZXJzX3NjaG9vbFwiLFwiYXJnc1wiOlwiMTA1OTMwNjUxNjA2XCJ9IiwKImVtcGxveWVyOjAiOiJ7XCJyZW1lXCI6XCJ1c2Vyc19lbXBsb3llclwiLFwiYXJnc1wiOlwiMTUyNDMxNDQxNDg5MDg4XCJ9fQ==		
	Screen name	Base64-encoded JSON

Appendix C. Matching Profiles Through Backlinks

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

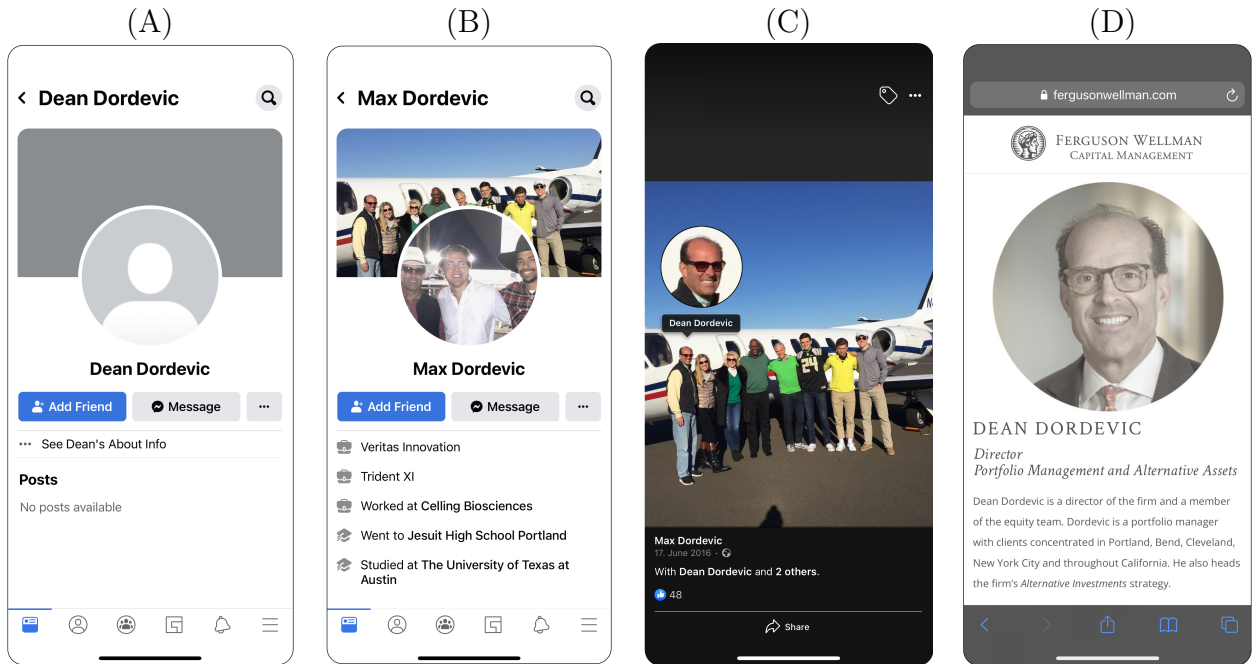


Fig. C.I. Matching Profiles with Restrictive Privacy Settings. This figure presents the restricted profile of one of our sample individuals (subfigure A); the profile of the sample individual's son (subfigure B); a photo of the sample individual on the son's profile (subfigure C); and a portrait of the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

Appendix D. Facebook Interactions

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

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

REFERENCES

- Cai, Ye, and Merih Sevilir, 2012, Board connections and M&A transactions, *Journal of Financial Economics* 103, 327–349.
- Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.
- Chen, Huaizhi, Lauren Cohen, Umit Gurun, Dong Lou, and Christopher Malloy, 2020, IQ from IP: Simplifying search in portfolio choice, *Journal of Financial Economics* 138, 118–137.
- Chevalier, Judith, and Glenn Ellison, 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* 114, 389–432.
- Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008, The small world of investing: Board connections and mutual fund returns, *Journal of Political Economy* 116, 951–979.
- Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2010, Sell-side school ties, *Journal of Finance* 65, 1409–1437.
- Coval, Joshua D., and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811–841.
- Cremers, Martijn, Antti Petajisto, and Eric Zitzewitz, 2013, Should benchmark indices have alpha? Revisiting performance evaluation, *Critical Finance Review* 2, 1–98.
- Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.
- Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2011, Holdings data, security returns, and the selection of superior mutual funds, *Journal of Financial and Quantitative Analysis* 46, 341–367.
- Engelberg, Joseph, Pengjie Gao, and Christopher A. Parsons, 2012, Friends with money, *Journal of Financial Economics* 103, 169–188.

- Engelberg, Joseph, Pengjie Gao, and Christopher A. Parsons, 2013, The price of a CEO's rolodex, *Review of Financial Studies* 26, 79–114.
- Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.
- Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.
- Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.
- Festinger, Leon, Stanley Schachter, and Kurt Back, 1950, Social pressures in informal groups; a study of human factors in housing. .
- Haythornthwaite, Caroline, 2005, Social networks and internet connectivity effects, *Information, Community & Society* 8, 125–147.
- Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu, 2007, Whom you know matters: Venture capital networks and investment performance, *Journal of Finance* 62, 251–301.
- Jones, Jason J., Jaime E. Settle, Robert M. Bond, Christopher J. Fariss, Cameron Marlow, and James H. Fowler, 2013, Inferring tie strength from online directed behavior, *PloS ONE* 8, 1–6.
- Kazemi, Vahid, and Josephine Sullivan, 2014, One millisecond face alignment with an ensemble of regression trees, in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1867–1874.
- Livnat, Joshua, and Richard R. Mendenhall, 2006, Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts, *Journal of Accounting Research* 44, 177–205.
- Massa, Massimo, Jonathan Reuter, and Eric Zitzewitz, 2010, When should firms share credit with employees? Evidence from anonymously managed mutual funds, *Journal of Financial Economics* 95, 400–424.

- Patel, Saurin, and Sergei Sarkissian, 2017, To group or not to group? Evidence from mutual fund databases, *Journal of Financial and Quantitative Analysis* 52, 1989–2021.
- Pool, Veronika K., Noah Stoffman, and Scott E. Yonker, 2015, The people in your neighborhood: Social interactions and mutual fund portfolios, *Journal of Finance* 70, 2679–2732.
- Weller, Brian M., 2018, Does algorithmic trading reduce information acquisition?, *Review of Financial Studies* 31, 2184–2226.

Table I. Summary Statistics: Facebook Data

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

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

Continued on next page.

Table I. – continued from previous page.

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

^{a)} Note that Panel A reports statistics on data disclosed by the sample individuals on their Facebook profiles, while Panel B reports statistics on Facebook data that—albeit being linked to the individuals’ profiles in one way or the other—have not necessarily been gathered from these profiles, but may also stem from other sources (e.g., while Panel A indicates that 920 fund managers from our sample disclose at least one of their family members’ profiles, Panel B indicates that the data include family member profiles belonging to 1,383 fund managers—3,390 members in total).

^{b)} Collecting photos is computationally expensive, which is why ~40% of the firm officers’ photos were not yet collected as of this draft.

Table II. Summary Statistics: Facebook-identified Sample of Funds

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

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

Table III. Fund Manager–Firm Officer Facebook Friendships

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

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

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

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

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

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

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

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

Table VI. Portfolio Sorts: Monthly Returns on Connected Stocks with Interactions by Visibility

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

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

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

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

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

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

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

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

Table IX. Portfolio Sorts: Daily Returns on Connected Stocks by Visibility and News Announcements

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

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

Table X. Returns: Cross-sectional Fama-Macbeth Regressions by Visibility

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

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

Table XI. Additional Robustness Tests

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

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

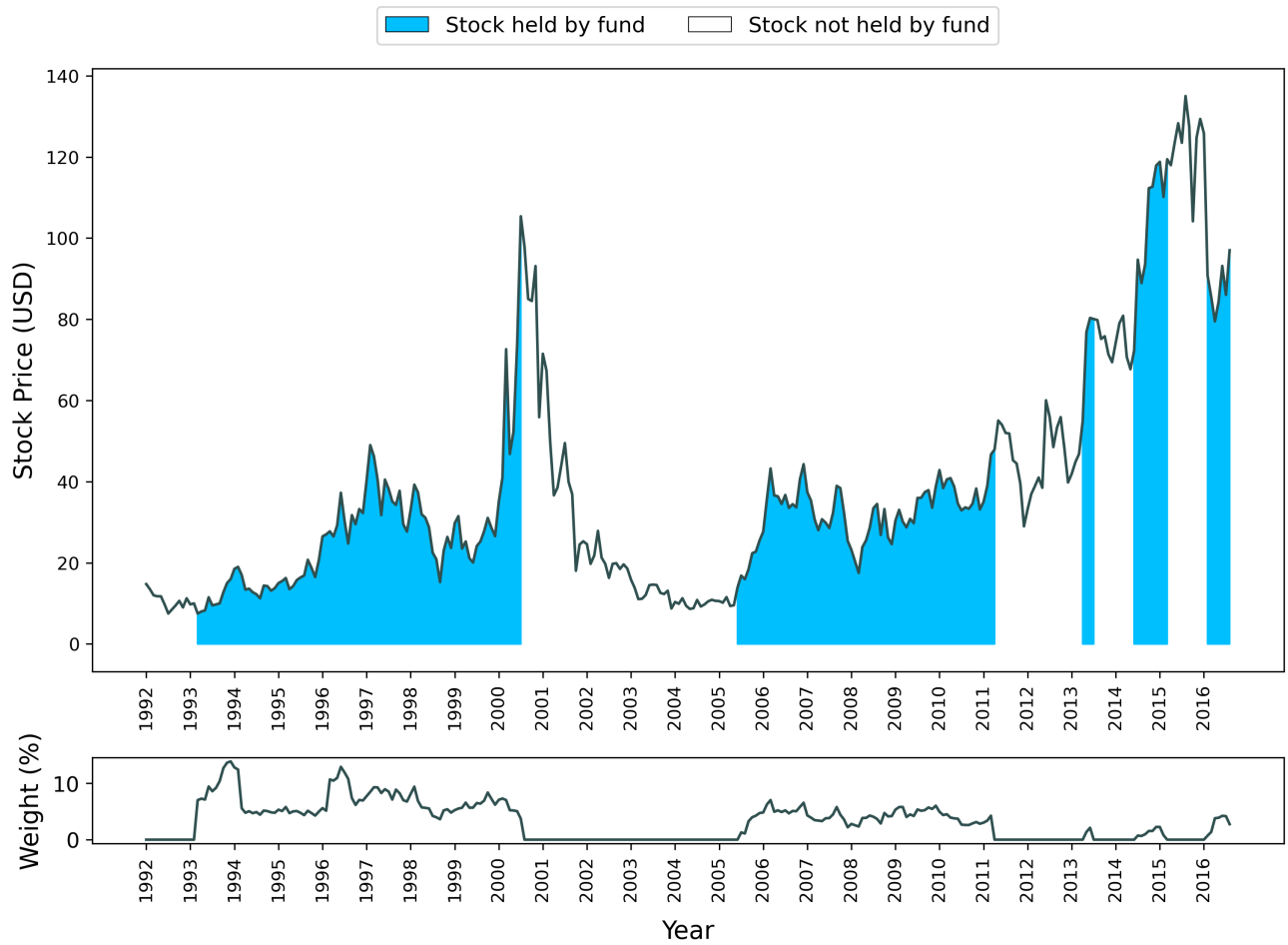


Fig. 1. Fund Manager Bergelmir’s Holdings in Ananke’s Firm. The upper chart of this figure plots the evolution of the stock price of CEO Ananke’s stock in the period 1992–2016. The blue shaded area indicates the time period during which Ananke’s stock was held by Bergelmir’s fund. The white shaded area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

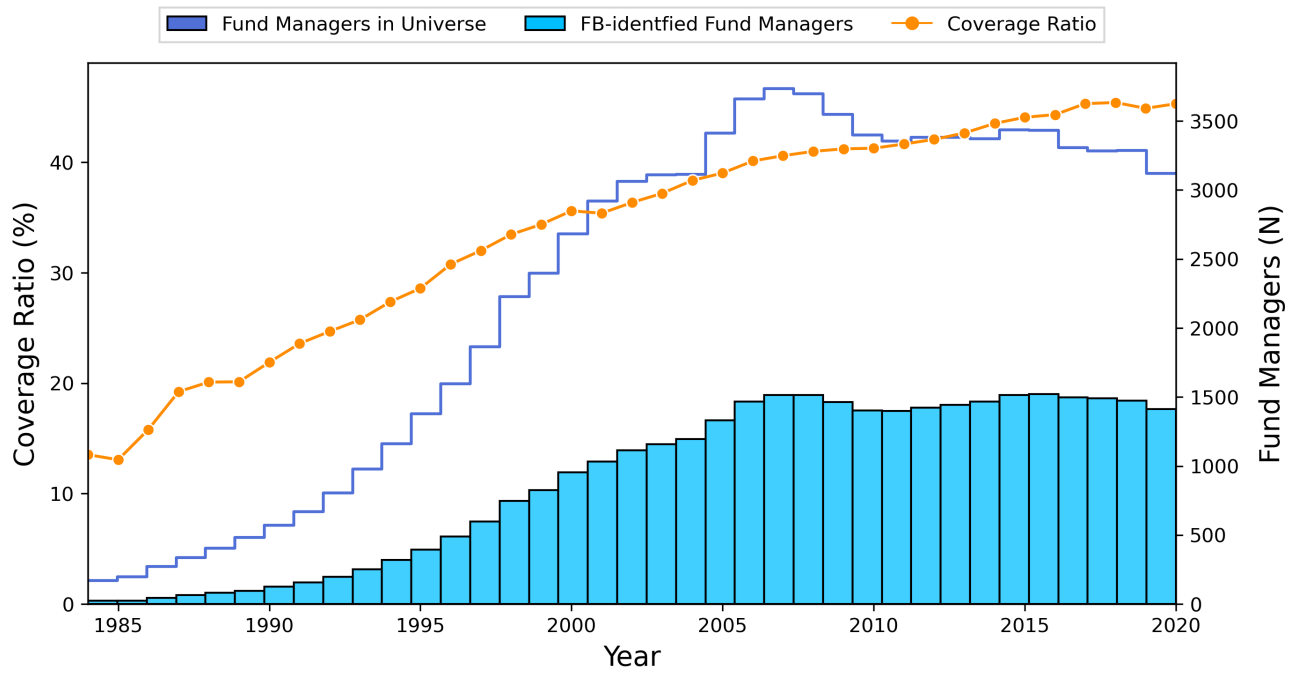


Fig. 2. Coverage of Facebook-identified Fund Managers. This figure illustrates our sample coverage (orange dotted line) of Facebook-identified (FB-identified) fund managers (blue bars, absolute values) relative to all fund managers serving in the U.S-domiciled benchmark universe of actively managed U.S.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

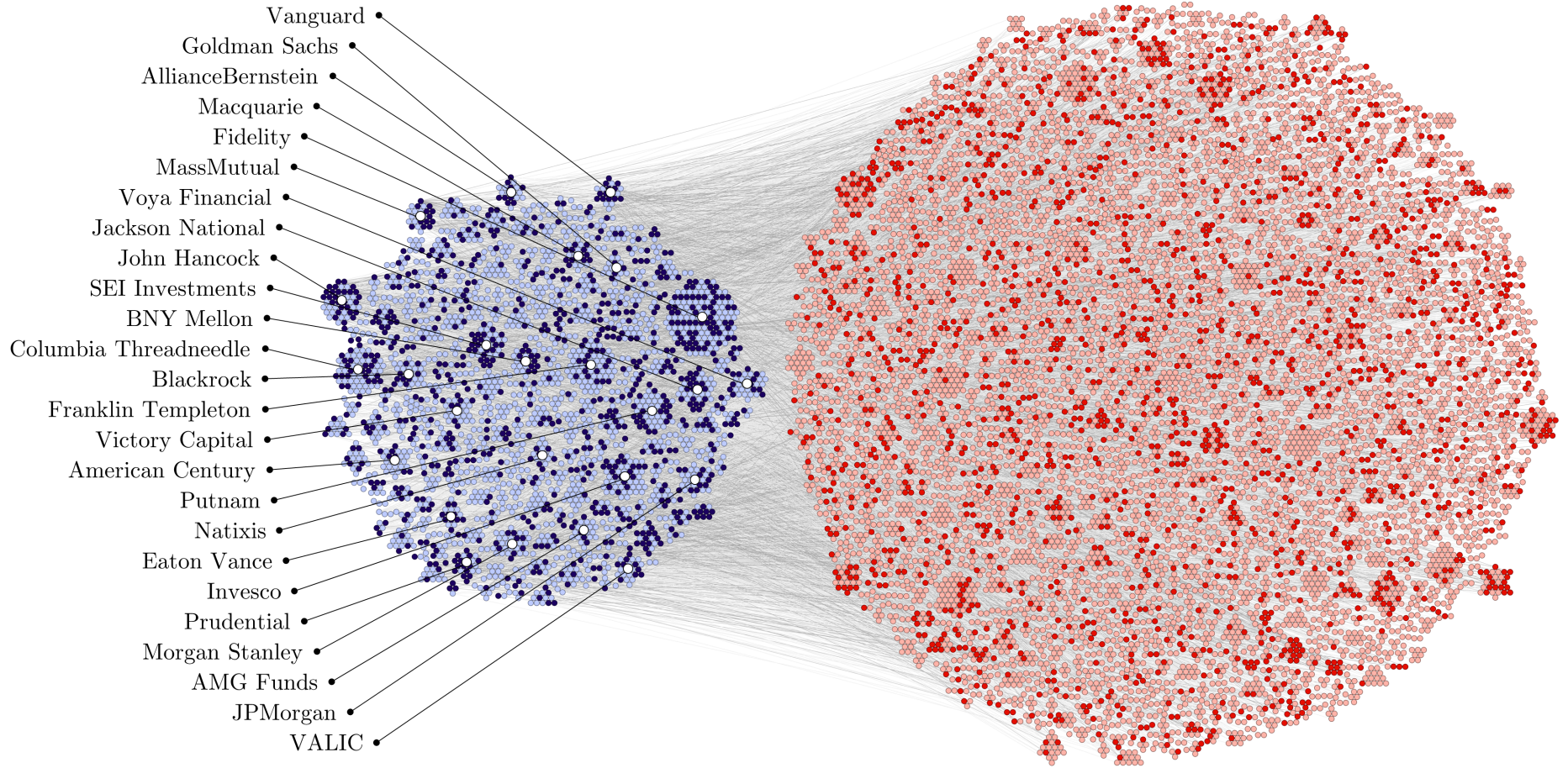


Fig. 3. Graph of Connected Fund Manager–Firm Officer Pairs. This graph illustrates the subsample of fund managers (blue shades) and firm officers (red shades) that form the subset of connections that we classify as tradable. We denote traded fund manager–firm officer connections within the set of tradable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

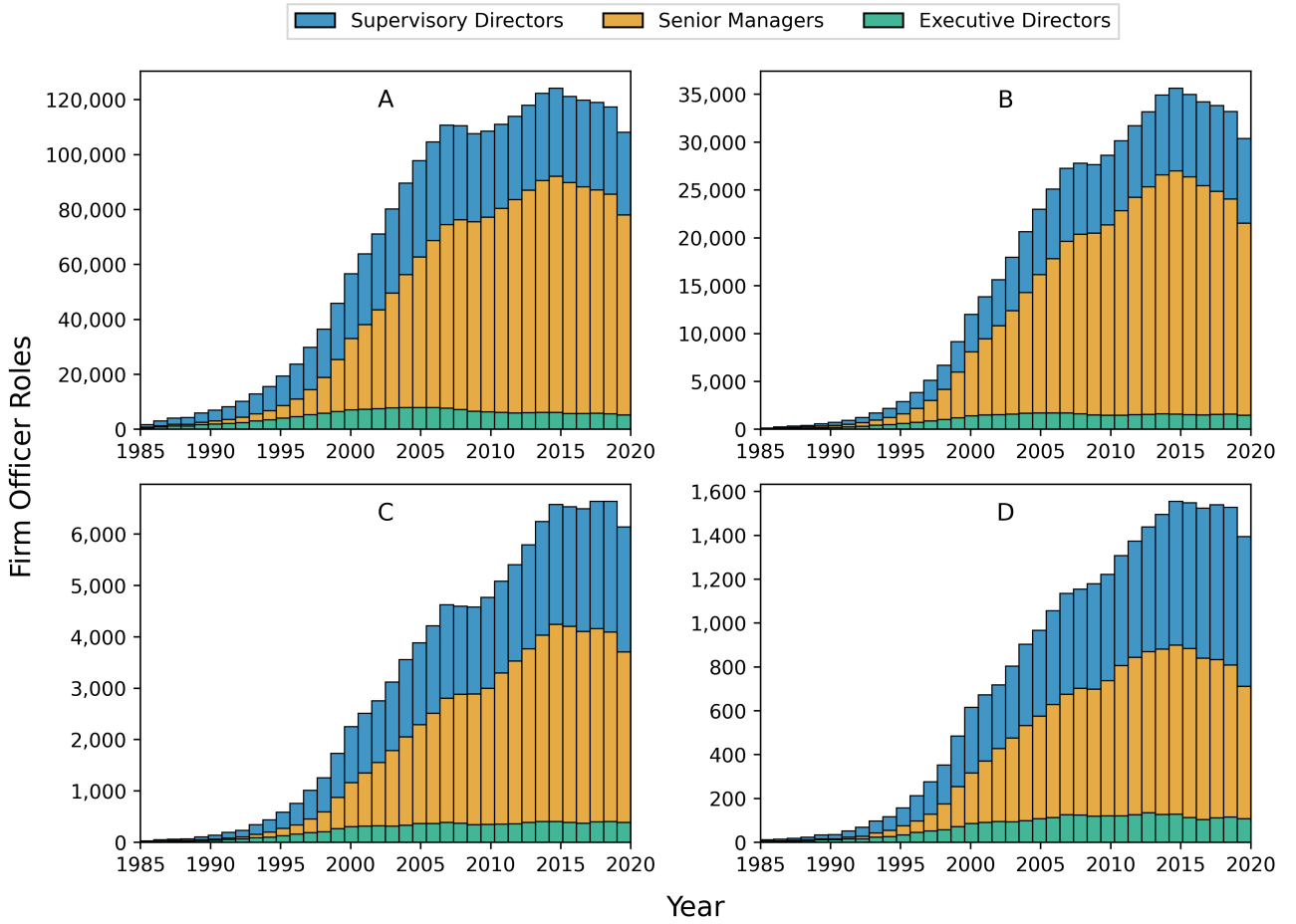


Fig. 4. Distribution of Firm Officer Roles by Seniority. This figure illustrates the distribution roles occupied by the sample of firm officers heading the firms held by Facebook-identified funds, broken down by seniority level. Subplot A details the distribution of roles occupied by all 267,106 firm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

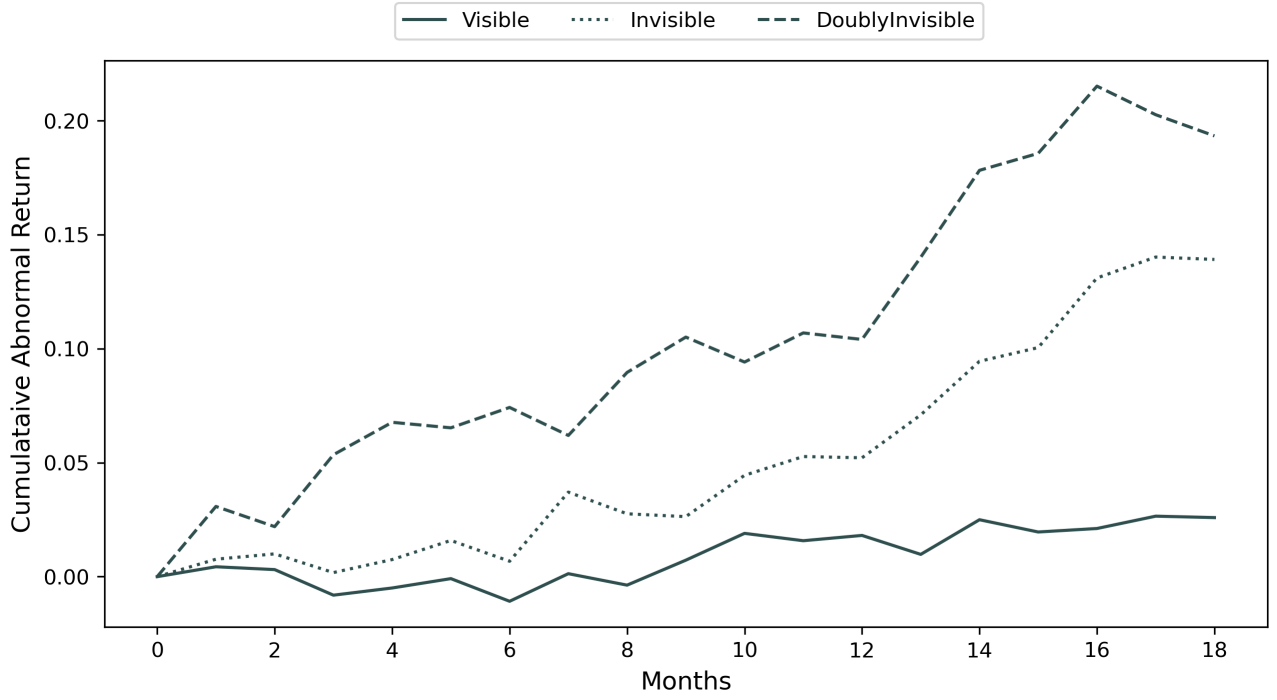


Fig. 5. Cumulative Abnormal Returns on Connected Stocks. This figure presents weighted-average cumulative abnormal returns for the first 18 months following a fund’s purchase of a connected stock. We define connected stocks as firms that are headed by one of the fund manager’s then-active firm officer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

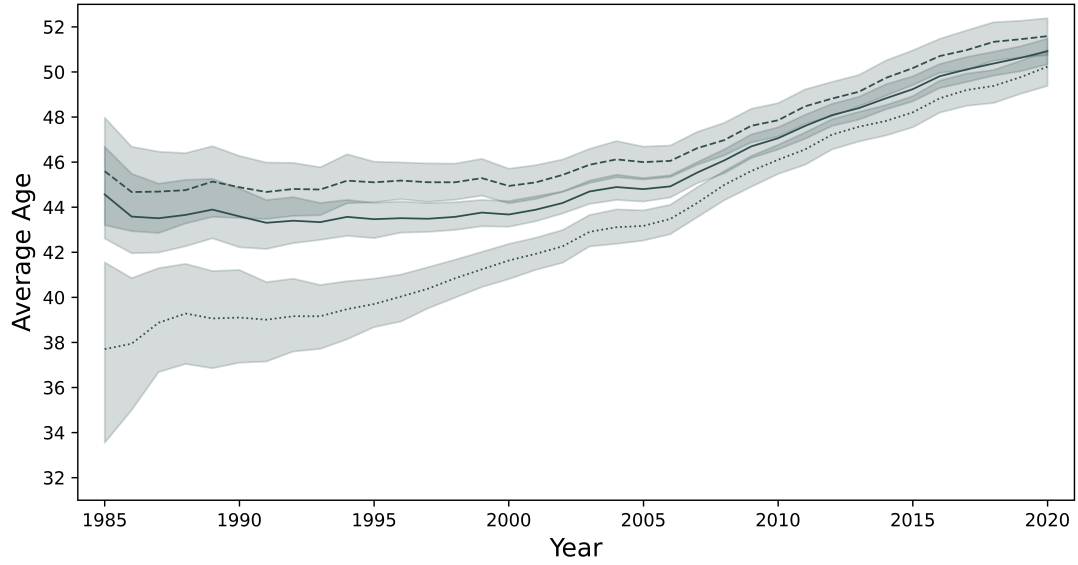


Fig. 6. Age of Facebook-identified and Non-identified Fund Managers. This figure compares the average age of all fund managers (solid line) in the initial sample of domestic actively managed U.S. equity mutual funds covering the period 1984–2020 to both the average age of Facebook-identified fund managers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

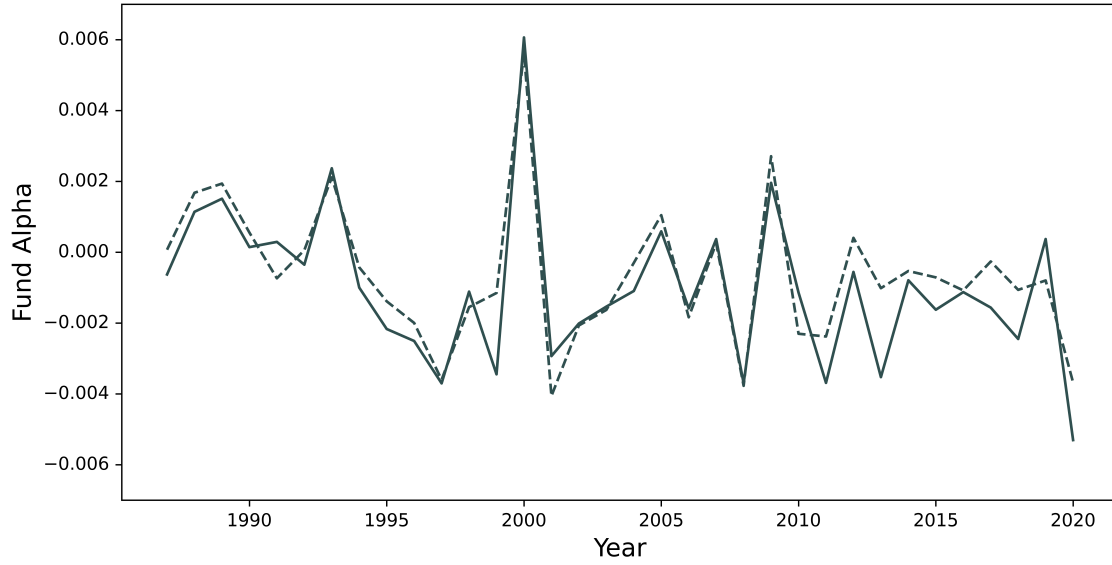


Fig. 7. Performance of Facebook-identified and Non-identified Funds. This figure compares the performance of funds run by Facebook-identified fund managers (dashed line) and the performance of the funds run by non-identified fund managers (solid line) across the sample period 1984–2020. Fund performance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

In Military We Trust: The Effect of Managers' Military Background on Mutual Fund Flows^{*}

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ABSTRACT

This paper shows that trust-building characteristics of fund managers affect purchase decisions of mutual fund investors. We exploit variation in fund managers' prior affiliations with the U.S. military, a well-trusted institution, and relate it to fund flows. Funds with ex-military managers receive significantly higher flows and have a 6.5% faster annual growth rate relative to other funds. Investor inclination toward these managers strengthens with their military involvement and its salience and with nationwide confidence in the military. Military managers' superiority in competition for investor funds is not due to variation in fund or managerial attributes and is robust to alternative explanations.

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What determines the decision to invest in one mutual fund over another? On average, mutual funds are known to persistently underperform passive investment strategies net of fees (Jensen (1968); Carhart (1997)). Nonetheless, investors continue to pay billions of dollars in fees to managers and advisers absent proof that they provide sufficient performance to compensate for their fees (Bergstresser, Chalmers, and Tufano (2009); Fama and French (2010); Hoechle, Ruenzi, Schaub, and Schmid (2018)). That is, either the market for asset management is inefficient (investors pay fees without being compensated) or fund and manager-specific factors beyond returns alone guide the decision to invest in a mutual fund (Hortaçsu and Syverson (2004)). In this paper, we provide support for the view that distinct trust-building attributes of fund managers affect the purchase decisions of mutual fund investors.

Trust plays a pivotal role in the various decisions we make, from facilitation of personal relationships to participation in economic activities (Knack and Keefer (1997)). Investment decisions are no exception. As suggested by Guiso, Sapienza, and Zingales (2004), trust reflects a general reliance on the integrity and fairness of the financial system and may serve as an explanation to the limited stock market participation puzzle. With regard to asset management, Mullainathan, Schwartzstein, and Shleifer (2008) indicate that the majority of advertisement campaigns by investment advisers and mutual funds draw on trust and less on past performance. Kostovetsky (2015) shows that investors attach value to their relationship with the asset management company, which affects their capital allocation decisions when ownership changes. In the model of Gennaioli, Shleifer, and Vishny (2015), managerial qualities, personal connections, familiarity and persuasive advertising underlie trust in a manager, which helps reduce the investor's perception of the riskiness of investments and correspondingly justifies manager fees and influences investment decisions. Following this line of reasoning, we investigate whether potentially trust-related biographical characteristics of mutual fund managers, specifically their prior engagement in the military, affect the investment choices of mutual fund investors.

A manager's prior military affiliation may promote investor trust for several reasons. We argue that such a background may serve as a signal that alleviates the investor's uncertainty regarding the manager's motives and prospective actions. First, military service demands a high degree of personal commitment and dedication that may translate to more compliant and ethical behavior in later civilian employment. Koch-Bayram and Wernicke (2018) find that ex-military CEOs are less inclined to engage in financial misconduct. In this regard, trust functions as an implicit contract, which serves as a substitute for costly monitoring, and investors likely prefer managers who require less monitoring. In addition, evidence from peer-to-peer lending suggests that lenders discriminate in favor of individuals that display signs of military involvement (Pope and Sydnor (2011)). Further, serving in the military may indicate a high level of patriotism, which has been found to provide important guidance for social behavior (Huddy and Khatib (2007)). Military service may also signify social identity. In particular, individuals tend to follow the actions of others seen as members of their own social group (Cialdini and Goldstein

(2004)) and likely increase cooperation with them (Blader and Tyler (2009)). Thus, a shared social identity between investor and manager may induce trust. Finally, ex-military personnel may be perceived as being better able to fulfill the investor’s expectations. The possibility of such perceptions is supported by research showing that the perceived qualities of ex-military individuals cast candidates in a positive light during electoral campaigns (Teigen (2013)), serve as a productivity screening device in a civilian labor market (De Tray (1982)), and enhance success in corporate executive positions (Duffy (2006)).

In this paper, we posit that mutual fund managers with prior military background have an advantage when competing for investor funds because they are perceived as having certain military-associated characteristics that foster trust. Consequently, investors are more likely to allocate capital to funds managed by military-experienced individuals, even in the absence of evidence suggesting that they have superior investment skills relative to their nonmilitary peers. In addition, we posit that such trust-mediated allocation of assets is likely to be more pronounced during episodes of extreme performance realization and heightened confidence in the military and when background information is presented saliently.

To investigate our hypothesis, we use a novel data set of U.S. equity mutual funds that contains biographical information of fund managers. The U.S. mutual fund setting entails unique opportunities for studying the effects of fund manager’s military background on investor capital allocation decisions for two reasons. First, it allows disentangling effects related to a military background from differences in other fund or managerial attributes, including performance. Second, the U.S. military is the most trusted of all institutions in American society and is historically perceived to be an effective and well-run establishment.¹ Likewise, U.S. military personnel are associated with the highest levels of honesty and ethical standards.

Our main empirical findings indicate that public information about a manager’s prior military experience affects fund flows. Mutual funds managed by individuals with a military background have on average 10.6 percentage points higher annualized net flows relative to comparable funds with managers who have a nonmilitary background. Further, all else being equal, a mutual fund managed by an individual with a military background has an annualized growth rate that is up to 6.5% higher relative to other funds. The observed economically sizable effect of managers’ military background on fund flows is not subsumed by variation in commonly used flow-related fund or manager-specific attributes. Further, it is robust to several alternative explanations and remains unchanged even when we restrict the analysis to funds that are almost identical in terms of main observable characteristics.

The results from several additional tests indicate that the content and salience of information disclosures of a military background influence mutual fund investor decisions. We find that fund managers whose military service is disclosed as being prolonged and including heroic

¹Historical data from Gallup’s Confidence in Institutions survey suggests that U.S. citizens — independent of their party affiliation — gave the highest confidence rating to the military, out of all institutions in society, including the church, academia, the congress, the presidency, newspapers (media), the police, the criminal justice and medical systems and so forth, in every year over the 1975–2017 period.

achievements and meritorious service in a combat zone attract additional annual flows of 6.5% compared with managers who only disclose that they served in the military. The fund flow effect is more pronounced when investors are exposed to salient, eye-catching information and when they obtain this information with little effort on their part. Moreover, the effect of managers' military background only occurs in the sample of single-managed funds; it is suppressed in team-managed funds. In addition, confirming the presumption that military background may serve as a substitute for costly monitoring and reduce investors' perception of investment riskiness, we find that ex-military managers are less likely to engage in window dressing activities and overall exhibit more ethical behavior relative to their nonmilitary peers.

We perform several tests to investigate the relation between the managers' military experience and fund flows more closely. Our findings shed light on the role that trust may play in investor decisions. An association exists between investors' buying and selling behavior toward military-managed mutual funds and the nationwide confidence in the U.S. military and perception of security. We find that periods with a high level of trust in public institutions, and the military in particular, are associated with distinct partisan attitudes of investors toward military-managed funds. In contrast, during periods of relatively low confidence in the military and low perceived security, investors tend to allocate less capital to funds managed by ex-military individuals. Moreover, we observe that ex-military managers' fund flows plunge following the exogenous events of military-related scandals that may have adversely affected trust in the military.

To further support the trust-related asset allocation conjecture, we conduct a difference-in-differences analysis around the dates of managerial turnover. In the absence of any other fundamental events and all else being equal, managers with a military background receive net fund inflows that are 5.7 percentage points higher during the first month of active management relative to other managers. The difference in fund flows following the induction of military-experienced managers is persistent, while the two groups exhibit parallel movements in fund flow outcomes in the absence of a manager change. We also show that flow differences between military- and nonmilitary-managed funds are particularly large for extreme performance realizations. Military managers have higher fund flows relative to their nonmilitary counterparts following both extremely good and extremely poor fund performance. Collectively, the results of these tests support the conjecture that trust induced by a manager's military background influences mutual fund investors' decisions.

In addition, we determine that a substantial fraction of investors are likely to consider fund manager background information when making their investment decisions. First, we perform an online survey of mutual fund investors. The survey results indicate that the majority of mutual fund investors know their fund managers and are aware of the manager's profile when they are investing. Second, we conduct an online fund investment experiment to gather additional evidence on the relation between a manager's military background and fund flows. In the experiment, we ask participants (U.S. mutual fund investors) to allocate money between two

funds. We keep the fund and basic manager information constant, but we randomly assign a military background to managers. Results indicate that participants invest significantly more money into a fund when it has an ex-military manager. In contrast, when we specify no prior military affiliation for managers of both funds, we find no significant difference in asset allocation.

Our finding of ex-military managers' relative superiority in attracting fund flows raises an intriguing equilibrium question: Why would not all mutual funds employ military-experienced individuals? A potential answer is that the supply of qualified individuals with military experience may be too limited to meet the increasing demand for mutual fund managers over the sample period of our study. This limitation may consequently prevent fund management companies from appointing more ex-military individuals to their funds, even though such appointments would be advantageous. In the same vein, Benmelech and Frydman (2015) suggest that firms are constrained in hiring corporate executives with a military background because the supply of such individuals is insufficient. In addition, we consider several alternative answers to our question; for example, fund management companies may simply be unaware of the flow effect we uncover, or ex-military managers may perform worse. However, we do not find these explanations to be consistent with our data. Finally, we acknowledge other potential costs of hiring ex-military managers (e.g., the possibility of higher compensation), which we are not able to address within our setting and leave for future research.

Our empirical findings are consistent with the broad implications of portfolio management delegation models, which emphasize the role of trust (Gennaioli et al. (2015)). In particular, our findings support the view that trust in the manager that is induced by salient background information may reduce investors' perception of investment riskiness. Investors who seek to reduce anxiety around risky investment choices hire a money manager and base the hiring on manager characteristics. Thus, military-experienced managers are likely to be perceived as money guardians having military-associated qualities. While our study does not directly test the Gennaioli et al. (2015) theory, our key results can be interpreted naturally under the description of trust-mediated fund allocation that this theory offers. Our findings that trust induces fund flows also support the key premises of theoretical models of coarse thinking (Mullainathan et al. (2008)) and strategic persuasion (Glazer and Rubinstein (2004)).

The empirical findings in our study further contribute to the vast literature on the determinants of mutual fund flows. Previous studies relate fund flows to various fund and managerial characteristics, including past fund performance (Berk and Green (2004), among others), advertisement (Jain and Wu (2000)), fund name changes (Cooper, Gulen, and Rau (2005)), fund ratings (Del Guercio and Tkac (2008)), manager gender (Niessen-Ruenzi and Ruenzi (2019)), and manager name (Kumar, Niessen-Ruenzi, and Spalt (2015)), among others. On a general level, our study relates to that of Cici, Gehde-Trapp, Göricke, and Kempf (2018), who show that both fund managers and fund families can benefit from a manager's experience outside the fund management industry.

More broadly, our study adds to the literature that emphasizes how the unique attributes of military-experienced managers affect economic outcomes (Malmendier, Tate, and Yan (2011); Benmelech and Frydman (2015)). Evidence from our study also complements earlier literature on how an individual’s military experience influences later life socioeconomic achievements (Sampson and Laub (1996); MacLean and Elder Jr (2007)) and aids the development of qualities that can be beneficial in the labor market (Jackson, Thoemmes, Jonkmann, Lüdtke, and Trautwein (2012)). To the best of our knowledge, our study is the first to relate prior military experience to asset management and to analyze customer-based perception of ex-military individuals.

The remainder of the paper proceeds as follows. Section I describes the data set and the data collection process and provides basic statistics. Section II focuses on the relationship at the center of the study and examines the effect of a manager’s military background on fund flows. Section III presents evidence that the observed relationship can be attributed to military-associated partisanship. Section IV presents the supplementary analysis, followed by Section V, which concludes the paper.

I. Data and Sample Design

We rely on multiple data sources to identify our sample and obtain information for the empirical analysis. In this section, we describe these data sources, outline the process of identifying managers with a military background, and provide the sample descriptive statistics. Appendix A provides supplementary details on the construction of all main variables used in the empirical part of the study.

A. Data on Mutual Funds

Data on mutual funds come from CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP MF) and Morningstar Direct Mutual Fund Database (MS Direct). First, we obtain data on fund share class characteristics for the set of actively managed domestic equity-only U.S. mutual funds from the CRSP MF. The data are then aggregated at the fund level by weighting the respective fund share classes with the corresponding total net assets. The main variable of interest in the empirical analysis is net fund flows. We do not observe flows directly, so we infer flows from fund returns and total net assets. Following standard practice in the literature (e.g., Sapp and Tiwari (2004); Frazzini and Lamont (2008)), we compute flows F_t^i for fund i in month t as

$$F_t^i = \frac{TNA_t^i - TNA_{t-1}^i}{TNA_{t-1}^i} - r_t^i \quad (1)$$

where TNA_t^i is fund i ’s total net assets in month t and r_t^i stands for fund i ’s net return in

month t . To ensure that the results are not unduly influenced by outliers, we follow Kumar et al. (2015) and drop fund flow observations below the 1st percentile and those above the 99th percentile.²

Second, we establish a match between MS Direct and CRSP MF fund classes by carefully following the data appendix provided by Pástor, Stambaugh, and Taylor (2015), who identify matches relying on CUSIPs as well as the funds' tickers. Further, we restrict the sample to include only the funds that were managed by a single manager for at least one month over their entire lifespan.³ Following the rationale of Agarwal, Ma, and Mullally (2015), we exclude cases in which single managers run more than four funds at the same time because these managers are likely to be team managers. We also remove funds reportedly managed by anonymous managers.

To obtain the data on fund holdings, we match CRSP MF with Thomson Reuters Mutual Fund Holdings Database (MF Holdings) using the MFLINKS tables. Only holdings of common stocks (share codes 10 and 11) are considered, and information on stocks is obtained from CRSP and Compustat databases.

B. Identifying Managers with a Military Background

We obtain the fund manager names as well as the start and end dates of their management period at the respective fund via MS Direct. The choice of this database is in line with Patel and Sarkissian (2017), who show that the fund manager information provided by MS Direct is more accurate than the data provided by CRSP MF. We extract the fund managers' short profiles and, if available, information on academic degrees, certifications, and affiliations from MS Direct. We restrict the sample to all fund-month observations for which a single manager was managing the fund for at least one month. In total, after the Morningstar-CRSP match, we identify 2,903 funds over the sample years from 1991 to 2017.

To establish a complete profile for each manager, we perform a comprehensive cross-database search and obtain additional information from Morningstar, Bloomberg, Marquis Who's Who, Financial Industry Regulatory Authority (FINRA), LinkedIn, SEC filings, Intelius database, GI Search engine, Ancestry.com, Legacy.com, fund company websites, and articles in U.S. newspapers from LexisNexis and Newspapers.com. To guard against the possibility of wrong matches, we drop observations from the sample whenever we get multiple matching profiles or conflicting information from various sources. We restrict our sample to fund managers for whom we observe Morningstar and/or Bloomberg profiles and identify the date of birth. As a result, we are able to collect information on the personal characteristics and complete biographical information, including the prior military background of the fund managers. If a

²Additionally, we check that the main results persist when we use raw fund flows, winsorize the observations, drop observations below the 5th percentile and above the 95th percentile, or exclude funds with total net assets lower than \$1 million.

³Although we also consider a sample of team-managed funds in Table VI, our focus in this study is on single-managed mutual funds.

military affiliation exists for a manager, we can usually extract an extensive military profile, including information about training, dates of service, involvement in military conflicts, military rank, and military awards.⁴ Figure B1, Figure B2, and Figure B3 in Appendix B provide military profile examples from Morningstar, Bloomberg, and fund firm advertising materials.

Importantly, we define a fund manager as having military experience prior to joining the fund management industry only if this information was available to investors during the manager’s corresponding active management period. For example, the manager’s Morningstar, Bloomberg, LinkedIn or fund company website profile at the time of active management may clearly state the prior military experience. If the manager was active in the past, we make sure that such information was freely circulating and available to investors at some point during the manager’s active period. Specifically, for each fund manager in our sample we review whether information on military affiliation was disclosed in SEC filings, prospectuses, U.S. newspapers, or any of the manager and fund family-related internet resources during the manager’s active period. We further enrich this data by combining it with legacy web content from fund firms’ historical websites that we access through the Internet Archive’s Wayback Machine available at archive.org.⁵

In total, our final sample consists of 1,858 (73.92% of total) individuals single-managing 2,448 funds (84.33% of funds that were single-managed for at least one month). Within this set, 229 of the funds (9.35% of the sample) are single-managed by 123 (6.62% of the sample) managers with a military background (served in the military).⁶ Additionally, we identify 159 funds that were managed by teams that included at least one manager with military experience.

C. Sample Characteristics

Table I separately reports statistics for funds managed by individuals with and without prior military experience. Comparing the sample means for the two groups of funds, we find a significant difference in the net fund flow measure but not in other characteristics. Mutual funds run by managers with a military background have annualized fund flows that are 10.6

⁴However, in some cases we have to rely only on vague background description, e.g., “...was a decorated officer in the U.S. Marine Corps...”

⁵For every domain of a fund firm’s website, we request the full history of all snapshots recorded by the Internet Archive. We download the entire content linked to the last available snapshot of a given month by querying the Wayback Machine’s API. Fund firms from our sample start registering domains in 1993. First websites are launched in 1995 and often commented or advertised in newspapers. The earliest snapshots of our fund firms’ websites stored in the archive date back to 1996, the same year the Internet Archive started to crawl the web. We retrieve domains of fund firms that have closed down or changed their domain name through advertisements and articles in historical newspapers via newspapers.com. In addition, we are able to retrieve historical domain names through Usenet newsgroups and finance-related magazines (e.g., Money or Kiplinger’s Personal Finance).

⁶This number compares favorably to the share of military-experienced managers documented in the corporate finance literature. Benmelech and Frydman (2015) show that the share of ex-military corporate executives is approximately 6% in recent years. Moreover, the overall share of individuals who served in the military is 6.3% of the total U.S. population according to the Department of Veterans Affairs Veteran Population Projection Model 2016.

percentage points higher relative to funds managed by nonmilitary individuals (t-statistic of 5.06). In contrast, we observe no economically or statistically significant variation across the groups in any other fund characteristic, including return, risk, size, age, expenses, and turnover. There are no differences in the distribution channels, the Morningstar ratings, or the share of expenses set aside for marketing purposes. Importantly, we observe virtually no heterogeneity in portfolio holdings between military and nonmilitary managers. For example, managers with military experience do not invest more in defense stocks relative to other managers.

Manager characteristics show no statistically significant variation across the two groups in most cases. In particular, we find no difference between military and nonmilitary managers' marital status, educational background, mutual fund industry experience, fund tenure, name-specific attributes, or media coverage. The only exception is that managers with prior military experience tend to be older. Later in this paper, we show that the main result on the relation between military background and fund flows remains unaltered after controlling for the managers' biological age.

D. A First Look at the Military Trust – Fund Flow Relationship

To preliminarily explore whether military-related attitudes affect the decisions of U.S. mutual fund investors, we plot the average annual fund flow difference between managers with and without military background against Gallup's survey-based military confidence index.

As an illustrative example for this link, Figure 1 depicts the evolution of the two indicators over time. The dynamics of the fund flow difference coincide reasonably well with the evolution of the military confidence index. Managers with military experience enjoy higher relative fund inflows during periods of high confidence in the U.S. military institution, while episodes of relative fund outflows occur around periods of low confidence in the military. The correlation coefficient is 0.41. Further, the extreme values of Gallup's measure of satisfaction with the nation's military strength and preparedness (for the periods when available) also correspond to the episodes of relatively large inflows (outflows) into (from) the funds managed by military-experienced individuals. This simple relationship suggests a potential role of military-related partisanship in the asset allocation process of mutual fund investors.

II. Military Background of Mutual Fund Managers and Fund Flows

This section presents empirical results on the relation between military experience of mutual fund managers and fund flows.

A. Baseline results

Given that the U.S. military has the highest confidence (trust) rating among all institutions in American society throughout the sample years, we conjecture that social affection and military-associated partisanship may affect asset allocation decisions of mutual fund investors. Therefore, prior military experience of mutual fund managers, other traits being equal, could draw capital flows into funds managed by such individuals. To test this conjecture, we examine aggregate investor behavior at the fund level and investigate whether military-managed funds attract higher inflows than nonmilitary-managed funds. In particular, we estimate regressions with monthly net fund flows as the dependent variable.

In the regression analysis, we relate net fund flows to a *Military* dummy variable that equals one if the fund is single-managed in a given month by an individual with prior military experience, and zero if a manager does not have a military background. Importantly, the *Military* indicator variable covers only fund managers whose background information is publicly available to the investors during the managers' active management period. The set of controls is composed of fund characteristics, including *Fund return*, *Fund performance rank*, *Fund size*, *Fund age*, *Fund risk*, *Expense ratio*, *Turnover ratio*, *Family flows* and *Lagged fund flows*, and manager-specific attributes, such as *Fund tenure* and mutual fund *Industry tenure*. *Fund performance rank* is computed as the performance relative to all other funds in the same market segment in a given month. *Fund risk* is the time series standard deviation of the fund return using the rolling past 12-month return observations. Segment is based on the Morningstar fund style indicator, and controls are lagged by one month. We double-cluster standard errors by year and fund to allow for correlation between repeated observations from the same fund, and we show that our results are unlikely to be induced by some unobservable factors or any heterogeneous trends by including period, segment, family, fund, and interaction fixed effects. Estimation results are presented in Table II.

The results of the flow regressions are consistent with the conjecture that military-experienced mutual fund managers, all else being equal, attract higher fund flows. Flows into military-managed funds are significantly higher than those into nonmilitary-managed funds. The coefficients on the main variable of interest, the *Military* dummy, are positive and statistically significant in all specifications of the model. In column (1), we present the estimates after including time-varying control variables but no fixed effects. The impact of the *Military* dummy is positive and significant at the 1% level (coefficient = 0.005, t-stat. = 3.80). In columns (2) through (6), we add various fixed effects as well as alternative controls for fund performance and lagged fund flows.

Specifically, in columns (2) through (4), we present estimates of the specifications with segment, year, and segment-by-month-year fixed effects. The coefficient estimates on the *Military* dummy are positive and significant at the 1% level, ranging from 0.003 to 0.005. Further, a possibility exists that fund families that are better at attracting client flows are also better at

attracting managers with potentially beneficial characteristics such as military experience. In addition, families that are better at marketing may also provide more information about their managers. Thus, in column (5) we include family-by-month-year fixed effects. In this setting we are able to compare flows to funds with and without an ex-military manager in the same family at the same time. Comparing within family-month-year, we observe a similar magnitude of the military effect with the point estimate on the *Military* dummy being once again positive and statistically significant (coefficient = 0.003, t-stat. = 2.16). In column (6), we include fund fixed effects, which allows us to identify the military manager effect from managerial turnover within funds and to control for unobservable factors at the fund level that can potentially influence fund flows. The estimate on the *Military* indicator is positive (coefficient = 0.003) and statistically significant (t-stat. = 1.93). This outcome suggests that neither time-invariant unobserved heterogeneity at the segment, family, or fund level, nor time-varying heterogeneous trends drive our results.⁷ Overall, this section indicates that fund managers' military experience is positively related to fund flows.

The effect is also economically significant: the coefficient estimates imply that a fund managed by an individual with a military background, depending on the model specification, grows by about 3.2 to 6.5 annualized percentage points more than a comparable fund run by a manager with no military experience. The magnitude compares favorably to the mean annual net fund flows of 22.4% in Table I.

B. *Robustness of the Results*

In this section, we closely consider several alternative explanations for our baseline findings. Results are presented in Table III.

First, we ensure that our results are robust to several conventional alterations of our main setup. Kronlund, Pool, Sialm, and Stefanescu (2020) show that saliently presented information about long-term mutual fund performance, particularly one-year returns, affects investor capital allocation decisions. Therefore, in tests (1) through (3) we augment the baseline flow regression (column 3 of Table II) with controls for past performance, namely three-month, one-year, and five-year returns. Although past performance appears to be an important determinant of flows, results of these tests indicate that the observed military effect is not attenuated. We find that the estimates are significant and remarkably similar in economic magnitude to the baseline results, even in a more limited sample of test (3).

Demographic attributes of mutual fund managers may influence fund flows. Niessen-Ruenzi and Ruenzi (2019) show that gender-related discrimination affects fund flows, such that female-managed funds receive significantly lower inflows than similar male-managed funds. Roussanov and Savor (2014) show that single men, including mutual fund managers, are substantially

⁷In addition, we check that the observed military effect remains unchanged when we double-cluster standard errors on fund family and month-year (coefficient = 0.003, t-stat. = 2.79) instead of fund level and month-year as in the baseline specification (3) of Table II.

different in managerial behavior relative to married men, while research in psychology suggests that people tend to trust married individuals more than single individuals (Rahn and Transue (1998)). Inclusion of demographic controls in test (5) shows that inferences remain unchanged, suggesting that our results are not simply a by-product of demographic attributes.⁸

Alternatively, our main variable of interest may indirectly proxy for manager’s educational background because military service can pave the way to a better and less expensive education through various military tuition assistance programs. Indeed, in Table I, we show that military managers on average are slightly better educated, being more likely to have a graduate degree. However, the results reported in test (6) indicate that our inferences do not change when we account for the educational effects on fund flows.

Network may be another factor that affects fund flows. Agarwal, Lu, and Ray (2021) show that money managers use opportunities to network and attract fund flows even when attending charitable events. Cohen, Frazzini, and Malloy (2008) report that mutual fund managers benefit from shared educational networks with corporate board members, and the benefit is particularly pronounced for graduates of highly recognized institutions. In test (7), we check whether the higher networking potential of Ivy League graduates affects our results. We also recognize that the wealth and income of mutual fund managers’ parents affect future fund performance (Chuprinin and Sosyura (2018)). Correspondingly, we propose that the parental professional network may help managers to build connections and facilitate fund inflows. With this in mind, we use specification (10) to check if the parental involvement in fund management can explain our results. Results of both tests indicate that our findings are robust to alternative explanations related to educational and parental networks.

Another explanation for our baseline results is that investors pay more attention to salient managerial characteristics such as names, and military managers may simply have names that sound familiar to U.S. investors. Such familiarity can in turn explain the observed heterogeneity in fund flows. Kumar et al. (2015) document significantly lower inflows into funds managed by individuals with foreign-sounding names than into other funds. We implement a machine-learning algorithm from Ye, Han, Hu, Coskun, Liu, Qin, and Skiena (2017) to define foreignness of a manager’s name. The results reported in test (9) indicate that both magnitude and significance of the main coefficient estimate remain when we control for foreignness of managers’ names.

Recent evidence shows that experience outside the fund management industry gives managers an information advantage, which results in a higher propensity to hold more and to pick better stocks from the area of their expertise (Cici et al. (2018)). Therefore, we check that investors’ preference for military-managed funds is neither due to a potentially higher share of defense stocks in total holdings (test (4)) nor affected by the manager’s expertise in other

⁸Even though previous research consistently finds no significant impact of manager’s biological age on fund flows, we also control for age because it is the only managerial attribute that shows statistically significant variation across the two groups in Table I, Panel B.

industries (test (8)).

Mutual fund investors may be attracted to funds that reinforce their market position and acquire customers by conducting a marketing campaign. Barber, Odean, and Zheng (2005) show that investors tend to purchase funds that draw their attention through marketing or advertising. We therefore control for marketing expenses, which we define as the share of a fund’s expenses for marketing (from NSAR-B filings) in total expenses. Indeed, funds with a higher share of marketing expenses seem to attract higher fund flows, but importantly the effect of military experience of mutual fund managers on fund flows remains unchanged in the joint regression specification (11). Additionally, we control for media coverage of fund managers (test (13)), which is important for two reasons: (i) media coverage has been shown to affect net investor flows (Kaniel, Starks, and Vasudevan (2007)), and (ii) military managers may generally have a higher profile in U.S. society. We find that the effect of military background is not attenuated by including the managers’ media coverage control.

Next, we exclude index funds from the sample test (14) and control for distribution channels (12). Results for each of these alterations indicate that the coefficient estimate on the *Military* indicator variable is still statistically significant and economically meaningful. Finally, another concern is that the fund flow effect we uncover in Table II may simply be driven by investor preference for military individuals that is unrelated to presumed managerial qualities. If that is the case, we should observe similar military-related flow patterns for index funds. However, results reported in test (15) indicate that the military background effect is not present in the sample of index funds, which renders a simple preference explanation unlikely.

C. Degree of Involvement in the Military and Fund Flows

Previous sections suggest a robust link between the military experience of mutual fund managers and fund flows. This suggestion implies that information disclosures about the military background of an active manager influence mutual fund investor decisions. However, both the amount of information revealed and the details about the military experience vary considerably across managers. Some managers in the sample are medal-decorated war veterans, while others only communicate that they served in the military. In this regard, if there is information that draws attention to prolonged military service, heroic achievements, and meritorious service in a combat zone, it may amplify the effect on flows into funds managed by an individual with a military background. To investigate this possibility, we differentiate managers by their degree of involvement in the military and estimate flow regressions.

Table IV provides evidence of heterogeneity in fund flow effects across managers with various degrees of military involvement and recognition. The *Conflict/Medal* indicator variable is coded as one for funds managed by an individual who served a tour of duty in a conflict zone. In total, we identified 66 such funds, with 20% having managers who received United States Armed Forces awards and decorations, including the Bronze Star Medal, Purple Heart, Combat Action

Ribbon, service stars, and so forth. Further, to cover the other extreme of military involvement, we additionally identified 43 funds that are managed by managers who have undergone military training but have never served in the military. In particular, the *Military training* dummy takes the value of one if a manager graduated from any of the U.S. military schools and academies or voluntarily participated in any type of military training, but never served a period of active duty. The regression setup is similar to that applied in the previous section.

Consistent with the view that partisan investors allocate funds, among other things, based on a fund manager’s military background, we find that in both univariate sorting (Panel A) and regression analysis (Panel B) the *Conflict/Medal* variable is significantly and positively related to fund flows. Comparing the sample means for funds managed by individuals who served a tour of duty and for peer funds with managers who do not have such background, we find a remarkable difference of 21.9 annualized percentage points (t-statistic of 3.39) in net fund flow between the two groups. The coefficient on the interaction term *Military* $\times$ *Conflict/Medal* is positive and significant (coefficient = 0.005, t-stat. = 2.06). The magnitude compares favorably to the estimates of the *Military* dummy, indicating that managers who present themselves as war veterans attract more flows in comparison to those who just disclose that they served in the military. In contrast, *Military training* produces negative and not statistically significant estimates across all specifications. By construction, this variable largely captures military-related education of fund managers. In this, our results are consistent with prior research that documents no fund flow effects of managers’ education (Niessen-Ruenzi and Ruenzi (2019)).

D. *Salience of Information and Fund Flows*

Previous research suggests that cosmetic effects irrationally influence investor decisions. Hirshleifer (2001) suggests that even irrelevant, redundant, or outdated news affects security prices if presented saliently. Cooper, Dimitrov, and Rau (2001) document stock price reactions to timely firm name changes. Similarly, asset allocation decisions of mutual fund investors are influenced by cosmetic features of funds and fund managers, for instance, by style-related fund name changes (Cooper et al. (2005)), fund manager name disclosures (Kumar et al. (2015)), or other salient attention-grabbing information (Barber et al. (2005)). In this section, we explore if the observed relation between military experience and fund flows differs with respect to the salience of information investors are exposed to.

The investor’s level of effort to obtain information on the managers’ military background varies by manager. Therefore, we differentiate managers by the source that discloses the relevant information. Table V provides evidence on the fund flow effect for different means of information disclosure. The first group, *Investment media*, includes cases in which information on prior military experience is disclosed through investment media sources, namely, Morningstar and Bloomberg. The second group, *Personal disclosures*, covers cases in which this information is not available in investment outlets but can be found on fund company websites

or professional networks, such as LinkedIn. The third group, *Other sources*, includes cases in which military background information is only disclosed via major or regional newspapers and other alternative media outlets. This categorization differentiates the investor’s effort to obtain information. Correspondingly, we suggest that the probability of the investor becoming aware of the manager’s biographical facts is higher for the first two groups relative to the third group.

Additionally, we identify 37 funds with ex-military managers that are not included in our main sample since information on their military service was not publicly available during the period of active fund management. In these cases, the information only becomes available in managers’ obituaries. The *Post-mortem placebo* group in Table V covers managers for whom military affiliation is disclosed only in obituary notices after their death and not prior to it. As such, this last group serves as a placebo test.

The average flow differences between military and nonmilitary managers indicate a sharp distinction between the groups. Mutual funds with a manager whose prior involvement in the military is disclosed via investment media have 17.2% higher annualized fund flows (t-statistic of 3.52). Managers with slightly more salient disclosures attract 22.1% p.a. higher fund flows per annum (t-statistic of 6.27). In contrast, revealing this information through other sources that are less prominent has no effect on fund flows. The magnitudes of the monthly flow regression coefficient estimates favorably support the notion that the fund flow effect is more pronounced when investors are exposed to salient, attention-grabbing information. As expected, results from the placebo group of funds reveal no fund flow effect, which further supports this notion.

Thus far, the analysis has focused only on single-managed funds and excluded all team-managed funds. Next, we examine whether funds managed by teams that include individuals with prior military experience are able to attract more fund flows relative to funds that do not have such managers in their teams. For this purpose, we additionally identify 159 funds with at least one military manager who is part of the team and re-estimate the baseline regressions using the sample of team-managed funds. The regression setup is otherwise similar.

The fund flow effect of a manager’s military background is suppressed in team-managed funds. Table VI relates monthly net fund flows to a *Military team* dummy variable that equals one if the fund is managed in a given month by a team that includes a manager with a military background and zero otherwise. In columns (1) and (2), we present the estimates of regressions after including various controls along with segment and time fixed effects. The coefficient on the main variable of interest is positive but not statistically or economically significant (in the specification with lagged fund flows). Adding the share of military managers in a management team and several interaction terms with sources of information disclosure neither changes the baseline evidence nor reveals new results. The table’s main message is that no significant flow effect is present between funds with military managers in teams and funds managed by nonmilitary teams. This finding is consistent with the supposition that a manager’s personal background information is much less salient and eye-catching in team-managed funds relative to single-managed funds.

III. Evidence of Military-Based Partisanship

This section presents evidence that the observed relationship between a manager’s military background and fund flows can be attributed to the military-associated partisanship that affects asset allocation decisions of mutual fund investors.

A. *Fund Flows and Social Attitudes toward the Military*

Figure 1 provides illustrative evidence on how social attitudes toward the military institution and military-related partisanship affect the decisions of U.S. mutual fund investors. This example suggests that investors’ buying and selling behavior toward mutual funds managed by individuals with a military background positively correlates with the level of confidence and satisfaction with the U.S. military. In other words, investors tend to allocate more capital to military-managed funds when confidence in the military is high, while the difference in fund flows between military- and nonmilitary-managed funds is less pronounced in times of low confidence.

To provide formal statistical evidence on the link between partisan mutual fund investor decisions and a manager’s military experience, we conduct three additional tests. First, we repeat regressions of monthly net fund flows on the military indicator for periods of high and low levels of confidence in the military, classified based on the median level of the Gallup’s confidence in the military index from Figure 1. Second, we collect National Instant Criminal Background Check System (NICS) data on purchases of firearms, provided by the Federal Bureau of Investigation, and consider the information as an alternative proxy for nationwide confidence in the military institution.

Table VII first reports evidence on the fund flow effect for periods of low and high confidence in the military. The results reported in columns (1) and (2) show that in both cases the *Military* dummy is significantly positively related to fund flows, with estimates of 0.002 (t-statistic of 1.83) and 0.003 (t-statistic of 3.07) for low and high confidence periods, respectively. The magnitudes of the coefficients favorably support the notion that the fund flow effect is more pronounced when confidence in the military is relatively high.

Next, Table VII relates an alternative measure of confidence in the military (i.e., the change in purchases of firearms) to monthly net fund flows. Studies in psychology and political science document a strong link between the perception of insecurity and associated trust in public institutions. Blanco and Ruiz (2013) show that an individual’s perception of insecurity is negatively related to satisfaction with the political regime and confidence (trust) in public institutions, including the military.⁹ In the context of Figure 1, when the confidence in the military institution is low, the aggregate level of perceived insecurity is likely to be high and

⁹Other studies in political science suggest that trust in public (political) institutions is positively related to partisan strength (Hooghe and Oser (2017)), while an apparent distrust in politics can result in unwillingness to publicly declare a partisan identity despite attitudes to the contrary (Petrocik (2009)).

vice versa. Alongside, Diener and Kerber (1979), Cao, Cullen, and Link (1997), and Carlson (2012), among others, show that U.S. citizens perceive firearm purchases as a potential complex response to distrust in public institutions and anxieties regarding insecurity.¹⁰ Therefore, we consider purchases of firearms as an alternative measure of the confidence in the military.¹¹ The results reported in column (3) show that the coefficient on the interaction term between *Firearm checks (NICS)* and the *Military* dummy is negative and significant (coefficient = -0.003, t-stat. = -2.70). This outcome indicates that fund flows are lower for military-managed funds when the nationwide perceived insecurity is high and, correspondingly, the confidence in the military institution is low.

In specifications (4) and (5), we split the sample into periods of relatively high and low levels of insecurity, respectively. Results in column (4) suggest that during periods of positive change in firearm purchases, when the aggregate level of perceived insecurity is likely to be high, funds managed by military-experienced individuals tend to draw less pronounced investor interest and have difficulties in attracting fund flows. In contrast, results for the periods of negative changes in firearm purchases, in column (5), show that the estimate on the *Military* dummy is positive (coefficient = 0.004), statistically significant at the 1% level, and much higher in magnitude relative to its counterpart in column (4). This outcome suggests that periods of relatively low perceived insecurity and high level of trust in public institutions are associated with distinct investors' partisan attitudes toward military-managed mutual funds.

Overall, this evidence is consistent with the view that military-associated partisanship exists among mutual fund investors, and it provides additional support for the conjecture of trust-based investor asset allocation behavior toward military-managed mutual funds.

B. Fund Flows and Managerial Turnover

Mutual fund managers come and go. It has long been recognized that a fund manager change is one of the most informative occurrences in a mutual fund's lifetime. Khorana (1996) shows that on average the replacement of a mutual fund manager leads to subsequent under-performance. Chevalier and Ellison (1999) build on this evidence and, among other findings, indicate the potential inflow-related benefits of replacing a poor-performing manager. In a theoretical model, Dangl, Wu, and Zechner (2006) suggest that management replacements may be accompanied by capital inflows, depending on the tenure of the manager that is being replaced. Importantly, regardless of the reason why the change occurred, such an event draws the investors' attention and puts an incoming manager in the spotlight, providing a perfect setting for exploring the existence of military-based partisanship among mutual fund investors.

¹⁰Notably, the aforementioned papers do not explicitly state which public institution failures (the police or the military) trigger gun purchases the most; however, in all these papers, the need for protection and the perception of insecurity are found to be the main psychological reasons for firearm purchases.

¹¹Importantly, according to Gallup's Confidence in Institutions survey data, 34% to 51% of U.S. households had a gun in possession over the sample period of our study.

Therefore, we investigate the fund flow dynamics around the dates of managerial turnover. In particular, we examine whether funds that shift to managers with a military background subsequently exhibit different fund flows relative to funds that employ nonmilitary fund managers. We only consider instances when the incoming manager single-handedly manages the fund, and overlapping periods of management are excluded.

Figure 2 illustrates an increase in average monthly net inflows into both types of funds after the management change. Noteworthy, flows into funds managed by individuals with a military background are substantially higher than the ones into funds with nonmilitary managers. For both groups, fund inflows reach their maximum in the month of the manager change. In the subset of military-managed funds, inflows remain high for all the subsequent months, while funds managed by nonmilitary individuals experience an inflow decline to around the pre-turnover level. The differences in net inflows between the two groups over the 10 months following the managerial turnover are economically significant. Funds managed by individuals with military experience receive between 6.6% and 38.4% higher annualized fund flows.

Figure 3 provides additional evidence by presenting average flows for the two groups around the dates when a single manager leaves the fund. By contrast, we observe an outflow from funds previously managed by individuals with a military background during the month of managerial turnover, while flows into nonmilitary funds are essentially unaffected. The month in which the manager change occurs is the only period in the 20 months surrounding it that has an actual outflow. The difference amounts to a sizable -12.0 annualized percentage points.

While the above descriptive tests present some evidence of heterogeneity in fund flows between the two groups around the dates of managerial turnover, one can argue that the observed inflows are induced by the change in management itself rather than investor military-related partisanship affecting the asset allocation decision. That is, a fund company can choose to heavily advertise that it has replaced a manager, drawing attention to the superiority of an incoming manager relative to the manager that is being replaced. Jain and Wu (2000) show that advertised funds are indeed able to attract significantly higher inflows.

To alleviate this concern and address possible endogeneity between the two groups, we implement a difference-in-differences approach by comparing changes in fund flows around the dates of managerial turnover of funds with military management (treatment funds) to changes in fund flows of funds with nonmilitary managers (control funds). In this test, we restrict the sample to funds that only had one change from team to solo management over the sample period of our study, and we use the following specification:

$$F_t^i = \alpha_0 + \beta_1 Treat_i + \beta_2 (Treat_i \times Post_t) + \gamma X + \eta_j + \tau_t + \epsilon_{i,t} \quad (2)$$

where F_t^i is the net fund inflow of fund i , as specified in equation (1); $Treat_i$ is an indicator for funds that were ever managed by individuals with a military background and affected by the managerial turnover; $Post_t$ is an indicator variable that equals one for months of solo manage-

ment period and zero otherwise; X is a vector of control variables; and, η_j and τ_t are segment and period fixed effects, respectively. In the above model, the treatment occurs at different times and the full set of period dummies is included. Our main results are unaffected if we standardize the treatment periods. The primary coefficient of interest in the above specification is the coefficient β_2 on the difference-in-differences estimator, $Treat_i \times Post_t$, which indicates if the average change in fund flows from before the change to solo management to afterward was different in the two groups.

Table VIII reports the results for a difference-in-differences estimation according to equation (2). The coefficients on the interaction, $Treat_i \times Post_t$, are uniformly statistically significant regardless of the model specification. Coefficients equal 0.006 (t-stat. = 7.24) and 0.002 (t-stat. = 2.48) in columns (1) and (2), respectively. In column (1), we report the estimates after including just the segment and period fixed effects and no control variables, and in column (2), we introduce a set of control variables detailed in Section II. These findings are also economically meaningful; all else being equal, the coefficient estimates imply that individuals with a military background receive up to 6.7 annualized percentage points higher net fund inflows than others. Importantly, we find that in both specifications, $Treat_i$ indicator reports small and insignificant coefficients, suggesting that the treatment and control funds exhibit parallel movements in their fund flow outcomes in the absence of the treatment shock. The pre-change parallel trend in fund flows between the two groups is further confirmed in columns (3) and (5), where we augment the difference-in-differences design with interaction terms of the $Treat_i$ variable with periods preceding the managerial change. Findings indicate that no statistical difference in the outcome variable exists prior to the management rotation. In contrast, the coefficients on the interaction terms of the $Treat_i$ variable with post-change periods in column (4) and (5) suggest that the net fund inflows increase following the induction of military-experienced managers. The fund flow effect is the most pronounced in the first month of active management ($Treat_i \times Post_0$), indicating that managers with a military background receive 5.7% higher inflows during the first month of active management relative to other managers. The difference in fund flows between the two groups is persistent, however, it slightly weakens over time.

The evidence of this section is hard to reconcile with an alternative fundamental-based explanation and supports the notion that military-induced trust in the manager affects investors' buying and selling behavior toward mutual funds.

C. A Closer Look at the Flow-Performance Relationship of Military-Managed Funds

Investors are ultimately concerned about performance outcomes. Thus, in this section we investigate if the observed flow patterns are also reflected in the distribution of performance realizations of mutual funds. Specifically, we explore whether an investor's willingness to allocate more capital to military-managed funds than to other funds persists after both extreme positive

and negative performance months.¹² Given our previous results, we expect that managers with a military background attract relatively more flows regardless of the extremity of performance outcomes.

Table IX relates monthly net fund flows to the performance of mutual funds. Column (1) shows that the coefficients on the main variable of interest, the interaction term *Military* $\times$ *Performance rank*, is positive and statistically significant (coefficient = 0.010, t-statistic of 6.10). This outcome suggests that fund flows are higher for those military-managed funds that are at the top of the performance ranking. In other words, the observed differences in fund flows between the two groups can be attributed to significantly higher capital inflows into mutual funds with military-experienced managers following the months of outperformance.

Barber et al. (2005) show that the fund flow-performance relationship is in fact nonlinear. Therefore, the remaining specifications in Table IX estimate a quadratic performance-flow relationship. The coefficient estimates in columns (3) and (4) reveal that the interaction term of the dummy for military managers with squared past performance is uniformly statistically significant and positive, while the interactions with linear past performance are negative, emphasizing the non-linearity of the flow-performance relationship. This outcome indicates that the difference between military and nonmilitary-managed funds is especially large for extreme performance realizations. In particular, the results suggest that military-managed mutual funds not only have higher fund flows following extremely good performance, but also following months of very poor return realizations relative to their nonmilitary-managed counterparts. These findings are largely unaffected by the inclusion of various fixed effects in the regressions.

D. Micro-level Evidence from an Online Experiment

The key assumption of this paper is that the majority of investors are likely to be sensitive to fund manager background information when making investment decisions. To verify this assumption, we perform an online survey among U.S. mutual fund investors via Amazon Mechanical Turk (AMT). Specifically, we ask 200 mutual fund investors whether they knew and considered the fund manager’s profile at the time of investing. Sixty-seven percent of the respondents reply in the affirmative.

Results of Section IIC and Section IID suggest that investors are likely to base their purchase decisions partially on a manager’s personal background information and that military-associated partisanship exists among mutual fund investors. However empirically controlling for all other potential drivers of fund flows in our setting is not possible. Thus, we conduct an online experiment via AMT to further investigate the relation between managers’ military affiliation and fund flows. The procedure allows us (i) to control for fund characteristics, so we can rule out statistical discrimination-related explanations of our results, and (ii) to examine the

¹²We rely on scaled performance ranks to gauge the performance outcomes. Performance rank represents the position of the fund’s monthly return relative to all other funds in the same market segment (based on Morningstar style boxes).

impact of investor characteristics on investment decisions, in contrast to the previous empirical analysis focusing on aggregate investor behavior at the fund level. As in Kumar et al. (2015), we recruit individuals at AMT to complete a hypothetical fund investment task in which they are required to split an investment of 100 dollars between two funds, which are labeled “fund A” and “fund B”.¹³

Our investment experiment is conducted with 804 individuals who self-report that they are located in the United States and own mutual funds. We provide subjects with information about each fund A and B, including fund segment, size, inception date, expense ratio, annual turnover, the top five holdings, past performance, a short description of the investment objective, and a short profile describing the fund manager.¹⁴ The experiment lasts four rounds. In each round, participants split 100 dollars between two funds. To avoid subjects learning that the experiment is about military affiliation and to ensure that our experimental results are robust, one of the two funds is managed by an ex-military manager only in rounds 2 and 4, while neither fund is managed by such individual in rounds 1 and 3. In round 2 both funds have very similar fund attributes, but in round 4 we assign negative past returns to fund A.

Next, subjects are randomly assigned to one of two groups. The key feature of the experiment is that in rounds 2 and 4 half of the individuals observe that fund A is managed by an ex-military fund manager, whereas fund B is managed by a nonmilitary manager. In rounds 1 and 3, individuals of both groups observe only nonmilitary-managed funds. Hence, any difference in investment behavior between the two groups can solely be attributed to the fund manager’s military background.

Table X presents the results of this experiment. Table X, Panel A shows that AMT participants invest 3.36 dollars more in the fund A when it has a manager with military experience. Results of both rounds 2 and 4 uniformly suggest that subjects allocate more money to the fund with an ex-military manager. Moreover, the inclination toward military-experienced managers persists when subjects are confronted with negative past returns of the military-managed fund (round 4), corroborating the evidence in Section IIIC. In contrast, when we specify no prior military affiliation to managers of both funds (untabulated placebo rounds 1 and 3), we find no significant difference in asset allocation.

Results reported in Table X, Panel B provide further evidence on the relation between fund manager military background and fund flows, while focusing on specific investor characteristics.¹⁵ In columns (2) and (3), we investigate subsamples of subjects by party affiliation (i.e., Democrats and Republicans). The participants self-report party identification. We find the military background effect on investment allocation decisions in both subsamples, with the co-

¹³We thank Alexandra Niessen-Ruenzi for providing us with the experimental setup.

¹⁴Each of the fund profiles represents a hypothetical diversified equity mutual fund singlehandedly run by a male manager with an American-sounding name, e.g., “Charles Miller.”

¹⁵Additionally, when we exclude AMT participants who spent less than two minutes on the experiment from our sample, we find that the observed effect strengthens with participation time, indicating that our results are not induced by AMT workers who did not take the task seriously.

efficients of 4.32 (t-stat of 1.72) for the Democrats and 4.53 (t-stat of 1.89) for the Republicans. This outcome is consistent with Gallup’s survey evidence that U.S. citizens, independent of their party affiliation, perceive military-affiliated individuals as trustworthy. In column (4), we use several additional interaction terms and show that our results are more pronounced among older investors.

We find that the effect of a fund manager’s military background on the amount invested in a fund is economically sizable, but lower in magnitude than the effect that we document in our CRSP/Morningstar sample.¹⁶ This result makes intuitive sense because participants are likely to pay less attention to a manager’s profile when they do not have their own money at stake. Further, in our experimental setting, the military background effect is lower in magnitude compared to the relatively more salient effects related to gender and manager name documented in Kumar et al. (2015) and Niessen-Ruenzi and Ruenzi (2019).

Overall, the results of this section further confirm the previously observed relation between managerial military background and fund flows and suggest that the majority of investors consider manager background information when making their investment decisions.

IV. Additional Tests

A. *Military Background and Window Dressing*

Previous research suggests that investors likely prefer managers that require less monitoring (Gennaioli et al. (2015)). In the context of our paper, investors may view managers’ military background as an indicator of potentially more compliant and ethical behavior that reduces perceived investment risk. Consequently, an intriguing question is whether ex-military managers live up to investors’ expectations and actually act more ethically relative to other managers.

To answer this question, we examine whether managers with military experience are less likely to engage in window dressing activities relative to nonmilitary managers. Solomon, Soltes, and Sosyura (2014) argue that investors pay attention to portfolio holdings reports and, among other things, evaluate managers based on their particular stock picks. Consequently, some fund managers window dress their portfolios (remove poorly performing holdings) before filing dates in an attempt to deceive investors. These practices are generally viewed as unethical at best and may even be illegal (Lakonishok, Shleifer, Thaler, and Vishny (1991); Patel and Sarkissian (2013)). Following Agarwal, Gay, and Ling (2014), we rely on two measures of window dressing, namely Rank Gap and Backward Holding Return Gap (BHRG). Rank Gap is a relative window dressing measure that captures inconsistency between a fund’s performance rank and the two ranks based on winner and loser stocks proportions in the reported holdings. BHRG is the difference between the net return of a hypothetical portfolio that is based on the

¹⁶To the best of our knowledge, no major military-related events occurred around the dates of the experiment (August 2019) that could negatively affect our results.

fund’s reported holdings and the fund’s actual return. The time period is from 2003 — the year from which funds were required to file holdings information on a quarterly basis — to 2017.

Table XI relates a manager’s military background to the two window dressing measures. The coefficients on the military dummy variable are uniformly negative and statistically significant. This result suggests that managers with a military background engage in significantly less window dressing relative to their nonmilitary peers. In other words, they are less likely to remove poorly performing holdings before filing dates. Moreover, we observe this pattern regardless of whether the fund is in the top or bottom quintile of performance within its segment prior to the holdings report. While acknowledging the existence of other potential explanations, we suggest that these findings point to the conclusion that ex-military managers demonstrate more compliant and ethical behavior relative to others. Additional cross-database screening for evidence of managerial misconduct of various kinds revealed no instances of ex-military managers in our sample being involved in any illegal activity.¹⁷

B. Matched Sample Analysis

To guard against the possibility of a spurious relationship between military background and fund flows caused by sample-specific unobserved characteristics of funds or managers, we perform two different matching procedures. In doing so, we attempt to bring the sample properties of the control (nonmilitary) funds as close as possible to the military-managed funds. Thus, we assume that if the observed characteristics of the two groups of funds are identical, then the unobserved attributes are likely to be similar as well.

Table XII presents results from a matched sample analysis. We use two approaches to match funds. First, for each observation with a military-experienced manager, we search for nonmilitary-managed twin funds with similar fund or managerial characteristics. In doing so, we require values of the non-categorical variables for nonmilitary fund in a given month to be within 5% of those of a military-managed fund. The set of characteristics includes fund’s segment, family, size, age, share of marketing expenses, performance, and manager’s gender, biological age, industry tenure, and foreignness of a name. In all cases, we require the matching attributes to be from the same month and drop all other nonmilitary funds’ observations that do not have a matching military counterpart in a given month. Second, we perform the propensity score nearest neighborhood matching procedure on the set of fund characteristics, including fund performance, fund size, expense ratio, turnover, fund age, and lagged fund flows. Then we re-estimate the baseline flow regression (column 3 of Table II) based on the resulting matched samples.

Results of the matched sample analysis show a uniformly positive and statistically significant impact of the *Military* dummy on fund flows. The magnitudes of the coefficients in specifications

¹⁷Similar to Egan, Matvos, and Seru (2019), we collect data from FINRA BrokerCheck. The data include all disciplinary events, including civil, criminal, and regulatory events, as well as disclosed investigations for all registered brokers and the set of investment advisers who are also registered as brokers.

(2) to (16) compare favorably to the estimate in (1), suggesting that in 13 out of 15 cases confining the sample to better matches in terms of observable characteristics results in a similar or more pronounced effect of manager’s military background on fund flows. Moreover, when we match funds based on fund segment and manager gender, and additionally require the matching funds to be in the same fund family (in (5)) or to have very similar returns (in (10)), and when we perform propensity score matching (in (12) to (16)), the sample size shrinks significantly, but statistical significance remains. This evidence indicates that restricting the analysis to more similar funds does not alter the baseline results on the military background effect, which means that an unobservable variable explanation of our results is unlikely.

C. *Alternative Measures of Fund Flows*

Thus far, the main dependent variable of this paper has been relative net fund flows, that is, the percentage change in total assets under management, net of internal growth. However, recent studies question the reliability of the relative fund flow measure due to apparent violations of additive constraint. Spiegel and Zhang (2013), for instance, suggest using a fund’s market share instead. Therefore, in this section, we test two alternative specifications of the fund flow measure, namely, the absolute dollar flows and the change of a fund’s market (segment) share as dependent variables.

Table XIII reports results for the two alternatively specified fund flow measures. Our findings confirm the existence of a positive impact of the managerial military experience on fund flows for both measures. In columns (1) and (2), coefficient estimates of the *Military* dummy in all-inclusive flow regressions with the absolute dollar flows as the dependent variable are still positive and significant. Results are also economically meaningful, with military managers receiving \$3.3 million higher monthly fund flows on average relative to their nonmilitary counterparts. Further, results of the quantile regression with the change of a fund’s segment share as the dependent variable also reveal that the coefficient estimate of the main variable of interest, the *Military* dummy, is positive and significant at the 1% level (t-statistic of 5.15). Thus, the inference that a military background of mutual fund managers affects fund flows remains unchanged.

D. *Fund Performance and Persistence*

Next, we examine whether the observed relationship between military background and fund flows arises from the possibility that investors rationally prefer managers with a military background due to their potential superiority in generating risk-adjusted performance or higher performance persistence. Table XIV, Panel A, reports the risk-adjusted alpha estimates of a hypothetical long-short portfolio that assumes a long position in all military-managed funds and a short position in all nonmilitary-managed funds in our sample. Regardless of the factor model, the difference portfolio does not deliver any economically or statistically significant

risk-adjusted alphas. All alpha estimates, based on either net or gross performance, are close to zero and far from being statistically significant (t-statistics ranging from 0.38 to 1.50). This suggests that significant performance differences between military and nonmilitary managers are unlikely. As an additional test, we compare fund performance persistence of military and nonmilitary managers. Performance persistence is computed as the average time-series standard deviation of monthly performance ranks. The results of Table XIV, Panel B reveal no statistically significant difference between the two groups, indicating that military managers do not deliver more stable performance relative to other managers.

The evidence of this section suggests that investor inclination toward military-managed funds is unlikely to be associated with rational performance-chasing investor behavior. Rather, it provides additional support to the notion that trust in the manager induced by that individual's military background affects investors' buying and selling behavior toward mutual funds.

E. Potential Equilibrium Outcomes of Hiring Ex-Military Managers

Our findings suggest that fund management companies are likely to benefit from hiring managers with a military background because they are associated with relatively higher fund flows. However, taking into account the advantages of hiring ex-military individuals, an important question remains: Why then are most mutual funds not managed by individuals with military experience?

A potential answer to this question is that the supply of qualified military-experienced individuals may be too low to meet the increasing demand for mutual fund managers over the sample period of our study. Figure 4A plots the share of ex-military fund managers and education level of veterans by birth cohort, illustrating the shift in educational attainment of military personnel. This evidence suggests that in the first part of the twentieth century, the likelihood of highly educated individuals serving in the military was higher relative to all other men in the population. Perhaps, among other things, this finding may be related to the fact that prior to 1951 potential military inductees were not permitted to postpone service to attend college.¹⁸ Following the change in the selection process, the proportion of men with college degrees in the military substantially decreased. Consequently, the share of ex-military personnel among mutual fund managers followed a similar path and remained low from the mid-1950s cohorts onward. Thus, the decreased supply of highly educated military-experienced individuals is likely to be inadequate to meet the demand for fund managers, illustrated in Figure 4B by the steadily declining share of fund managers with a military background among all managers over the sample period.

Several other potential reasons exist for why fund management companies do not widely employ military-experienced fund managers. One possibility is that they may simply be unaware

¹⁸See Bound and Turner (2002) for more information on other potential reasons for the observed differences in educational attainment of military personnel across various cohorts.

of the flow effect that we uncover in this paper. However, we observe that within our data set, the vast majority of fund companies reveal general background about their active managers through easily accessible media sources. In addition, the results of Section IID indicate that fund companies have fund flow benefits associated with disclosing information through such information outlets, suggesting that most of the fund management companies are likely to act strategically in revealing information about a manager’s military background. Another possibility is that fund companies are reluctant to employ ex-military managers because these managers perform worse than others. However, we find that managers with a military background do not exhibit significantly different skills or managerial traits relative to other managers, and if anything, they tend to be more ethical. Overall, we find no supportive evidence for these alternative mechanisms. We acknowledge that other equilibrium mechanisms that we are not able to address in our setting are possible (e.g., higher compensation paid to managers with military experience).

V. Conclusions

In this paper, we investigate whether biographical characteristics of mutual fund managers, specifically prior engagement in the military, influence investor asset allocation decisions. We suggest that distinct trust-building attributes of fund managers with prior military experience result in investors perceiving them as money guardians with military-associated qualities. Thus, investors are more likely to allocate capital to funds managed by military-experienced individuals, even when these managers do not exhibit superior investment skill compared with their nonmilitary peers. We find that mutual funds with military-experienced managers have annualized net fund flows that are 10.6 percentage points higher and grow by up to 6.5% faster per annum relative to comparable funds run by managers who do not have such a background. Military managers’ superiority in competing for investor funds is robust to several alternative explanations, and cannot be explained by fund or managerial attributes, including performance. Additionally, we find that the content and salience of disclosures about the military background also influence investor decisions; that is, the fund flow effect is more pronounced when investors are exposed to salient, accentuated information.

Although we observe no evidence of rational statistical reasons for such investor decisions, results from several tests provide support for trust-mediated allocation of assets. We find that investors’ buying and selling behavior toward military-managed funds is related to nationwide confidence in the military, ratified by distinct investors’ partisan attitudes toward these funds during the episodes of heightened trust. Consistent with this finding, we observe that ex-military managers experience significantly lower fund flows following the exogenous events of military-related scandals that have adversely affected nationwide trust in the military. Further, we find that military managers have higher fund inflows relative to their nonmilitary counterparts following both extremely good and poor performance. The difference-in-differences

analysis around the dates of managerial turnover reveals that, even without any other fundamental events and all else being equal, incoming managers with a military background receive significantly higher net fund flows relative to other managers. In an experimental setting in which we randomly assign military background to managers and eliminate the possibility for rational choice explanations, we find that subjects invest significantly more money in a fund when it is managed by an ex-military manager. Last, using investor-level information, we observe that military-induced asset allocation is unaffected by investor political party identification but is more pronounced among older investors.

Taken together, the findings of this paper suggest that military-associated trust-building attributes of fund managers influence mutual fund investor decisions. The empirical findings of this paper provide support to portfolio management delegation theories, particularly those emphasizing the role of trust, and can be interpreted under the description of trust-mediated fund allocation offered in them. Future research could further investigate the causes and effects of trust in the asset management industry. One direction for future research would be an exploration of the potential for trust-induced investor decision-making related to other economic agents (e.g., corporate executives, financial analysts, and hedge fund managers). Finally, it might be useful to explore other managerial characteristics that could potentially foster investor trust and affect investor purchase decisions.

Appendix A. Variable Description

Table AI. Descriptions of Main Variables and Sources.

This table provides descriptions and sources of variables used in our study. The following abbreviations are used: CRSP - CRSP Survivorship Bias Free Mutual Fund Database; MS - Morningstar Direct Database; BL - Bloomberg; MQ - Marquis Who's Who database; FINRA - BrokerCheck; LI - LinkedIn; SEC - SEC filings, NSAR-B filings; INT - Intelius database; GI - GI Search engine; ANC - Ancestry.com; LEG - Legacy.com; FW - Fund company websites; LN - LexisNexis; NP - Newspapers.com; Gallup - Gallup's Confidence in Institutions survey; FBI - Federal Bureau of Investigation NICS database; AE - Authors' estimations; MC - Manually collected.

Variables	Description	Source
Panel A: Dependent Variables		
Fund flows	Monthly net percentage fund flows, computed as $(TNA_t^i - TNA_{t-1}^i(1 + r_t^i))/TNA_{t-1}^i$, where TNA_t^i is the fund i 's total net assets in month t and r_t^i stands for the net return in month t .	CRSP, AE
Absolute dollar flows	Monthly absolute dollar value of fund flows, computed as $TNA_t^i - TNA_{t-1}^i(1 + r_t^i)$, where TNA_t^i is the fund i 's total net assets in month t and r_t^i stands for the net return in month t .	CRSP, AE
Change of a fund's market (segment) share	A fund's market (segment) share in a given month divided by the fund's market (segment) share in the previous month, where the segment share is a fraction of a fund's TNA in the average segment TNA.	CRSP, AE
Panel B: Main Independent Variables		
Military	Dummy variable equal to one if a fund is single-managed by an individual with a military background in a given month, and zero otherwise.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Military team	Dummy variable equal to one if a fund management team includes a manager with prior military background in a given month, and zero otherwise.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Conflict/Medal	Dummy variable equal to one if a fund is single-managed by an individual who served a tour of duty in a conflict zone and, 0 otherwise.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Military training	Dummy variable equal to one if a manager has never served in the military but has graduated from any of the U.S. military schools and academies or voluntarily participated in any type of military training, and zero otherwise. Based on additionally collected data.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Panel C: Fund Variables		

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Table AI – continued from previous page.

Variables	Description	Source
Military team share	Share of military-experienced managers in a fund management team.	MS, BL, MQ, FW, LI, SEC, GI, LN, NP, AE, MC
Returns (raw)	A fund's monthly raw net return.	CRSP
Performance rank	Performance rank based on a fund's monthly return relative to all other funds in the same market segment (based on the Morningstar style boxes) in a given month normalized to be between 0 and 1.	CRSP, AE
Performance rank ²	Squared value of performance rank.	CRSP, AE
Three-months returns	A fund's net return over the past three months.	CRSP, AE
One-year returns	A fund's net return over the past 12 months.	CRSP, AE
Five-year returns	A fund's net return over the past 60 months.	CRSP, AE
Fund risk	Time series standard deviation of a fund's returns using the rolling twelve-months window of past returns.	CRSP, AE
Fund age	Logarithm of a fund's age in full years from the date the fund was first offered, as defined in CRSP.	CRSP, AE
Fund size	Logarithm of a fund's total net assets in million USD.	CRSP, AE
Turnover ratio	A fund's turnover ratio.	CRSP
Expense ratio	A fund's expense ratio in %.	CRSP
Marketing expenses	Share of a fund's marketing expenses in its total expenses.	SEC, AE, MC
Family flow	Average of fund flows over all funds belonging to the same fund family as a given fund in a given month, net of flows in a fund itself.	CRSP, AE
No load fund	Dummy variable equal to one if a fund does not charge a front-end load fee in a given month, and zero otherwise.	CRSP
Retail fund	Dummy variable equal to one if a fund is a retail fund in a given month and 0 otherwise.	CRSP
Institutional fund	Dummy variable equal to one if a fund is an institutional fund in a given month, and zero otherwise.	CRSP
Defense holdings	Share of defense stocks in total fund's portfolio in a given month.	TR
Lagged fund flow	One month lagged flows of a given fund.	CRSP, AE
Investment media	Dummy variable equal to one for funds that disclose information on manager's prior military experience through investment media sources, and zero otherwise.	MC, MS, BL

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Table AI – continued from previous page.

Variables	Description	Source
Personal disclosures	Dummy variable equal to one if information on manager’s prior military experience is not available in investment outlets, but on fund company websites or professional networks, and zero otherwise.	MC, FW, LI
Other sources	Dummy variable equal to one if military background information is only disclosed via major or regional newspapers or other alternative media outlets, and zero otherwise.	MC, NP
Post-mortem placebo	Dummy variable equal to one if military background information is only disclosed in obituary notices after manager passing, but not prior to that. Based on additionally collected data.	MC, LEG
Panel D: Manager-Specific and Other Variables		
Age	Biological age of a manager in years in a given month.	MS, BL, INT, FW, NP, MC
Married (Marital status)	Dummy variable equal to one if a fund manager is married in a given month, and zero otherwise.	MS, INT, FW, NP, MC
Fund tenure	Tenure of a manager in years in a given month, computed as difference between a current date and the date when the manager has started managing the fund.	MS, FINRA, AE
Industry tenure	Tenure of a manager in years in a given month, computed as difference between a current date and the date when the manager joined the fund management industry.	MS, FINRA, AE
Bachelors only	Dummy variable equal to one if a manager has a bachelor’s degree as the highest degree earned, and zero otherwise.	MS, BL, LI, MQ, MC
MBA and above	Dummy variable equal to one if a manager has a MBA/PhD/JD/MD degree as the highest degree earned, and zero otherwise.	MS, BL, LI, MQ, MC
Ivy league	Dummy variable equal to one if a manager has any degree from an Ivy league school, and zero otherwise.	MS, BL, LI, MQ, MC
Foreign name	Dummy variable equal to one if a manager’s name is perceived as non-English sounding (but rather as African, Asian, Arabic, Hispanic, etc.), and zero otherwise. Estimations are based on Ye et al. (2017)’s machine-learning algorithm.	AE
Non-financial industry experience	Dummy variable equal to one if a manager has prior non-financial industry experience, and zero otherwise.	MS, BL, LI, MC
Media coverage	Number of articles in the LexisNexis “U.S. newspapers” universe referencing the manager in the headline or story body in a given month.	LN, MC

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Table AI – continued from previous page.

Variables	Description	Source
Father manager	Dummy variable equal to one if a manager's father has worked in the asset management industry, and zero otherwise.	MS, MQ, ANC, LEG, NP, MC
Confidence in the military index	Normalized confidence in the military index in a given year, computed as ratio of "great deal confidence" to "very little/none confidence" respondents in a given year. Survey data is based on a random sample of approximately 1,000 adults, aged 18 and older, from all 50 U.S. states.	Gallup, AE
Satisfaction with the military	Normalized satisfaction with the nation's military strength and preparedness index in a given year.	Gallup, AE
Firearm checks (NICS)	The percentage change in the number of background checks on purchases of firearms conducted through the National Instant Criminal Background Check System.	FBI, AE

Appendix B. Military Background Information

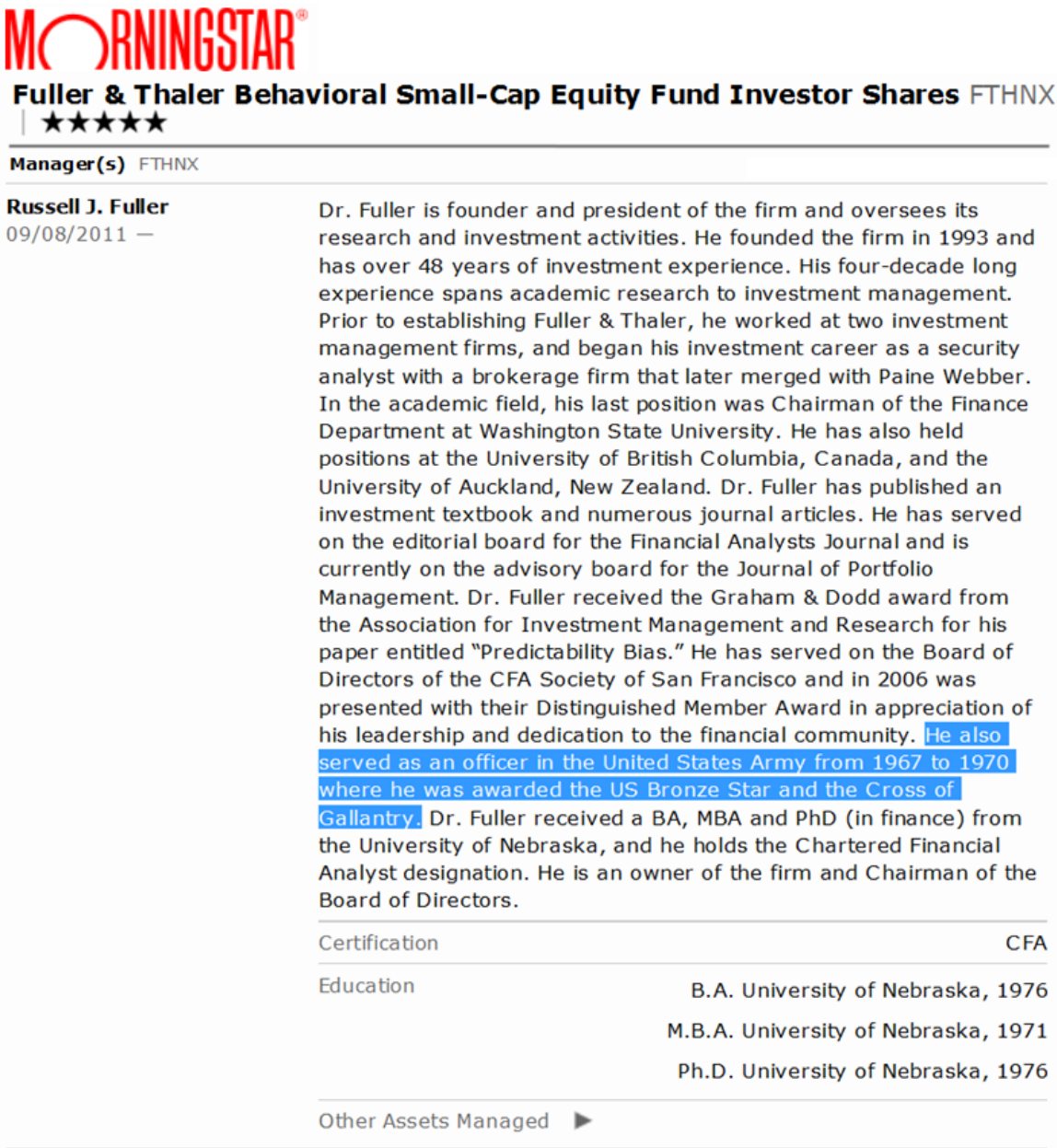


Figure B1. Morningstar sample profile of a fund manager with military background. This figure shows an exemplary manager profile retrieved from Morningstar Direct. The information regarding the manager’s military background is highlighted in blue.

Bloomberg

Executive Profile

Anthony Eugene Sutton

Portfolio Manager & Analyst, Redwood Investments, LLC

Age	Total Calculated Compensation	This person is connected to 0 Board Member in 0 organization across 3 different industries.
55	--	

Background

Mr. Anthony Eugene Sutton, also known as Tony, is a Portfolio Manager and Analyst since 2012 at Redwood Investments, LLC. Mr. Sutton joined the firm in 2010 and serves as Portfolio Manager for SMID growth and Analyst for the large cap core and large cap growth strategies. His primary research coverage includes biotechnology, medical equipment, software, and services. Prior to joining this, Mr. Sutton was a Managing Director and Portfolio Manager at Putnam Investment Management, LLC. He joined the firm in 2001. Prior to this, he was a Specialty Growth Analyst at Putnam Investment Management covering health care, biotechnology, defense, and technology. Mr. Sutton was an Associate Analyst at Fidelity Management and Research from 1989 to 1993 and Portfolio Manager at Cabot Money Management from 1995 to 1998. He also served as the Chief Investment Officer at McDonald-Sutton Asset Management, LLC from 1998 to 2001. Mr. Sutton is a combat-decorated former US Marine, specializing in intelligence with extended tours served in the Middle East and Central America from 1982 to 1988. He began his investment career at Fidelity Investments and following graduate school, he managed growth portfolios for private clients. Mr. Sutton received M.B.A from MIT Sloan School of Management in 1993 and B.A. from Monmouth University in 1989.

Figure B2. Bloomberg sample profile of a fund manager with military background. This figure shows an exemplary manager profile retrieved from Bloomberg Executive Profiles. The information regarding the manager's military background is highlighted in blue.

Princeton Global Asset Management LLC

Investment Professionals

RONALD K. STRIBLEY, Managing Director, has implemented an investment philosophy focused on the “Value Style” for over 30 years. During this period he developed and refined a systematic and disciplined investment process that seeks to find equities which have low Price to Earnings Ratios with tangible evidence of improving corporate fundamentals. He is the founder of Stribley Capital Management. Ron was a partner in The Ayco Company L.P., a wholly owned subsidiary of Goldman Sachs, where he created, implemented, and managed a Value Style Portfolio. Prior to joining Ayco, Ron was First Vice President for The Glenmede Trust Company, where he managed in excess of \$2.5 Billion including the large capitalization US equity Pew Charitable Trust portfolio. Ron is a CFA® Charterholder since 1975 and has passed the NASD Series 7 and 66 examinations. He received his BSBA degrees from Babson College and then served a tour of duty in Viet Nam with the 11th Armored Calvary Regiment and was awarded the Bronze Star. Following his honorable discharge as a 1st Lieutenant, he completed his Masters at Babson College.

Figure B3. A fund firm’s sample profile of a fund manager with military background. This figure shows an exemplary manager profile retrieved from a fund firm’s advertising materials. The information regarding the manager’s military background is highlighted in blue.

REFERENCES

- Agarwal, Vikas, Gerald D Gay, and Leng Ling, 2014, Window dressing in mutual funds, *Review of Financial Studies* 27, 3133–3170.
- Agarwal, Vikas, Yan Lu, and Sugata Ray, 2021, Are hedge funds’ charitable donations strategic?, *Journal of Corporate Finance* 66, 101842.
- Agarwal, Vikas, Linlin Ma, and Kevin Mullally, 2015, Managerial multitasking in the mutual fund industry, CFR Working Papers 13-10 [rev.], University of Cologne, Centre for Financial Research (CFR).
- Barber, Brad M, Terrance Odean, and Lu Zheng, 2005, Out of sight, out of mind: The effects of expenses on mutual fund flows, *Journal of Business* 78, 2095–2120.
- Benmelech, Efraim, and Carola Frydman, 2015, Military CEOs, *Journal of Financial Economics* 117, 43–59.
- Bergstresser, Daniel, John M R Chalmers, and Peter Tufano, 2009, Assessing the costs and benefits of brokers in the mutual fund industry, *Review of Financial Studies* 22, 4129–4156.
- Berk, Jonathan B, and Richard C Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.
- Blader, Steven L, and Tom R Tyler, 2009, Testing and extending the group engagement model: Linkages between social identity, procedural justice, economic outcomes, and extrarole behavior, *Journal of Applied Psychology* 94, 445.
- Blanco, Luisa, and Isabel Ruiz, 2013, The impact of crime and insecurity on trust in democracy and institutions, *American Economic Review* 103, 284–88.
- Bound, John, and Sarah Turner, 2002, Going to war and going to college: Did World War II and the GI Bill increase educational attainment for returning veterans?, *Journal of Labor Economics* 20, 784–815.
- Cao, Liquan, Francis T Cullen, and Bruce G Link, 1997, The social determinants of gun ownership: Self-protection in an urban environment, *Criminology* 35, 629–658.
- Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.
- Carlson, Jennifer D, 2012, ‘I don’t dial 911’: American gun politics and the problem of policing, *British Journal of Criminology* 52, 1113–1132.
- Chevalier, Judith, and Glenn Ellison, 1999, Career concerns of mutual fund managers, *Quarterly Journal of Economics* 114, 389–432.

- Chuprinin, Oleg, and Denis Sosyura, 2018, Family descent as a signal of managerial quality: Evidence from mutual funds, *Review of Financial Studies* 31, 3756–3820.
- Cialdini, Robert B, and Noah J Goldstein, 2004, Social influence: Compliance and conformity, *Annual Review of Psychology* 55, 591–621.
- Cici, Gjergji, Monika Gehde-Trapp, Marc-André Göricke, and Alexander Kempf, 2018, The investment value of fund managers’ experience outside the financial sector, *Review of Financial Studies* 31, 3821–3853.
- Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008, The small world of investing: Board connections and mutual fund returns, *Journal of Political Economy* 116, 951–979.
- Cooper, Michael J, Orlin Dimitrov, and P Raghavendra Rau, 2001, A rose.com by any other name, *Journal of Finance* 56, 2371–2388.
- Cooper, Michael J, Huseyin Gulen, and P Raghavendra Rau, 2005, Changing names with style: Mutual fund name changes and their effects on fund flows, *Journal of Finance* 60, 2825–2858.
- Dangl, Thomas, Youchang Wu, and Josef Zechner, 2006, Market discipline and internal governance in the mutual fund industry, *Review of Financial Studies* 21, 2307–2343.
- De Tray, Dennis, 1982, Veteran status as a screening device, *American Economic Review* 72, 133–42.
- Del Guercio, Diane, and Paula A Tkac, 2008, Star power: The effect of Morningstar ratings on mutual fund flow, *Journal of Financial and Quantitative Analysis* 43, 907–936.
- Diener, Edward, and Kenneth W Kerber, 1979, Personality characteristics of American gun-owners, *Journal of Social Psychology* 107, 227–238.
- Duffy, Tim, 2006, Military experience & CEOs: Is there a link?, Korn/Ferry International Report.
- Egan, Mark, Gregor Matvos, and Amit Seru, 2019, The market for financial adviser misconduct, *Journal of Political Economy* 127, 233–295.
- Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.
- Fama, Eugene F, and Kenneth R French, 2010, Luck versus skill in the cross-section of mutual fund returns, *Journal of Finance* 65, 1915–1947.
- Frazzini, Andrea, and Owen Lamont, 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* 88, 299–322.

- Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2015, Money doctors, *Journal of Finance* 70, 91–114.
- Glazer, Jacob, and Ariel Rubinstein, 2004, On optimal rules of persuasion, *Econometrica* 72, 1715–1736.
- Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2004, The role of social capital in financial development, *American Economic Review* 94, 526–556.
- Hirshleifer, David, 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533–1597.
- Hoechle, Daniel, Stefan Ruenzi, Nic Schaub, and Markus Schmid, 2018, Financial advice and bank profits, *Review of Financial Studies* 31, 4447–4492.
- Hooghe, Marc, and Jennifer Oser, 2017, Partisan strength, political trust and generalized trust in the United States: An analysis of the general social survey, 1972–2014, *Social Science Research* 68, 132–146.
- Hortaçsu, Ali, and Chad Syverson, 2004, Product differentiation, search costs, and competition in the mutual fund industry: A case study of S&P 500 index funds, *Quarterly Journal of Economics* 119, 403–456.
- Huddy, Leonie, and Nadia Khatib, 2007, American patriotism, national identity, and political involvement, *American Journal of Political Science* 51, 63–77.
- Jackson, Joshua J, Felix Thoemmes, Kathrin Jonkmann, Oliver Lüdtke, and Ulrich Trautwein, 2012, Military training and personality trait development: Does the military make the man, or does the man make the military?, *Psychological Science* 23, 270–277.
- Jain, Prem C, and Joanna Shuang Wu, 2000, Truth in mutual fund advertising: Evidence on future performance and fund flows, *Journal of Finance* 55, 937–958.
- Jensen, Michael C, 1968, The performance of mutual funds in the period 1945–1964, *Journal of Finance* 23, 389–416.
- Kaniel, Ron, Laura T Starks, and Vasudha Vasudevan, 2007, Headlines and bottom lines: Attention and learning effects from media coverage of mutual funds, Working Paper, University of Texas.
- Khorana, Ajay, 1996, Top management turnover an empirical investigation of mutual fund managers, *Journal of Financial Economics* 40, 403–427.
- Knack, Stephen, and Philip Keefer, 1997, Does social capital have an economic payoff? A cross-country investigation, *Quarterly Journal of Economics* 112, 1251–1288.

- Koch-Bayram, Irmela F, and Georg Wernicke, 2018, Drilled to obey? Ex-military CEOs and financial misconduct, *Strategic Management Journal* 39, 2943–2964.
- Kostovetsky, Leonard, 2015, Whom Do You Trust?: Investor-Advisor Relationships and Mutual Fund Flows, *Review of Financial Studies* 29, 898–936.
- Kronlund, Mathias, Veronika Krepely Pool, Clemens Sialm, and Irina Stefanescu, 2020, Out of sight no more? The effect of fee disclosures on 401(k) investment allocations, NBER Working Paper No. 27573.
- Kumar, Alok, Alexandra Niessen-Ruenzi, and Oliver G Spalt, 2015, What’s in a name? Mutual fund flows when managers have foreign-sounding names, *Review of Financial Studies* 28, 2281–2321.
- Lakonishok, Josef, Andrei Shleifer, Richard H Thaler, and Robert W Vishny, 1991, Window dressing by pension fund managers, *American Economic Review* 81, 227–231.
- MacLean, Alair, and Glen H Elder Jr, 2007, Military service in the life course, *Annual Review of Sociology* 33, 175–196.
- Malmendier, Ulrike, Geoffrey Tate, and Jon Yan, 2011, Overconfidence and early-life experiences: The effect of managerial traits on corporate financial policies, *Journal of Finance* 66, 1687–1733.
- Mullainathan, Sendhil, Joshua Schwartzstein, and Andrei Shleifer, 2008, Coarse thinking and persuasion, *Quarterly Journal of Economics* 123, 577–619.
- Niessen-Ruenzi, Alexandra, and Stefan Ruenzi, 2019, Sex matters: Gender bias in the mutual fund industry, *Management Science* 65, 3001–3025.
- Pástor, Luboš, Robert F Stambaugh, and Lucian A Taylor, 2015, Scale and skill in active management, *Journal of Financial Economics* 116, 23–45.
- Patel, Saurin, and Sergei Sarkissian, 2013, Deception and managerial structure: A joint study of portfolio pumping and window dressing practices, Working Paper, University of Western Ontario.
- Patel, Saurin, and Sergei Sarkissian, 2017, To group or not to group? Evidence from mutual fund databases, *Journal of Financial and Quantitative Analysis* 52, 1989–2021.
- Petrocik, John Richard, 2009, Measuring party support: Leaners are not independents, *Electoral Studies* 28, 562–572.
- Pope, Devin G, and Justin R Sydnor, 2011, What’s in a picture? Evidence of discrimination from prosper.com, *Journal of Human Resources* 46, 53–92.

- Rahn, Wendy M, and John E Transue, 1998, Social trust and value change: The decline of social capital in American youth, 1976–1995, *Political Psychology* 19, 545–565.
- Roussanov, Nikolai, and Pavel Savor, 2014, Marriage and managers’ attitudes to risk, *Management Science* 60, 2496–2508.
- Sampson, Robert J, and John H Laub, 1996, Socioeconomic achievement in the life course of disadvantaged men: Military service as a turning point, circa 1940-1965, *American Sociological Review* 347–367.
- Sapp, Travis, and Ashish Tiwari, 2004, Does stock return momentum explain the ”smart money” effect?, *Journal of Finance* 59, 2605–2622.
- Solomon, David H, Eugene Soltes, and Denis Sosyura, 2014, Winners in the spotlight: Media coverage of fund holdings as a driver of flows, *Journal of Financial Economics* 113, 53–72.
- Spiegel, Matthew, and Hong Zhang, 2013, Mutual fund risk and market share-adjusted fund flows, *Journal of Financial Economics* 108, 506–528.
- Teigen, Jeremy M, 2013, Military experience in elections and perceptions of issue competence: An experimental study with television ads, *Armed Forces & Society* 39, 415–433.
- Ye, Juntong, Shuchu Han, Yifan Hu, Baris Coskun, Meizhu Liu, Hong Qin, and Steven Skiena, 2017, Nationality classification using name embeddings, in *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, CIKM ’17, 1897–1906 (ACM, New York, NY, USA).

Table I. Fund and Manager Characteristics

This table reports fund and manager characteristics for our sample of funds managed by individuals with prior military experience and for the peer managers who do not have such experience. Both groups of funds are restricted to fund managers who single-managed U.S. domestic equity funds at some point between 1991 and 2017. The differences between the group means and the corresponding t-statistics, clustered by fund for fund attributes and clustered by manager for manager attributes, are reported in columns (3) and (4), respectively. Panel A reports fund characteristics. Fund flows are the net percentage flows of the fund in a given month (annualized), as specified in equation (1). Other fund characteristics include: raw returns (annualized); performance rank of the fund in a given month relative to all other funds in the same market segment; fund risk (time series standard deviation of the fund returns using the rolling past twelve month return observations); fund age as the natural logarithm of fund age in years in a given month; fund size as natural logarithm of the fund's size in million USD; turnover ratio; expense ratio; marketing expenses as the share of marketing expenses (NSAR-B filings) in total expenses; Morningstar rating; family flows as the monthly growth rate of fund's family; defense holdings as the share of defense stocks in total fund's portfolio in a given month; and indicator variables for no load, retail, and institutional funds. Panel B reports specific manager characteristics, including biological age, fund and industry tenure, and share of managers with foreign name. The panel also reports the fractions of managers by their top degree and Ivy league school attainment. Manager's media coverage is the number of times a fund manager is mentioned in a given month in the headline or story body of all U.S. newspapers.

Panel A: Fund Characteristics				
Variable	Military managers (1)	Other managers (2)	Difference (3)	t-statistic (4)
Fund flows	0.224	0.118	0.106	5.06
Returns (raw)	0.096	0.091	0.005	0.79
Performance rank	0.556	0.552	0.004	1.13
Performance rank ²	0.394	0.390	0.004	0.95
Fund risk	0.045	0.047	-0.001	-1.27
Fund age	1.882	2.056	-0.174	-1.38
Fund size	4.887	5.078	-0.190	-0.94
Turnover	0.863	0.827	0.036	0.31
Morningstar rating	3.175	3.098	0.077	0.62
Expense ratio	0.012	0.012	-0.001	-1.47
Marketing expenses	0.341	0.332	0.009	0.35
Family flows	0.010	0.006	0.007	1.65
No load fund	0.219	0.197	0.022	0.49
Retail fund	0.719	0.873	-0.154	-0.88
Institutional fund	0.489	0.476	0.012	0.27
Defense holdings	1.379	1.485	-0.106	-0.78
Panel B: Manager Characteristics				
Age	53.003	46.773	6.230	3.96
Married	0.851	0.856	-0.005	-1.17
Fund tenure	8.038	6.513	1.524	1.19
Industry tenure	11.144	9.155	1.989	1.80
Bachelors only	0.237	0.288	-0.051	-0.80
MBA top	0.682	0.587	0.095	1.22
PhD/JD/MD top	0.054	0.059	-0.004	-0.11
Ivy league bachelors	0.215	0.149	0.066	0.87
Ivy league MBA	0.230	0.227	0.003	0.04
Ivy league	0.406	0.305	0.101	1.04
Foreign name	0.229	0.298	-0.069	-0.87
Media coverage	2.405	2.192	0.214	0.56

Table II. Military Background of Mutual Fund Managers and Fund Flows

This table relates managers' military background to fund flows. The dependent variable is monthly net percentage fund flows. The main independent variable is the military dummy that equals one if a fund is single-managed by an individual with military background in a given month, and zero if the manager does not have a military background. The set of control variables is comprised of variables described in Table I and in Appendix A. All control variables, except family flows, are lagged by one month. Segment is defined by the Morningstar fund style indicator. Specification (1) reports results of percentage fund flow regression without fixed effects. Regression specifications (2) to (6) include period, segment, family, fund, and/or interaction fixed effects. Period FE stands for month-year fixed effects. Standard errors are double-clustered by fund and month-year. The corresponding t-statistics are reported in parentheses.

	Dependent Variable: Fund Flows					
	(1)	(2)	(3)	(4)	(5)	(6)
Military	0.005 (3.80)	0.005 (3.42)	0.003 (3.20)	0.003 (3.27)	0.003 (2.16)	0.003 (1.93)
Fund returns	0.071 (9.37)	0.168 (9.74)				
Performance rank			0.012 (15.78)	0.013 (16.38)	0.008 (11.55)	0.011 (14.43)
Lagged fund flow			0.415 (43.48)	0.412 (43.54)	0.268 (28.26)	0.340 (35.04)
Fund risk	-0.181 (-11.68)	-0.291 (-12.23)	-0.143 (-9.33)	-0.302 (-9.88)	-0.083 (-5.90)	-0.116 (-6.94)
Fund size	-0.002 (-9.97)	-0.002 (-8.28)	-0.001 (-10.43)	-0.001 (-10.46)	-0.001 (-7.92)	-0.006 (-15.49)
Fund age	-0.007 (-16.75)	-0.007 (-16.53)	-0.004 (-15.61)	-0.004 (-15.60)	-0.003 (-10.68)	-0.000 (-0.10)
Turnover	-0.000 (-1.00)	-0.000 (-0.76)	-0.000 (-0.91)	-0.000 (-0.90)	-0.001 (-2.49)	-0.001 (-1.79)
Expense ratio	0.079 (2.92)	0.096 (3.23)	0.041 (2.00)	0.043 (2.05)	0.181 (2.94)	0.032 (0.82)
Family flows	0.462 (24.01)	0.397 (19.85)	0.278 (19.07)	0.274 (18.95)	0.360 (34.29)	0.257 (16.25)
Industry tenure	-0.000 (-0.23)	0.000 (1.42)	0.000 (1.34)	0.000 (1.31)	0.000 (0.22)	-0.000 (-1.72)
Fund tenure	-0.000 (-2.79)	-0.000 (-3.36)	-0.000 (-2.85)	-0.000 (-2.76)	0.000 (0.75)	-0.000 (-0.14)
Segment FE	No	Yes	Yes	No	No	No
Period FE	No	Yes	Yes	No	No	Yes
Segment $\times$ Period FE	No	No	No	Yes	No	No
Family $\times$ Period FE	No	No	No	No	Yes	No
Fund FE	No	No	No	No	No	Yes
Adj. R-squared	0.087	0.099	0.266	0.270	0.610	0.300
N of funds	2,412	2,412	2,412	2,412	2,064	2,380
Observations	170,371	170,371	170,371	170,371	136,799	170,338

Table III. Alternative Explanations and Robustness of the Results

This table reports results of robustness tests. Specifically, this table shows the estimates of net percentage fund flows regressed on the military dummy, but, depending on the robustness test, flow regressions include additional control variables or are estimated with an adjusted sample of funds. Additional control variables for managerial attributes include manager's gender, biological age, marital status, education, prior experience, foreignness of a name, father background, and media coverage. Additional control variables for fund attributes include long-term performance; retail, institutional and no load fund indicators; the share of defense stocks in the fund portfolio; and the share of fund marketing expenses in a given month. All of the variables are described in Appendix A. The setup also includes the standard set of control variables and is otherwise identical to the specification (3) of Table II. Standard errors are double-clustered by fund and month-year.

Alternative explanations		Dependent Variable: Fund Flows			
		Coefficient	t-statistic	N of funds	Observations
(1)	Return 3-months control	0.002	2.97	2,403	168,901
(2)	Return 1-year control	0.002	2.20	2,297	155,467
(3)	Return 5-year control	0.002	2.18	1,612	96,689
(4)	Defense holdings share control	0.002	2.22	2,167	76,967
(5)	Coefficient estimates (military) when controlling for demographics				
	Gender	0.003	3.16	2,412	170,371
	Gender and age	0.003	3.93	2,399	169,123
	Gender, age and marital status	0.004	4.05	2,242	153,147
(6)	Coefficient estimates (military) when controlling for degree				
	Bachelors only	0.003	3.13	2,406	169,843
	MBA and above	0.003	3.25		
(7)	Controlling for the level of recognition of education				
	Military	0.003	3.11	2,402	169,556
	Ivy league	0.001	3.45		
(8)	Non-Financial industry experience				
	Military	0.003	3.17	2,406	169,887
	Non-financial industry experience	0.000	0.21		
(9)	Foreign name				
	Military	0.003	3.32	2,412	170,371
	Foreign name	-0.001	-2.79		
(10)	Manager's family background				
	Military	0.004	2.98	1,014	56,656
	Father fund manager	0.002	1.41		
(11)	Marketing expenses				
	Military	0.004	3.18	1,665	101,465
	Marketing expenses	0.000	3.98		
(12)	Coefficient estimates (military) by distribution channels				
	Retail fund	0.003	3.24	2,404	170,264
	Institutional fund	0.003	3.09	2,404	170,264
	No load fund	0.003	3.21	2,412	170,371
(13)	Manager's media coverage control				
	Military	0.002	2.38	1,391	134,293
	Media coverage	0.000	0.14		
(14)	Excluding index funds	0.005	2.83	2,154	153,447
(15)	Placebo: Subsample of index funds	0.002	0.45	258	16,899

Table IV. Fund Flows and the Degree of Military Involvement

This table relates percentage fund flows to the managers' degree of involvement in the military. Panel A presents results of a univariate sorting by the Conflict/Medal dummy and the Military training indicator variable. The Conflict/Medal dummy equals one if a fund is managed by an individual who served a tour of duty in a conflict zone, and zero otherwise. The Military training dummy covers another extreme of military involvement and takes the value of one if a manager has never served in the military but has graduated from any of the U.S. military schools and academies or participated in any type of military training and zero otherwise. The Conflict/Medal indicator variable represents a subset of military managers, while the Military training dummy covers additionally collected data on managers who have just undergone military training. Panel B shows the estimates of net percentage fund flows regressed on the aforementioned variables and on the interaction term with the military dummy. The setup of the regressions includes the standard set of control variables and is otherwise identical to the baseline specification (3) of Table II. Standard errors are double-clustered by fund and month-year and t-statistics are reported in parentheses.

Panel A: Univariate sorting	Fund Flows			
	Military managers	Other managers	Difference	t-statistic
Conflict/Medal	0.029	0.010	0.018	3.39
Military training	0.010	0.010	-0.001	-0.16

Panel B: Regression analysis	Dependent Variable: Fund flows			
	(1)	(2)	(3)	(4)
Military	0.002 (2.70)	0.002 (2.55)		
Military $\times$ Conflict/Medal	0.005 (2.06)	0.006 (2.15)	0.007 (2.70)	
Military training	-0.003 (-1.42)			-0.001 (-0.66)
Controls	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.266	0.266	0.266	0.266
N of funds	2,412	2,412	2,412	2,412
Observations	170,371	170,371	170,371	170,371

Table V. Information Distribution Channels and Fund Flows

This table presents mean fund flows estimates from univariate sorting (Panel A) and coefficient estimates of net percentage fund flows from the regressions (Panel B) by four distinct distribution channels for military background information disclosure. The Investment media indicator variable equals one for funds that disclose information on the manager's prior military experience through investment media sources, namely, Morningstar and Bloomberg, and zero otherwise. The Personal disclosures dummy is coded as one if this information is not available in investment outlets, but on fund company websites or professional networks, and zero otherwise. The Other sources variable takes the value of one if military background information is only disclosed via major or regional newspapers or other alternative media outlets, and zero otherwise. The Post-mortem placebo variable is one for cases in which military affiliation is disclosed in obituary notices after manager passing, but not prior to that. The first three variables represent subsets of military managers, while the Post-mortem placebo dummy covers additionally collected data. Panel B shows the estimates of net percentage fund flows regressed on the aforementioned variables. We use the same regression setup, including the standard set of control variables, as in the baseline specification (3) of Table II. Standard errors are double-clustered by fund and month-year and t-statistics are reported in parentheses.

Panel A: Univariate sorting	Fund flows			
	Military managers	Other managers	Difference	t-statistic
Investment media	0.025	0.010	0.014	3.52
Personal disclosures	0.028	0.010	0.018	6.27
Other sources	0.011	0.010	0.000	0.11
Post-mortem placebo	0.011	0.010	0.000	0.11

Panel B: Regression analysis	Dependent Variable: Fund flows			
	(1)	(2)	(3)	(4)
Investment media	0.006 (3.14)			
Personal disclosures		0.007 (4.39)		
Other sources			-0.001 (-1.00)	
Post-mortem placebo				-0.002 (-1.39)
Controls	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.266	0.267	0.266	0.266
N of funds	2,412	2,412	2,412	2,412
Observations	170,371	170,371	170,371	170,371

Table VI. Managers' Military Background and Fund Flows: Team-Managed Funds

This table reports the estimates of the regressions with monthly net percentage fund flows as the dependent variable and military team indicator as the explanatory variable. The military team dummy takes the value of one if a fund management team includes a manager with prior military background in a given month and equals zero if there are no military-experienced individuals in a management team that manages a fund. The setup of the regressions includes the standard set of control variables (apart from manager-specific industry experience and fund tenure controls) and is otherwise identical to regression specifications of Table II. Specifications (3) and (4) additionally include interaction terms with the share of military-experienced managers in a management team and with three distinct information distribution channels (specified in Table V), respectively. Standard errors are double-clustered by fund and month-year and t-statistics are reported in parentheses.

	Dependent Variable: Fund Flows			
	(1)	(2)	(3)	(4)
Military team	0.000 (0.11)	0.000 (0.15)	-0.001 (-0.39)	0.001 (0.25)
Military team share			0.003 (0.43)	
Military team $\times$ Investment media				0.001 (0.35)
Military team $\times$ Personal disclosures				-0.001 (-0.55)
Military team $\times$ Other sources				-0.001 (-0.20)
Lagged fund flow		0.397 (34.68)	0.397 (34.68)	0.397 (34.69)
Performance rank	0.012 (12.91)	0.009 (14.34)	0.009 (14.33)	0.009 (14.33)
Fund risk	-0.284 (-10.63)	-0.159 (-8.73)	-0.159 (-8.73)	-0.159 (-8.74)
Fund size	-0.000 (-1.03)	-0.000 (-0.17)	-0.000 (-0.16)	-0.000 (-0.11)
Fund age	-0.008 (-18.63)	-0.004 (-17.53)	-0.004 (-17.52)	-0.004 (-17.49)
Turnover ratio	0.001 (3.48)	0.001 (3.29)	0.001 (3.28)	0.001 (2.28)
Expense ratio	0.048 (0.63)	0.022 (0.47)	0.022 (0.47)	0.019 (0.40)
Family flow	0.294 (15.76)	0.211 (14.66)	0.211 (14.67)	0.211 (14.64)
Segment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.080	0.232	0.232	0.232
N of funds	2,019	2,019	2,019	2,019
Observations	184,183	184,183	184,183	184,183

Table VII. Fund Flows, Confidence in the Military, and Perceived Insecurity

This table relates fund flows to the nationwide confidence in the military and perceived insecurity. The table reports estimates of the regressions of monthly net fund flows on the military dummy for periods of high and low levels of confidence in the military, as classified based on the median level of Gallup's normalized confidence in the military index. Second, it shows the estimates of monthly net percentage fund flows regressed on the military dummy interacted with lagged firearm checks (NICS). The setup of the regressions is otherwise identical to the baseline specification (3) of Table II. Standard errors are double-clustered by fund and month-year, t-statistics are reported in parentheses.

	Dependent variable: Fund flows				
	Confidence in Military index		NICS FBI Checks		
	Periods (years) of low confidence	Periods (years) of high confidence	NICS FBI checks on purchases (1998/12- 2017/12)	NICS FBI checks on purchases: Periods of pos. change	NICS FBI checks on purchases: Periods of neg. change
	(1)	(2)	(3)	(4)	(5)
Military	0.002 (1.83)	0.003 (3.07)	0.003 (3.16)	0.002 (2.45)	0.004 (3.29)
Military $\times$ NICS			-0.003 (-2.70)		
NICS			-0.006 (-1.26)		
Controls	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.272	0.262	0.246	0.243	0.248
N of funds	2,104	2,059	2,267	2,252	2,206
Observations	89,966	79,746	136,025	81,432	53,826

Table VIII. Fund Flows and Managerial Changes

This table presents evidence on ordinary least squares estimates of the difference-in-differences design of equation (2). The dependent variable is monthly net fund inflows. The sample is restricted to funds with only one episode of change to single management over the period between 1991 and 2017. $Treat_i$ is an indicator for funds that were ever managed by individuals with military background. $Post$ indicator takes the value of one if a fund is solo-managed, and zero if a fund is team-managed in a given month. Columns (3) to (5) present evidence on the timing of the effect of managerial turnover on fund flows by presenting estimates from a modified version of equation (2). $Pre1$ and $Pre2$ are indicator variables for observations one and two months prior to the managerial turnover, respectively. $Post1$, $Post2$, and $Post3$ are indicator variables for observations one, two, and three months, respectively, after the managerial turnover. $Post0$ is an indicator variable for observations that occur during the months of managerial turnover. Controls include: performance rank; fund size; fund risk; fund age; turnover ratio; expense ratio; and family flows. All control variables, except family flows, are lagged by one month and are defined in Table I and in Appendix A. Segment is defined by the Morningstar fund style indicator. Period FE stands for month-year fixed effects. Standard errors are double-clustered by fund and month-year and t-statistics are reported in parentheses.

	Dependent Variable: Fund Flows				
	(1)	(2)	(3)	(4)	(5)
$Treat_i$	0.001 (0.76)	0.002 (1.24)			
$Treat_i \times Post_t$	0.006 (7.24)	0.002 (2.48)			
$Treat_i \times Pre2$			0.004 (0.34)		0.004 (0.34)
$Treat_i \times Pre1$			0.005 (0.33)		0.005 (0.33)
$Treat_i \times Post0$			0.057 (3.66)		0.057 (3.66)
$Treat_i \times Post1$				0.034 (3.16)	0.046 (3.16)
$Treat_i \times Post2$				0.029 (2.89)	0.029 (2.90)
$Treat_i \times Post3$				0.027 (2.18)	0.027 (2.18)
Controls	No	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.033	0.088	0.078	0.078	0.078
N of funds	1,684	1,619	1,619	1,619	1,619
Observations	210,749	197,484	197,484	197,484	197,484

Table IX. Flow-Performance Relationship

The dependent variable is monthly net percentage fund flows. The independent variables include the military dummy and its interaction terms with lagged performance variables. The setup of the regressions is otherwise identical to the baseline specification (3) of Table II and includes the standard set of control variables. Standard errors are double-clustered by fund and month-year, t-statistics are reported in parentheses.

	Dependent Variable: Fund Flows			
	(1)	(2)	(3)	(4)
Military	0.004 (3.44)	0.010 (2.30)	0.012 (2.75)	0.011 (2.48)
Military $\times$ Performance rank	0.010 (6.10)	-0.024 (-1.94)	-0.031 (-2.50)	-0.025 (-2.05)
Military $\times$ Performance rank ²		0.016 (2.04)	0.020 (2.57)	0.016 (2.10)
Performance rank ²		0.011 (5.34)	0.010 (4.98)	0.012 (5.66)
Performance rank	0.012 (15.68)	-0.005 (-1.62)	-0.004 (-1.36)	-0.006 (-1.84)
Controls	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	No
Segment FE	Yes	Yes	Yes	No
Family FE	No	No	Yes	No
Segment $\times$ Period FE	No	No	No	Yes
Adj. R-squared	0.266	0.267	0.276	0.271
N of funds	2,412	2,412	2,406	2,064
Observations	170,371	170,371	170,363	169,857

Table X. Microlevel Evidence From an Online Experiment

This table presents results of the Amazon Mechanical Turk online investment experiment. Panel A shows the fraction of money invested in fund A if it is managed by a military-experienced manager or by a manager without such experience, the difference between the amounts invested, and the respective t-statistic. All participants have identified themselves as U.S. mutual fund investors. Panel B shows the estimates of money invested in fund A regressed on a Military fund dummy variable and participant demographic characteristics. The Military fund indicator takes the value of one for funds which are randomly assigned to be military-managed and zero otherwise. Controls include a gender dummy and a dummy for old investors (above median biological age). Columns (1) and (4) present results for the full sample of subjects. Columns (2) and (3) present results for the two subsamples by self-reported participant party affiliation, namely Democrats and Republicans. t-statistics are reported in parentheses.

Panel A. Average distributions (Rounds including military managers)				
	% of funds allocated to fund A if		Difference	
	military manager	nonmilitary manager	(mil. - nonmil.)	t-statistic
Round 2	63.04	59.50	3.54	1.96
Round 4	13.36	10.18	3.17	5.55
Round 2 + Round 4	38.20	34.84	3.36	2.20
Panel B. Regressions (Rounds including military managers)				
	All subjects	Democrats	Republicans	Interactions
	(1)	(2)	(3)	(4)
Military fund	3.36	4.32	4.53	0.68
	(2.20)	(1.72)	(1.89)	(0.27)
Female $\times$ Military fund				0.08
				(0.98)
Old $\times$ Military fund				5.42
				(1.77)
Adj. R-squared	0.01	0.01	0.01	0.01
Observations	1,608	610	658	1,608

Table XI. Ex-Military Managers and Window Dressing

This table relates manager's military background to window dressing activities. The dependent variable is either Rank Gap or Backward Holding Return Gap (BHRG). The main independent variable is the military dummy that equals one if a fund is single-managed by an individual with a military background in a given month, and zero if the manager does not have a military background. Rank Gap is the difference between a fund's performance rank and the two ranks based on winner and loser stock proportions in the reported holdings. BHRG is calculated as the difference between the net return of a hypothetical portfolio (based on the fund's holdings in the previous quarter) and the fund's actual return. The set of control variables is comprised of variables described in Table I and in Appendix A. All of the regression specifications include period and segment fixed effects. Period FE stands for quarter-year time fixed effects. Standard errors are based on clustering at the fund level. The corresponding t-statistics are reported in parentheses.

	Full Sample		Bottom 20% perf.		Top 20% perf.	
	Rank Gap	BHRG	Rank Gap	BHRG	Rank Gap	BHRG
Military	-0.024 (-2.96)	-0.006 (-1.68)	-0.018 (-1.82)	-0.009 (-2.63)	-0.020 (-1.83)	-0.010 (-2.90)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.198	0.059	0.216	0.088	0.191	0.119
N of funds	924	924	695	695	678	678
Observations	10,388	10,388	2,134	2,134	2,319	2,319

Table XII. Matching Funds

This table reports results of the matched sample analysis. In specification (1), we report the baseline regression results. In the following specifications, we keep the regression setup, but estimate regressions on various samples of matched funds. To identify a match for a military-managed fund, we find a nonmilitary-managed counterpart fund based on the similarities of the set of matching criteria in a given month. We use the following matching criteria: manager's gender, foreignness of a name, biological age, industry experience, and fund's segment, family, size, age, performance, expense ratio, turnover, and the share of marketing expenses (NSAR-B filings) in total expenses. The first matching procedure identifies nonmilitary funds as a match if values of the non-categorical variables are in the range of five percent from the military-managed counterpart fund values in a given month. In these regressions, the set of control variables is identical to the baseline specification and standard errors are double-clustered by fund and month-year. The table also reports the estimates of the propensity score nearest neighbourhood matching (the second matching procedure) on the set of fund characteristics and t-statistics based on the bootstrapped standard errors.

		Dep. Variable: Fund Flows		
		Coefficient	t-stat.	Obs.
(1)	No Matching (Table II, Specification 3)	0.003	3.20	170,371
Matching fund and manager characteristics:				
(2)	Time and gender	0.003	3.20	155,767
(3)	Time, gender, and foreign name	0.002	2.63	110,348
(4)	Time, gender, and segment	0.003	3.21	155,109
(5)	Time, gender, segment, and fund family	0.004	2.73	25,612
(6)	Time, gender, segment, and fund size	0.004	3.12	140,866
(7)	Time, gender, segment, and fund age	0.003	3.25	143,179
(8)	Time, gender, segment, and manager age	0.003	3.62	135,813
(9)	Time, gender, segment, and manager tenure	0.002	2.81	139,729
(10)	Time, gender, segment, and performance	0.003	2.26	20,934
(11)	Time, gender, segment, and marketing exp.	0.004	3.22	83,833
Propensity score matching on the following fund characteristics:				
(12)	Perf., and size	0.007	9.78	47,225
(13)	Perf., size, and expense ratio	0.006	6.85	26,103
(14)	Perf., size, expense ratio, and turnover	0.006	7.15	26,030
(15)	Perf., size, expense ratio, turnover, and age	0.005	6.49	25,962
(16)	Perf., size, expense ratio, turnover, age, and lagged flows	0.003	3.13	25,891

Table XIII. Alternative Dependent Variable Definition

This table reports results for the alternative measures of fund flows as dependent variables. We use absolute dollar flows and the change of a fund's market share as in Spiegel and Zhang (2013) instead of relative flows as dependent variable. Specifications (1) and (2) report the regression estimates of monthly absolute dollar flows on the military dummy. These specifications differ in fixed effects applied, but the regression setup is otherwise identical to the baseline specification of Table II and includes the standard set of control variables. Specification (3) reports regression estimates of the change of a fund's market (i.e., segment) share on the military dummy. We use quantile regressions to estimate the coefficient and also include the standard set of controls and fixed effects. For presentation purposes, we report the coefficient of change in a fund's market share as multiplied by 100. Standard errors are double-clustered by fund and month-year, t-statistics are reported in parentheses.

	Modified Dependent Variable		
	Absolute fund flows		Change in fund's market share
	(1)	(2)	(3)
Military	3.294 (1.88)	3.472 (2.02)	0.003 (5.15)
Controls	Yes	Yes	Yes
Segment FE	Yes	No	Yes
Period FE	Yes	No	Yes
Segment $\times$ Period FE	No	Yes	Yes
R-squared (Pseudo R ²)	0.067	0.070	0.200
N of funds	2,412	2,412	2,412
Observations	170,371	170,371	170,371

Table XIV. Fund Performance and Persistence

This table shows additional results for fund performance and performance persistence of military managers vs. nonmilitary managers. Panel A reports results from a regression with the equal-weighted return of a difference portfolio that is long in all funds that are single-managed by an individual with military background and short in all funds with nonmilitary managers as the dependent variable. The portfolio is rebalanced on a monthly basis. Estimates of fund performance are measured using the capital asset pricing model (column (1)), the Fama and French (1993) three-factor model (column (2)) and the four-factor model of Carhart (1997) in column (3). Results for both net and gross (before expenses) performance are reported. Panel B shows results for the average time-series standard deviation of monthly performance ranks of military and nonmilitary managers along with the differences between the group means. The corresponding t-statistics are in parentheses and are based on robust standard errors.

Panel A: Fund Performance: Military – Nonmilitary				
		CAPM $_t^{m-n}$	Three-Factor $_t^{m-n}$	Four-Factor $_t^{m-n}$
		(1)	(2)	(3)
Net performance				
	Alpha $_t$	0.000 (0.38)	0.000 (1.50)	0.000 (1.49)
	R-squared	0.012	0.202	0.202
Gross performance				
	Alpha $_t$	0.001 (1.03)	0.001 (1.24)	0.001 (1.22)
	R-squared	0.009	0.208	0.208
Panel B: Performance Persistence				
		Military managers	Nonmilitary managers	Difference
Persistence net		0.279	0.281	-0.002
Persistence gross		0.269	0.275	-0.006

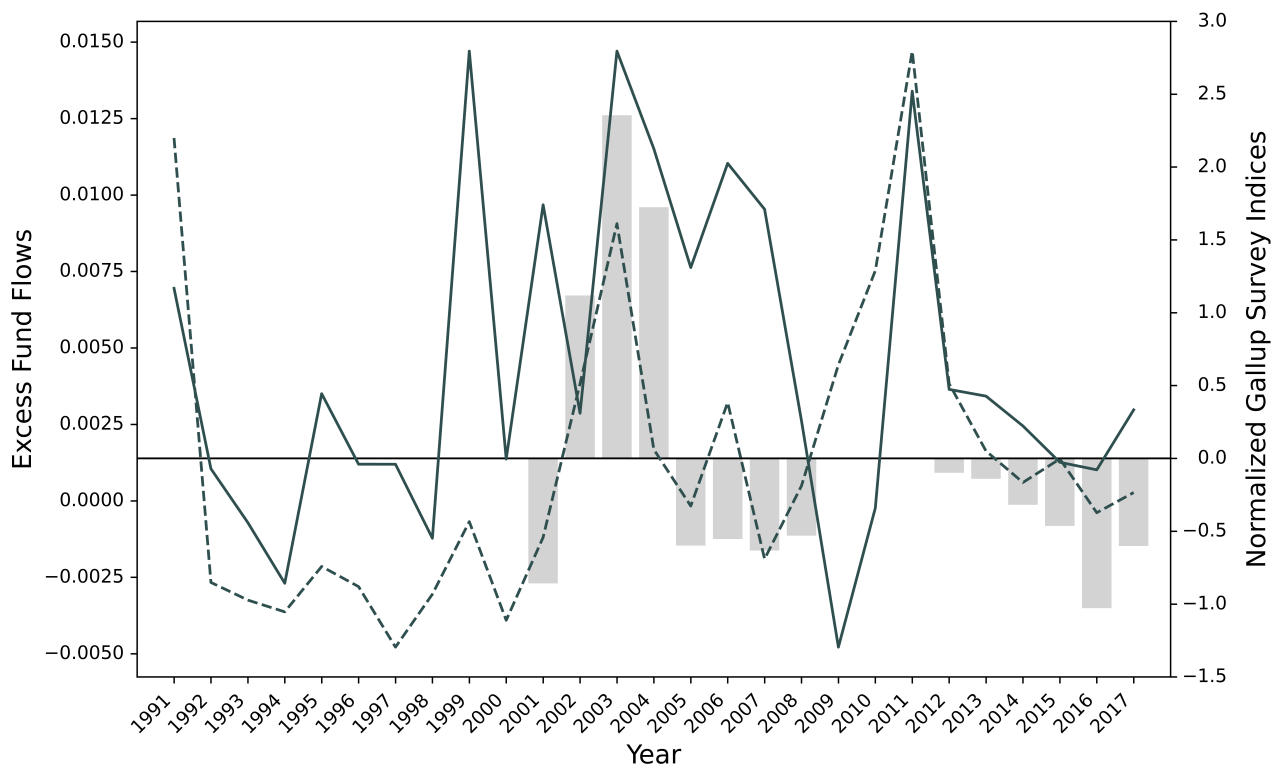


Figure 1. Difference in fund flows and confidence in military. Graph plots the time series of difference in fund flows between the funds that are single-managed by military managers and nonmilitary managers (solid line) and the dynamics of Gallup's normalized confidence in the military index (dashed line). Bars indicate the values of normalized satisfaction with the nation's military strength and preparedness (Gallup's Survey).

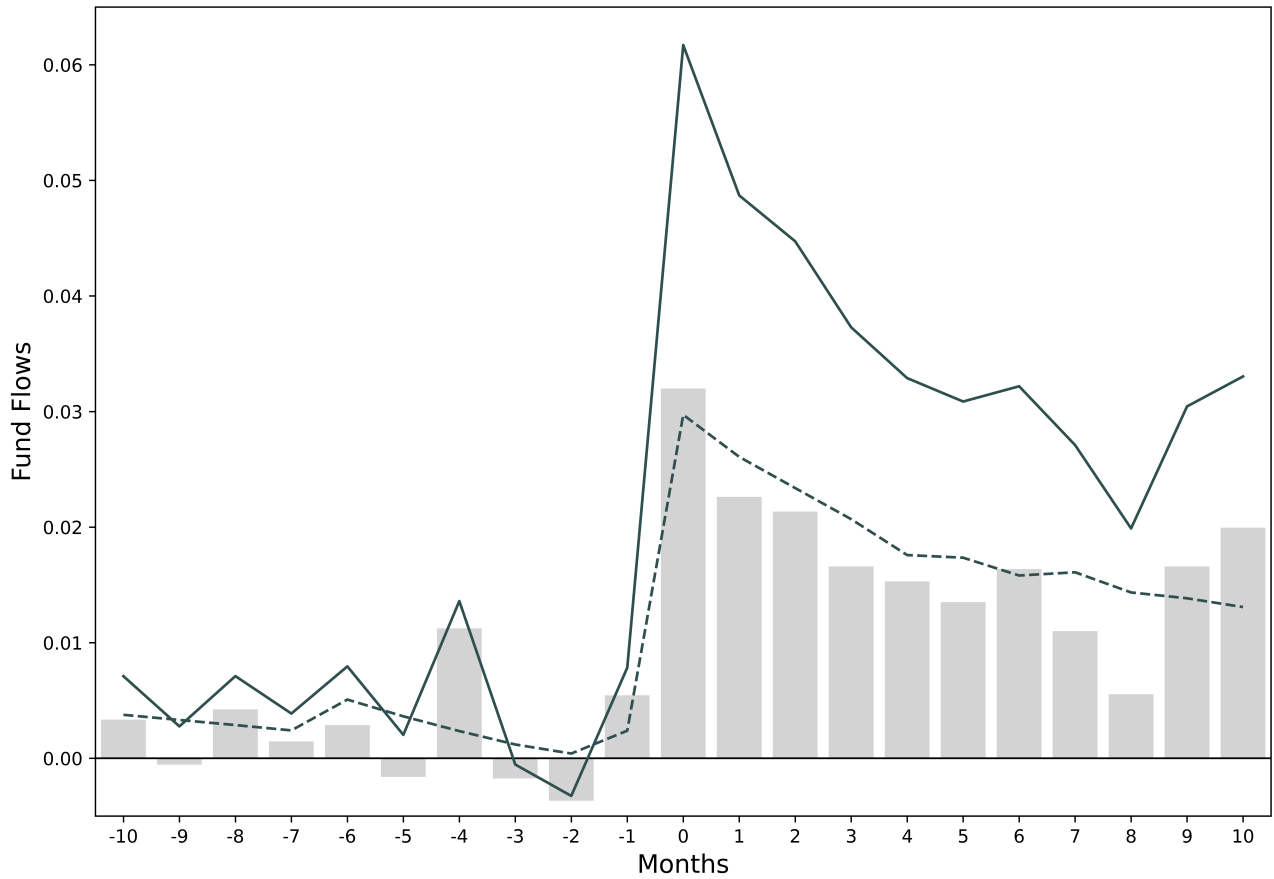


Figure 2. Dynamics of average monthly net inflows into military-managed funds vs. nonmilitary-managed funds. Graph plots the dynamics of net fund flows of funds that become single-managed by military managers (solid line) and the dynamics of net fund flows of funds that shift to single-management by nonmilitary managers (dashed line). Bars indicate the difference in net inflows between the two groups. Date zero is the month of manager change.

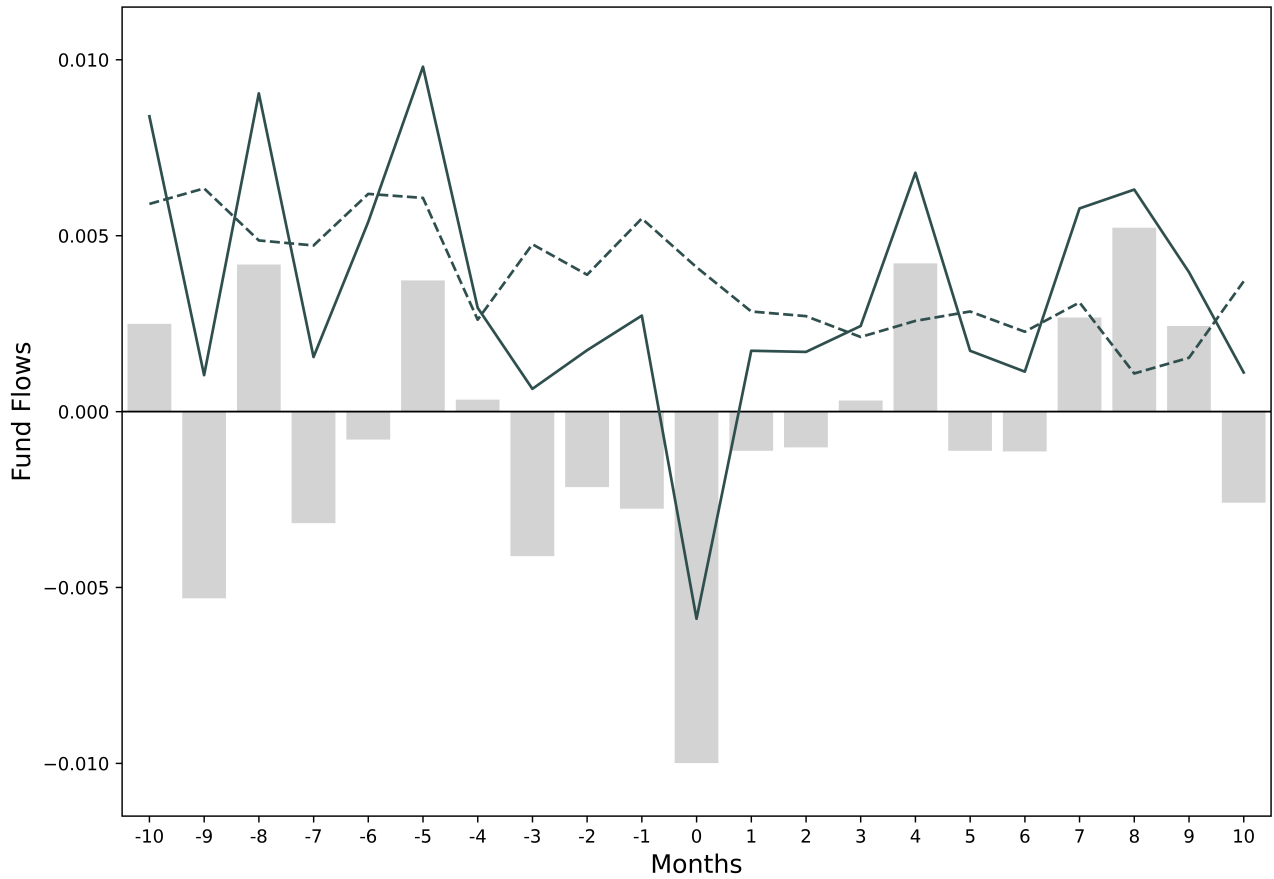


Figure 3. Dynamics of average monthly net inflows into military-managed funds vs. nonmilitary-managed funds around the dates of management change. Graph plots the dynamics of net fund flows of funds with leaving military managers (solid line) and nonmilitary managers (dashed line). Bars indicate the difference in net inflows between the two groups. Date zero is the month of manager change.

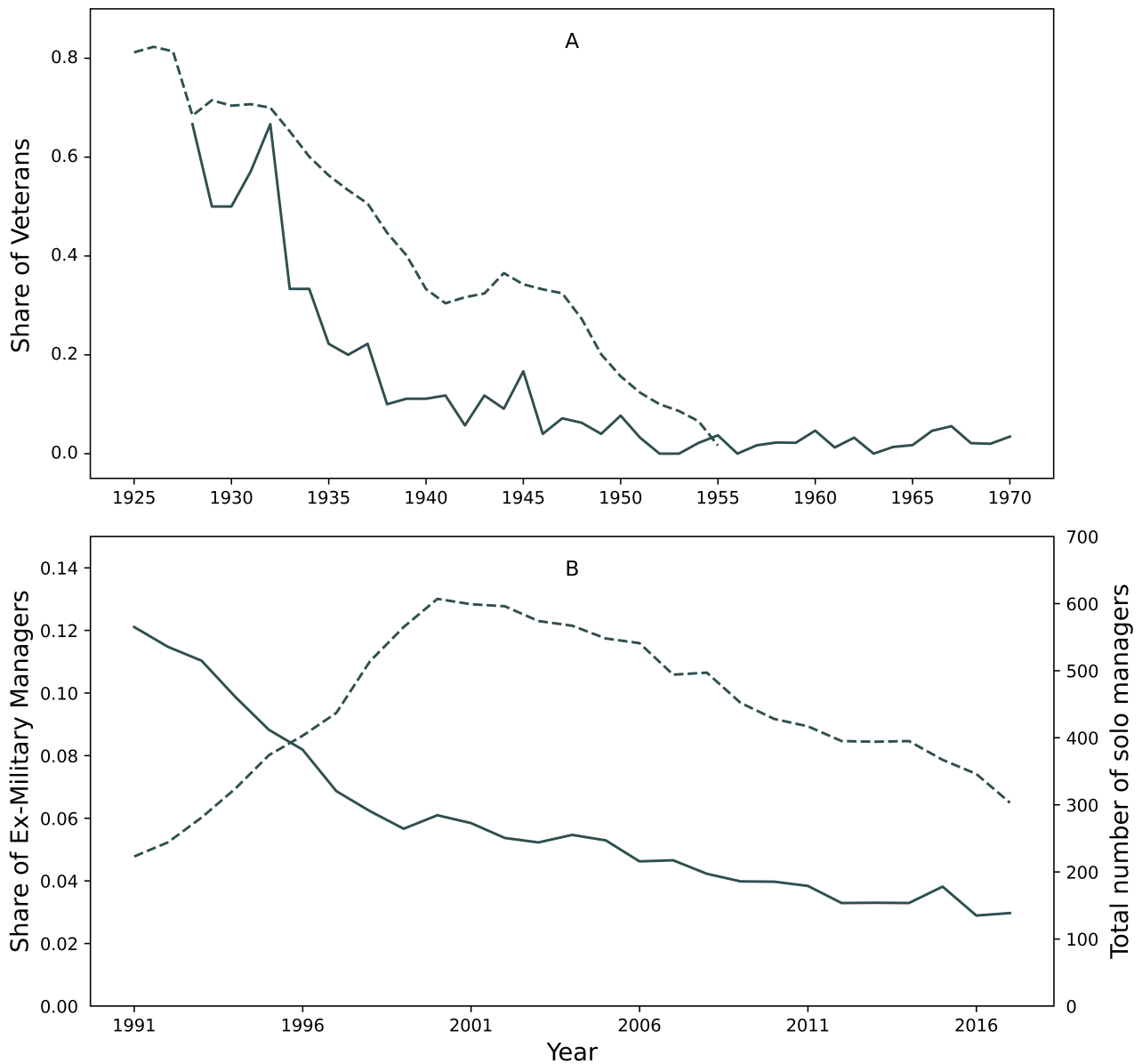


Figure 4. Share of veterans. A, among fund managers by birth cohort, 1925-1970. B, among fund managers by year, 1991–2017. Graph A depicts the share of veterans among all of the solo mutual fund managers in our sample by birth cohort (solid line) and the share of educational attainment (college level) of the veteran population using data from 3% of the 1980 decennial census, restricted to white males. Graph B plots the share of military managers who single-managed at least one U.S. equity mutual fund for at least one full month (solid line) in a given year and the total number of solo managers (dashed line) by year.

The Social Side of Investing: Fund Manager Networks and Portfolio Choice^{*}

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ABSTRACT

This study reveals private social networks among U.S. mutual fund managers and examines how network characteristics affect portfolio choice. I find that fund managers who are socially connected have more similar holdings and trades even after controlling for their location and employer. Stocks purchased together and simultaneously by managers within a network exhibit positive risk-adjusted returns suggesting that valuable information is shared through social interactions. Managers who are more central in a network tend to have higher risk-adjusted returns. Unlike prior empirical work, I directly measure social interactions between managers and, hence, disentangle the effects of such interactions from other effects, such as being exposed to the same media market.

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Generating ideas is a social process (e.g., Perry-Smith and Shalley (2003)). By communicating with others, individuals gain access to novel perspectives and unique knowledge. In financial markets, where information moves security prices, private social networks among professional investors can play a particularly important role when generating investment ideas. Early survey evidence in Shiller and Pound (1989) indicates that direct interpersonal communications between investors can shape their investment decisions. More recent research also suggests that professional investors trade stocks that they learn about from their peers. Fund managers who reside in the same geographical location (Hong, Kubik, and Stein (2005); Pool, Stoffman, and Yonker (2015)), who have work-related ties (Rossi, Blake, Timmermann, Tonks, and Wermers (2018); Gerritzen, Jackwerth, and Plazzi (2020)), or who share the same educational network (Qi, Li, Xie, and Ding (2020)) have been found to exhibit similar investment behavior.

Within the scholarship, this paper is the first to observe whether any two professional investors, indeed, know and communicate with each other.¹ I provide new and much more direct evidence of the importance of investor networks by studying social connections and interactions among U.S. mutual fund managers.² To uncover these connections and interactions, I rely on Facebook, the largest social network platform, with over 190 million active users in the United States, as of January 2021. Facebook users can declare friendship between each other and interact in various ways (e.g., through likes, comments, and tags).³ Because any friendship between two users on Facebook requires mutual consent, fund managers who are connected on Facebook at least know each other. To determine which managers are connected on Facebook, I locate their Facebook profiles and collect their set of friends. I classify two managers as “connected” if they are among each other’s set of friends, respectively. At the fund level, I classify two funds as “connected” if they have at least one pair of connected managers.

Although prior results are consistent with the hypothesis that professional money managers transmit investment ideas socially, my connection measure provides major advantages. First, as noted by several authors (e.g., Pool et al. (2015)), prior proxies for social connection are clearly noisy and likely fail to capture the true magnitude of the effects of social contact. Specifically, they have a high chance of wrongly classifying individuals as connected and include only a small fraction of an individual’s overall social network. The widespread use of Facebook and the profiles’ large sets of friends allow me to overcome these shortcomings. Second, because connection proxies are based on broader categories, such as same geographical location, correlation in portfolio choice between connected managers may be due to other effects that are difficult to

¹As Rossi et al. (2018) note, direct connections between fund managers are generally informal and undocumented. Unsurprisingly, as of this writing, no public database is available, even for a fee, that identifies exact connections between fund managers.

²Being used in several prior studies, the mutual fund industry offers an ideal setting to study the connectedness and interactions between investors due to the rich amount of information available on mutual fund managers and funds from regulatory filings.

³The “Like” button is a feature on the Facebook website, where users can like content such as status updates, comments, photos, and videos shared by other users. Similarly, the comment feature allows users to comment on other users’ content. Tagging other users on Facebook means to attach their profile link to shared content. Please refer to <https://www.facebook.com/help/935175519838326> for more detailed information.

rule out, such as being exposed to the same local media outlets (e.g., Hong et al. (2005)). The Facebook connection measure enables the creation of variation within these broader categories that is largely independent of other effects mentioned in the literature. Third, the richness of Facebook data allows for the classification of connections into different categories. Facebook profiles often contain detailed biographical information, for example, high school attended, which allows for drawing conclusions about where managers may know each other from. Also, interactions between managers in the form of likes, comments, and tags, allow the intensity of connections to be measured.

Almost half of the fund managers in my data set are connected to at least one other fund manager, and I first ask whether such connections trigger similarities in portfolio choice. In the spirit of Pool et al. (2015), I construct measures of pairwise overlap in holdings and trades for all funds, and test whether the overlap is greater when fund pairs are managed by socially connected and interacting managers. The portfolio overlap of funds managed by connected managers is 25.46% higher than that of nonconnected funds, even after controlling for fund family memberships, investment styles, and size. This difference increases when I improve identification by focusing on solo-managed funds and is more pronounced if fund managers interact with each other on Facebook. Remarkably, the difference remains statistically and economically significant after controlling for common proxies of social connection, suggesting that the effect of social connections and interactions on Facebook is not merely a reflection of residing in the same geographical location, having work-related ties, or sharing the same educational network. Results for trades are similar in magnitude.

Given the evidence that social connections among professional investors influence their portfolio choice, I next study the effect of such connections on investment performance. Despite growing evidence of correlated trading among connected investors, relatively little analysis links social connections to investment performance and opposite conclusions arise with different data and methods (e.g., Hochberg, Ljungqvist, and Lu (2007); Rossi et al. (2018)). By investigating performance, I can provide evidence of whether information is transmitted through networks of professional investors. In theory, the effect of social connections on performance is ambiguous. Connected managers may have better access to return-relevant information, as they receive more valuable signals, as suggested by information cascade models (e.g., Ellison and Fudenberg (1993)). However, if information is endogenously acquired at a cost, Han and Yang (2013) argue that social connections may reduce each manager's incentive to acquire costly signals, as they can free-ride on their connections.

My performance analysis proceeds in two steps. First, I analyze how funds' network position through their managers relates to fund-level performance. I adopt different measures of network centrality developed in the social network analysis literature⁴ and find that network centrality, particularly prestige centrality, is positively related to risk-adjusted fund performance. An increase in network centrality by one standard deviation improves a fund's monthly Carhart

⁴See Billio, Getmansky, Lo, and Pelizzon (2012) for a thorough discussion of different network measures.

(1997) four-factor alpha by 1.61 to 4.97 bps, depending on the specification. The effect is robust to controlling for several other fund and fund manager characteristics, including fund size, team size, and manager experience. Second, I provide stock-level evidence and evaluate the performance of connected managers' common holdings and trades. A long-short strategy based on common stock buys and sells by connected funds statistically outperforms with positive abnormal returns of up to 0.87% per month. This effect is slightly larger if fund managers interact with each other on Facebook. My estimates are similar in magnitude to those reported by Ammann, Cocharadt, Cohen, and Heller (2022), who study abnormal returns generated by information shared between Facebook-connected executives and fund managers.⁵

In additional analyses, I address reverse causality concerns, i.e., that Facebook connections among managers may be the result of similar investment choices in the past and a successful management career, by limiting the sample to connections that were established *ex ante*. The results remain similar in economic and statistic significance, suggesting that my findings are driven by network effects, rather than the other way around.

Taken together, my results indicate that interacting with peers influences the portfolio decisions of professional investors and that value-relevant information is transmitted through investor networks. My findings raise the question as to why professional money managers who may be competitors for returns and investor flows share information with each other. While I am not able to address this question in my setting, theoretical models (e.g., Abreu and Brunnermeier (2002)) suggest that informed traders may benefit from coordination. Also, as Pool et al. (2015) point out, the cost of sharing information in a mutual fund setting are not likely to be high (e.g, due to regulatory limits on the size of positions).

This paper is most closely related to the literature on how social relationships affect choices. In various domains, studies document a substantial impact of social interaction on decision making, for example, in automobile purchases (Grinblatt, Keloharju, and Ikäheimo (2008)) or labor markets (Bayer, Ross, and Topa (2008)). Regarding portfolio choices, investors appear to be influenced by their social connections to company executives (e.g., Ammann et al. (2022); Cohen et al. (2008)), to the local population (Coval and Moskowitz (2001)), and to their peers (e.g., Rossi et al. (2018); Hvide and Östberg (2015); Pool et al. (2015)). Confirming the initial assumptions of the latter papers, I find that a large portion of professional investors have private social ties to their peers and that they actively communicate with each other. My findings are consistent with the notion that professional investors influence each other by transmitting ideas through informal person-to-person relationships, lending support to the “social hypothesis” (Pool et al. (2015)) of investing .

⁵Notably, my estimates are larger in size than those reported by Pool et al. (2015) and Cohen, Frazzini, and Malloy (2008), who rely on location and education-based proxies for social connection.

The remainder of the paper proceeds as follows. Section I describes the data set and the data collection process, and provides basic statistics. In Section II, I begin the main empirical analysis by examining whether social connections are related to fund holdings and trades. In Section III, I evaluate the performance of connected managers’ common holdings and trades and use network centrality measures to study the relationship between manager centrality and performance. Section IV presents supplementary analyses, followed by Section V, which concludes the paper.

I. Data and Sample Composition

I combine data from several sources in this paper. Most notably, I use Morningstar Direct (MS Direct) to obtain data on mutual funds, fund managers, and funds’ stock holdings; CRSP and Compustat to obtain stock-level information; and Facebook to obtain information on social connections between fund managers.⁶

A. *Mutual Fund Data*

I initiate the sample construction with all funds in the MS Direct universe of U.S.-domiciled equity mutual funds.⁷ I include both defunct and active fund share classes to avoid potential survivorship bias. To adequately compare the portfolio choices of fund managers, I exclude index funds, international funds, money market funds, or funds that focus on bonds, commodities, and alternative asset classes from the sample.⁸

For each fund passing these initial filters, I obtain historical management data from MS Direct, which shows fund managers’ names, start and end dates of their active management periods, brief manager descriptions, and information on their educational backgrounds. I obtain fund holdings from MS Direct and merge these data with stock characteristics from the CRSP Monthly Stock Files and Compustat using historical CUSIPs.

Following these steps leaves me with 418,300 fund-month observations covering the period from January 1984 to December 2020. The sample includes 5,119 funds managed by 10,067 individual fund managers.

⁶The complete set of variables and data sources used in this paper is described in Appendix A.

⁷MS Direct is chosen due to several reasons. First, previous studies show that Morningstar’s holding data are more complete and available in higher frequency (see Elton, Gruber, and Blake (2011)). Second, Morningstar is more accurate in reporting the fund management structure (see, for example, Massa, Reuter, and Zitzewitz (2010) and Patel and Sarkissian (2017)). Third, Morningstar assigns a unique identification number to every fund manager, which considerably facilitates the tracking of fund managers over time and across funds.

⁸Regarding index funds, I follow standard procedure and remove funds that MS Direct classifies as such or funds whose names contain the word ‘index’ or ‘idx’. I further restrict the sample to funds with an assigned Morningstar category to properly control for investment style in later analyses.

B. Identifying Private Social Networks among Fund Managers

I study private social networks among fund managers based on their social connections to one another. To uncover these connections, I use Facebook as a laboratory, as it is the most important social network in the United States with 190 million active users, as of January 2021. Facebook users can create online profiles and connect with friends and family to communicate and share content. In mutual fund research, Facebook constitutes a novel source of data and was previously used only in Ammann et al. (2022).

To establish whether any two fund managers are socially connected, i.e. are “friends” on Facebook, I must identify both their Facebook profiles. A Facebook profile is a personal account created upon joining the platform. It typically comprises the user’s full name, profile picture, cover photo, and timeline, as well as a set of different sections describing the user, including work experience, educational background, places lived, family members, relationships status, photos, and likes.

B.1. Matching Facebook Profiles

For the 10,067 fund managers in my base sample, I initiate a matching process to identify their Facebook profiles. I collect extensive biographical information on managers to ensure unambiguous matching. First, I search for the fund managers’ most comprehensive names (i.e., nicknames, middle names, maiden names, family names adopted upon marriage, and suffixes) in FINRA’s BrokerCheck database, SEC’s IAPD database, and the CFA Institute’s Member Directory. Next, to gather data necessary for the matching process (e.g., degrees, graduation years, work histories, residences, portraits, birthdays, and family members), I conduct a cross-database search across multiple sources including LinkedIn profiles, Bloomberg executive profiles, biographies published by fund firms, filings with the SEC, obituaries, newspaper articles on newspapers.com, and alumni publications on ancestry.com.

I face the same challenges as Ammann et al. (2022) when identifying Facebook profiles of individuals: First, due to Facebook’s wide reach, many characteristics (e.g., name, workplace, education, location) are widely shared among Facebook’s user base and hence lose their discriminatory power. Second, Facebook users can restrict what others can see on their profile, which may require the collection of additional metadata (e.g., spouse’s name) to support the matching procedure. Third, as a response to the Cambridge Analytica controversy, Facebook has imposed substantial data access restrictions on its platform. Therefore, data required for this study cannot be accessed via an API, but must be manually collected through Facebook’s web interface.

My identification procedure carefully follows the one proposed by Ammann et al. (2022): In the first step, for each individual (target identity) in my sample, I retrieve a set of candidate profiles that indicate attributes similar to the target identity’s attributes (e.g., residence location and university). In the second step, I determine the candidate profiles’ probabilities to match

their respective target identities using a set of similarity and proximity scores that I compute based on the profiles’ content and friendship links. In the third step, I rank each target identity’s set of candidate profiles based on their aggregated scores and attempt to match the true profile from the candidate set, starting with the highest-ranking candidate profile and progressing to lower.⁹

In total, I identify the Facebook profiles for 3,936 (or 39.1%) of the 10,067 fund managers in the base sample involved in managing 4,078 (or 79.7%) of the 5,119 funds. My main sample for subsequent analyses is limited to fund-months run by fund managers with identified Facebook profiles. Team-managed fund-month observations are included in the sample if I identify the Facebook profile of at least one fund manager in the then-current team. My main fund-month sample includes 260,567 (or 62.3%) of the initial 418,300 observations.

B.2. Establishing Social Connections

A core feature of Facebook is that users can declare friendships between each other. To disclose potential friendship links between individuals in my sample, I must collect their sets of friends. Because Facebook users can hide their sets of friends by changing their “friend list” privacy settings, Facebook profiles in my sample may have a publicly declared or undeclared friend list. If a profile’s friend list is public, I can extract the profile’s whole set of friends. If it is not public, I follow Ammann et al. (2022) and uncover a profile’s set of friends in two ways: First, I recursively exploit a Facebook function that discloses mutual friends of two given users, provided that at least one of the two users’ friend lists is accessible. Second, I inspect the likes and comments given to certain profile photos and refer to the issuing users as friends of the respective profile owner, if the particular photo satisfies specific conditions.¹⁰

Following the collection of the profiles’ set of friends, I proceed to disclose friendship links between the individuals in my sample. The disclosure of ties between users in a social network is affected by the network’s directionality. To illustrate this concept, consider the example of users A and B, with sets of friends F_A and F_B . Given that mutual consent is required for a friendship link to form between their profiles, the friendship between A and B is said to be undirected. Because in an undirected network the friendship link (A, B) implies the existence of (B, A) , I can disclose the friendship between A and B with certainty either by locating A in F_B , or by locating B in F_A .

Taken together, I disclose 6,571 friendship links between the U.S. equity mutual fund managers in my sample. 1,923 (or 48.9%) of the 3,936 Facebook-identified fund managers are connected to a least one other fund manager on Facebook.

⁹Please refer to Ammann et al. (2022) for more details on the candidate selection, candidate ranking, and candidate matching.

¹⁰Please refer to Ammann et al. (2022) for more details on the exact procedure.

C. Sample Composition and Summary Statistics

Table 1 describes the collected data and reports the Facebook-related characteristics of the identified fund manager Facebook profiles (Panel A) and their social connections to one another (Panel B). In total, I process over 1.5 million candidate profiles to identify 3,936 individual fund managers on Facebook. The identified profiles contain various information that is used in the matching procedure: 91% show an individualized profile picture and 65% provide at least one photo beside their profile picture; 23% name members of their family; 20% indicate their relationship status; 36% and 45% list the high school and college they attended, respectively; 32% show the company they work for; 53% and 43% indicate their home town and where they currently reside, respectively. For 2,207 (or 56%) of the fund manager profiles, the friend lists are openly accessible. On average, a manager with a public friend list has 298 Facebook friends. For the 1,729 fund managers with nonpublic friend lists, I am able to locate 269,602 friends via other profiles' open friend lists and via likes and comments given to fund managers' profile photos. I process 125,443 photos along with 1,252,681 likes, 149,959 comments, and 28,834 tags. The average (median) fund manager uploads 40 (6) pictures to his or her profile, receives 428 (82) likes and 66 (13) comments on these pictures, and adds 30 (5) tags.

Panel B of Table 1 shows that, using the overall set of disclosed fund manager friends that contains 938,878 Facebook profiles, I uncover 6,571 social connections, i.e., friendship pairs, involving 1,923 unique fund managers. As noted in prior studies, connections between individuals can stem from various stages of life (e.g., Tesch (1983); Hartup and Stevens (1999)). In my sample, a large number of connections between fund managers is likely based on either attending the same college (1,451 connections) or working for the same past or current employer (1,785 connections). A total of 142 and 129 connections are based on growing up in the same hometown and attending the same high school, respectively, and were presumably established early in the fund managers' lives. I also note that a considerable number of 987 connections are likely the result of working together on the same mutual fund, which I will later take into account when testing portfolio overlaps.

Figure 1, Figure 2, and Figure 3 present graphic representations of the overall fund manager network (graph) by managers' current place of residence, educational institution, and fund firm, respectively. Every node represents a fund manager and edges are indicated by lines connecting two nodes. The node size indicates a node's number of edges. Figure 1 and Figure 3 illustrate that there are certain location and employer-based subnetworks (subgraphs), whereas education-based connections seem more dispersed, according to Figure 3.

Panel B of Table 1 further reports how many connections between fund managers are interacted. I define connections as interacted if one fund manager in the pair receives a like or comment from—or is tagged by—the other fund manager. In total, 1,808 (or 27.5%) of the connections are interacted, with 1,736, 367, and 53 connections involving likes, comments, and tags, respectively. Panel B also presents the number of fund managers depending on their

network size, i.e., how many connections they have with other fund managers. Almost half of the 1,923 managers that are connected with at least one other fund manager have between two and five network connections. A total of 125 managers in my sample are connected to more than 20 other fund managers.

Table 2 presents the annual coverage of Facebook-identified and connected fund managers, and the mutual funds they manage. The benchmark universe of funds consists of the 418,300 fund-month observations covering the period from January 1984 to December 2020, i.e., all domestic actively managed U.S. equity mutual funds from MS Direct after following the steps detailed in Section I.A. I classify fund-month observations as “FB-identified” if I identify the Facebook profile of at least one of the fund’s then-current managers. Similarly, I classify fund-month observations as “FB-connected” if I can identify a Facebook connection between at least one of the fund’s then-current managers and at least one of another sample fund’s then-current managers.

I average 888 unique FB-identified fund managers per year, constituting an annual average coverage of 33% of all managers active in the benchmark universe. The minimum coverage across the sample years is 12%. On average, 428 fund managers (or almost one sixth of the benchmark managers) are connected to at least one other fund manager on Facebook in a given year. The sample of funds managed by FB-identified managers averages 1,110 funds per year, which constitutes an annual average coverage of 52% of the funds that populate the benchmark universe, or 48% of the total assets under management in the benchmark universe, respectively. On average, 547 funds (or almost one fourth of the benchmark funds) are connected to at least one other fund through their managers’ Facebook connections in a given year.

II. Do Social Connections and Interactions Impact Fund Holdings and Trades?

My goal is to test whether pairs of funds that are connected socially through their fund managers are more likely to engage in social communication regarding investment ideas. I do so by conducting pairwise analyses of funds and their holdings and trades. I define an indicator variable $FBConnected_{i,j;t}$ that equals one for a specific fund pair (i, j) if at least one manager from fund i is connected on Facebook with at least one manager from fund j during period t . Similarly, I define $FBInteraction_{i,j;t}$ as an indicator variable equal to one if at least one manager from fund i is interacting (i.e., in the form of likes, comments, or tags) on Facebook with at least one manager from fund j during period t .

A. Measuring Portfolio Overlap

I closely follow Pool et al. (2015) and measure the portfolio overlap in holdings between fund i and j during period t as

$$PortOverlap_{i,j,t} = \sum_{k \in H_t} \min\{w_{i,k,t}, w_{j,k,t}\}, \quad (1)$$

where $w_{i,k,t}$ is fund i 's portfolio weight in stock k during period t , and H_t is the set of all stocks held by funds i and j , as reported at the end of period t . The overlap measure is aggregated to the fund level because analysis at the stock level would result in billions of observations.

I also measure overlap in trades, i.e., stock purchases and sales, between mutual funds. I again follow Pool et al. (2015) and define

$$BuyOverlap_{i,j,t} = \frac{\sum_{k \in T_t} \min\{I_{i,k,t}^+, I_{j,k,t}^+\}}{\min\{\sum_{k \in T_t} I_{i,k,t}^+, \sum_{k \in T_t} I_{j,k,t}^+\}} \quad (2)$$

and

$$SellOverlap_{i,j,t} = \frac{\sum_{k \in T_t} \min\{I_{i,k,t}^-, I_{j,k,t}^-\}}{\min\{\sum_{k \in T_t} I_{i,k,t}^-, \sum_{k \in T_t} I_{j,k,t}^-\}}, \quad (3)$$

where $I_{i,k,t}^+$ ($I_{i,k,t}^-$) is one if fund i increases (decreases) the number of shares in stock k between period $t-1$ and t , and zero otherwise. T_t is the union of all stocks traded by funds i and j . Hence, the numerators of the trade overlap measures are the absolute number of common buys and sales, respectively, of two connected funds. I then normalize these numbers by the minimum number of the funds' buys and sales, respectively, to make the measures range from zero to one. For example, suppose that fund i buys 40 and sells 60, and fund j buys 30 and sells 20 stocks in period t . If 10 buys and 5 sells are common to both funds, then $BuyOverlap_{i,j,t} = 10/30 = 33\%$ and $SaleOverlap_{i,j,t} = 5/20 = 25\%$.

B. Summary Statistics of Fund Pairs

Table 3 presents summary statistics of the portfolio overlap measures and other variables used in my analysis. I separately report means conditional on *FBConnected* for the full sample of fund pairs (1), fund pairs whose managers live in the same city (2), fund pairs whose managers worked at the same firm in the past (3), and fund pairs whose managers went to the same college (4). In the overall sample, average portfolio overlap between any two funds is 5.93%. The overlaps in holdings, purchases, and sales of FB-connected funds is much higher than that of unconnected fund pairs. FB-connected funds have an average overlap in holdings of 13.05%, compared to 5.90% for unconnected funds. The 7.15 percentage point difference in overlap is significant at the 1%-level. A similar picture emerges when looking at the buy and sell overlaps.

Subsamples (2), (3), and (4) allow me to compare FB-connected fund pairs to unconnected fund pairs within the broad categories typically used as proxies for social connection and interaction in the prior literature. In line with prior results, *SameCity* fund pairs (Hong et al. (2005); Pool et al. (2015)), *SamePastFirm* fund pairs (Rossi et al. (2018); Gerritzen et al.

(2020)), and *SameEdu* fund pairs (Qi et al. (2020)) exhibit larger overlaps. Importantly, within each subsample, the overlap in holdings, purchases, and sales of FB-connected funds is significantly higher than that of unconnected fund pairs. The differences in overlap are significant at the 1% level.

These findings are the first hint of my main result: that FB-connected funds have more overlap in their portfolios than unconnected funds, overall and within subsamples of common proxies for social connection. Compared to prior proxies, findings also suggest that being connected on Facebook reflects stronger social ties among fund managers with an increased probability of sharing and communicating investment ideas with each other. However, FB-connected funds are significantly more likely to be headquartered in the same city, be from the same fund family, have common managers, or have managers who manage at least one other fund together. As these factors may all contribute to the significantly higher overlap in portfolio holdings and stock trades of FB-connected funds, I control for them in next subsections' multivariate analyses.

Across all monthly fund-pair observations, 0.45% (0.17%) have at least one manager pair that are connected (interacting) on Facebook. While this may appear to be a small number of fund pairs, about 49% (30%) of the sample funds in each month have at least one manager who is connected (interacting) on Facebook with a manager at another fund. Naturally, the share of FB-connected or FB-interacted monthly fund-pair observations becomes much larger in subsamples (2), (3), and (4).

Table 3 also shows that 10.17% of monthly fund-pair observations have at least one pair of managers in the same city; 10.18% have at least one pair sharing the same past employer; 1.83% have at least one pair with a degree from the same university; and 1.41% belong to the same fund family.

C. Social Connection and Holdings

To formally test the hypothesis that FB-connected funds are more likely to make similar investment decisions, I follow Pool et al. (2015) and estimate the regression

$$\begin{aligned} PortOverlap_{i,j,t} = & \alpha + \beta_1 FBConnected_{i,j,t} + \beta_2 FBInteraction_{i,j,t} \\ & + \gamma_1 SameCity_{i,j,t} + \gamma_2 SamePastFirm_{i,j,t} + \gamma_3 SameEdu_{i,j,t} \\ & + \Gamma' OtherControls_{i,j,t} + \epsilon_{i,j,t}, \end{aligned} \quad (4)$$

where $PortOverlap_{i,j,t}$ is defined as in Equation 1, $FBConnected_{i,j,t}$ and $FBInteraction_{i,j,t}$ are dummy variables that are one if at least one manager from fund i is connected and interacting, respectively, with at least one manager from fund j during period t . $SameCity_{i,j,t}$ is a dummy variable that is one if at least one manager from fund i resides in the same city as at least one manager from fund j in period t ; $SamePastFirm_{i,j,t}$ is a dummy variable that is one if at least

one manager from fund i worked at the same fund firm in the past as at least one manager from fund j in period t ; $SameEdu_{i,j,t}$ is a dummy variable that is one if at least one manager from fund i has a college degree from the same university as at least one manager from fund j in period t ; and $Controls_{i,j,t}$ is a vector of control variables presented in Table 3.

If social connections have an impact on mutual fund managers' investment choices, then I expect β_1 in Equation 4 to be positive. The coefficient estimate β_1 represents the incremental increase in portfolio overlap from managers being connected on Facebook beyond the influence of common variables used to proxy for social connection. The effects of local media and "local investor relations" (Hong et al. (2005)) are captured by $SameCity_{i,j,t}$. The effects of investment skills and strategies learned at a common previous workplace or university are captured by $SamePastFirm_{i,j,t}$ and $SameEdu_{i,j,t}$, respectively. Moreover, I expect β_2 to be positive, as it represents the incremental increase in portfolio overlap from managers interacting with each other on Facebook beyond just being connected.

Table 4 shows the coefficient estimates and t-statistics of various specifications of Equation 4. I cluster standard errors by each fund in the pair so that repeated observations of a fund can be correlated.¹¹ In column 1, I include only $FBConnected$ and the baseline control variables. β_1 is 1.51 and significantly positive (at the 1%-level), suggesting an additional portfolio overlap of 1.51 percentage points for FB-connected fund pairs, compared to unconnected funds. Given the average portfolio overlap of 5.93%, this is equivalent to over $1.51/5.93 = 25.46\%$ greater commonality in holdings. Adding $FBInteraction$ to the regression in column 2 results in $FBConnected$ still being significantly positive, which implies that non-interacting FB-connected fund managers also exhibit higher portfolio overlap. β_2 is 1.65 (significant at the 1% level), indicating that FB-interacted funds have an additional portfolio overlap of 2.55 percentage points, compared to unconnected funds. To put the effects of FB-connections and FB-interactions into perspective: in a similar setting, Hong et al. (2005) estimate the same-city effect to be 0.54%. Pool et al. (2015) document an effect of up to 1.29% for "neighbor funds", i.e., fund pairs whose managers (or at least one of them) live within 2.6 normalized miles of each other.

Estimates on the baseline control variables are also of interest. Unsurprisingly, matching on Morningstar's size or value/growth categories is important in explaining the portfolio overlaps of a given mutual fund pair, with large-cap fund pairs having the greatest similarities. In line with Pool et al. (2015), among the other fund linkages, having a manager in common ($CommonMgr$) has the largest positive effect, followed by having managers who manage a third fund together and belonging to the same fund family. These effects may be due to shared analysts and other stock-selection resources.

¹¹Two-way clustering at the fund level for each fund in the pair is important, as I conduct pairwise analyses. Regressions in this subsection and the following subsection contain $N - 1$ overlaps for each fund in each quarter. A fund's portfolio contributes to multiple observations in each quarter, and portfolios are persistent between quarters.

When controlling for common proxies of social connection in columns 3 to 5, both β_1 and β_2 remain significantly positive (at the 5% and 1% level, respectively). These numbers suggest that the effect of social connections and interactions on Facebook is not merely a reflection of residing in the same geographical location, having work-related ties, or sharing the same educational network.¹² However, the inclusion of each common proxy reduces the magnitude of β_1 . In the regression in column 5, where I include all common proxies at once, I can provide perspective on the effect of having FB-connected or FB-interacting managers by comparing coefficient estimates on *FBConnected* and *FBInteraction* to those on the other proxies and control variables. For example, the influence on fund holdings from social connection and interaction ($0.55 + 1.67$) is over twice as large as the influence of two funds with managers who worked at the same fund firm in the past (0.86) or who currently manage another fund together (1.03).

In column 6, I exclude fund pairs with common managers, as these pairs are much more likely to be FB-connected (see Table 3). In this specification, estimates on *FBConnected* and *FBInteraction* are 0.71 and 1.23, respectively (both statistically significant at the 1% level). Similarly, when excluding all fund pairs within the same fund family in column 7, the coefficient estimates on *FBConnected* and *FBInteraction* remain significantly positive and economically relevant. These results confirm that fund managers share information about their holdings even across non-interlocking funds and across fund families.

Finally, in column 7, I estimate Equation 4 restricting the sample to fund pairs that only include funds managed by a single manager. Because single fund managers are more likely to be the sole decision makers on the fund, I would expect that single-managed funds' portfolio composition is influenced more heavily by their manager's social connections and interactions, compared to team-managed funds. This expectation is supported by results in column 7. The coefficient estimate on *FBConnected* and *FBInteraction* is 2.69 and 1.74, respectively (both statistically significant at the 1% level). The estimates suggest that the effect of social connection (and interaction) on portfolio overlap leads to a 45% (74.7%) greater overlap compared to the average fund pair in the sample.

D. Social Connection and Trades

I next investigate whether FB-connected fund pairs are more likely to make similar trades than unconnected fund pairs. I therefore re-estimate the regression from Equation 4 and use *BuyOverlap_{i,j,t}* and *SellOverlap_{i,j,t}* (see Equation 2 and Equation 3, respectively) as the dependent variables:

¹²Results in column 3 confirm that the results of Hong et al. (2005) hold in my setting.

$$\begin{aligned}
BuyOverlap_{i,j,t} = & \alpha + \beta_1 FBConnected_{i,j,t} + \beta_2 FBInteraction_{i,j,t} \\
& + \gamma_1 SameCity_{i,j,t} + \gamma_2 SamePastFirm_{i,j,t} + \gamma_3 SameEdu_{i,j,t} \\
& + \Gamma' OtherControls_{i,j,t} + \epsilon_{i,j,t}
\end{aligned} \tag{5}$$

and

$$\begin{aligned}
SellOverlap_{i,j,t} = & \alpha + \beta_1 FBConnected_{i,j,t} + \beta_2 FBInteraction_{i,j,t} \\
& + \gamma_1 SameCity_{i,j,t} + \gamma_2 SamePastFirm_{i,j,t} + \gamma_3 SameEdu_{i,j,t} \\
& + \Gamma' OtherControls_{i,j,t} + \epsilon_{i,j,t}
\end{aligned} \tag{6}$$

Table 5 reports results from estimating these regressions using three different specifications for both purchases (columns 1 to 3) and sales (columns 4 to 6): a sample excluding fund pairs with common managers, a sample excluding same-family fund pairs, and fund pairs in which both funds are single-managed.

The results are similar to the numbers on overlap in portfolio holdings presented in Table 4. Fund pairs that have managers who are connected and interacting on Facebook have significantly more overlap in trades compared to unconnected fund pairs. For common buys, column 1 of Table 5 indicates that FB-connected (and FB-interacted) fund pairs have 0.78 (2.18) percentage points more overlap in purchases. Given an average *BuyOverlap* of 5.14 in my sample, this suggests a 15.18% (42.41%) greater commonality in purchases compared to unconnected funds. The effects also hold when excluding same-family fund pairs (column 2) and are more pronounced for the sample of single-managed fund pairs (column 3). The same specifications for common sells in columns 4 to 6 yield quantitatively similar results, implying that the effect of social connections and interactions is not limited to either stock purchases or sales. Interestingly, Pool et al. (2015) document that the impact of managers residing in the same geographical location is concentrated in stock purchases. One possible explanation is that the credibility of a negative signal shared by other fund managers may depend more strongly on whether the fund managers, indeed, know each other.

III. Social Connections and Mutual Fund Performance

Results so far indicate that social connections with peers play an important role in mutual fund managers' portfolio decisions. In this section, I investigate whether value-relevant information is transmitted through fund managers' social networks, or whether managers are just sharing personal sentiments and biases with one another. I first test whether social connections affect fund performance, and then provide stock-level evidence by examining the performance of FB-connected funds' common holdings and trades.

Prior research suggests that mutual fund managers possess superior private information about stocks they buy or sell (Chen, Jegadeesh, and Wermers (2000)) and that more skilled managers rely more on such information (Kacperczyk and Seru (2007)). Social connections among peers may be one source of private information.¹³ However, it is not clear *ex ante* whether funds whose managers are well-connected (or more central in a network) perform better or worse. Well-connected funds may have access to more return-relevant signals, including signals produced by themselves and signals shared by their peers. On the other hand, well-connected funds may have less incentive to produce their own signals, as they can free-ride on their peers' signals.

A. *Measuring Network Centrality*

There are various ways to measure network centrality (e.g., Billio et al. (2012)). Because each measure captures different aspects of a network, I follow Rossi et al. (2018) and consider three centrality measures to ensure robustness of my empirical results: degree centrality, value-weighted prestige centrality, and betweenness centrality. Degree centrality simply measures the number of direct connections a node has. Value-weighted prestige centrality weights a node's individual connections by their importance. Betweenness centrality takes into account how well-connected a node's connections are, i.e., the extent to which a node serves as a hub that connects other nodes.

Formally, degree centrality of node i in period t , $DegreeCen_{i,t}$, is defined as

$$DegreeCen_{i,t} = \frac{d_{i,t}}{N_t - 1}, \quad (7)$$

where $d_{i,t}$ is the number of i 's connected nodes in period t and N_t is the total number of nodes in the network in period t . For a specific node (i.e., fund) in the network, $DC_{i,t}$ can be interpreted as the probability that the node catches information flowing through the network.

Value-weighted prestige centrality incorporates the idea that some connections are more important than others. In my setting, I weight each network connection by the sum of total net assets under management (TNA). Formally, I define value-weighted prestige centrality of node i in period t , $PrestigeCen_{i,t}$, as

$$PrestigeCen_{i,t} = \sum_{j \neq i} g_{i,j,t} \frac{PrestigeCen_{j,t}}{d_{j,t}}, \quad (8)$$

¹³Importantly, one may ask why managers should share their costly knowledge with their peers. Various theories address this question. Stein (2008) argues that fund managers may share information because they gain valuable feedback from their peers in return. Another reason for information sharing may be to attract additional arbitrage capital from other investors, so that the prices of managers' undervalued portfolio positions are pushed to fundamental value (Crawford, Gray, and Kern (2017)).

where $g_{i,j,t}$ is the (i, j) entry of the weighted connection matrix in period t ; i and j refer to funds; and $d_{j,t}$ is the number of j 's connected nodes in period t .¹⁴

Betweenness centrality measures the number of geodesics (i.e., shortest paths) connecting different nodes go through a particular node. It captures how well situated a node is in terms of the paths on which it lies. Formally, betweenness of node i in period t , $BetweenCen_{i,t}$, is defined as

$$BetweenCen_{i,t} = \frac{\sum_{k \neq j; i \neq k; i \neq j} \frac{P_i(k,j)}{P(k,j)}}{(N_t - 1)(N_t - 2)/2}, \quad (9)$$

where $P_i(k, j)$ is the number of geodesics between nodes k and j that pass through i and $P(k, j)$ is the total number of geodesics between k and j .¹⁵

Table 6 presents summary statistics of the three centrality measures for the sample funds, along with other fund and fund manager characteristics used in subsequent analyses.

B. Predicting Mutual Fund Returns

To explore the relation between fund performance and network centrality, I estimate the following panel regression

$$FundAlpha_{i,t+1} = \alpha + \beta NetNorm_{i,t} + \gamma Controls_{i,t} + \epsilon_{i,t}, \quad (10)$$

where $FundAlpha_{i,t+1}$ is fund i 's four-factor alpha in period $t+1$. Alphas are calculated using monthly returns over a 24-month look-back period requiring at least 12 available return observations.¹⁶ $NetNorm_{i,t}$, represents a normalized form of each of the network centrality measures (as described in Equation 7, Equation 8, and Equation 9) of fund i in month t . To account for time-series trends in the overall network structure that could affect regression estimates, I normalize each network centrality measure by scaling it by the cross-sectional average, i.e., $NetNorm_{i,t} = Net_{i,t}/Net_t$, as suggested by Rossi et al. (2018). $Controls_{i,t}$ is a vector of control variables that have been found to influence mutual fund performance (see Table 6), including log of fund TNA ($Log(FundSize)$) and log of family TNA ($Log(FamSize)$) as proxies for fund and family size, respectively; fund expenses estimated by funds' lagged net expense ratio and turnover ratio; and fund age. I also control for fund manager characteristics variables such as $MgrMBA$ and $MgrTenure$.

¹⁴Equation 8 is identical to the Katz Centrality and is self-referential. Jackson (2010) provides details on how to solve for $PrestigeCen_{i,t}$. For disconnected components, $PrestigeCen$ is calculated individually for each component and then scaled according to the percentage of graph nodes in that component. Eigenvectors are always normalized such that the sum of all $PrestigeCen$ scores in each time period is 1.

¹⁵For concrete examples of all three measures, please refer to Jackson (2010) and Rossi et al. (2018).

¹⁶I obtain monthly Fama-French U.S. market ($Mkt-RF$), size (SMB), value (HML), and momentum (MOM) factors from Kenneth R. French's website.

Table 7 presents the coefficient estimates and t-statistics of various specifications of Equation 10, using normalized *DegreeCen* (columns 1 to 3), *PrestigeCen* (columns 4 to 6), and *BetweenCen* (columns 7 to 9) as my main independent variable of interest, *NetNorm*. To ease interpretation of the coefficients on *NetNorm*, it is standardized using its own unconditional standard deviation. I cluster standard errors by fund and month. All specifications include manager controls (see Table 6) and time fixed effects.

In column 1, the coefficient estimate on *NetNorm* is 1.83 and significantly positive at the 5% level. The coefficient is also economically meaningful. A one standard deviation in normalized *DegreeCen* is associated with a 1.83 bps increase in risk-adjusted monthly fund return (or 22 bps per annum). This result holds irrespective of including fund style (column 2) or fund family (column 3) fixed effects. The effect is comparable to that found for network centrality by Rossi et al. (2018), who analyze the connectedness between defined benefit pension fund managers in the UK. They find that a one standard deviation increase in centrality raises expected risk-adjusted returns by between 20 and 30 bps per annum.

The effect is also prevalent across the different centrality measures. Results indicate that a one standard deviation in normalized *PrestigeCen* (*BetweenCen*) is associated with a 2.57 to 4.97 (1.84 to 2.33) bps increase in risk-adjusted monthly fund return. The comparatively large effect of prestige centrality implies that being connected to more influential and larger funds (in terms of TNA) is of particular importance to generating risk-adjusted returns.

Taken together, coefficient estimates suggest a strongly positive effect of centrality on risk-adjusted performance. The results favorably support the notion that fund managers share value-relevant information through their social networks.

C. Stock-Level Evidence

Results from the previous sections suggest that fund managers' social connections to their peers play an important role in their portfolio decisions and that funds that are more central in the overall fund network exhibit better performance. I now explore potential mechanisms for these effects. The findings thus far are consistent with the notion that well-connected funds receive more value-relevant signals by gathering information from their network. If this is true, then the performance of connected funds' common holdings and trades should reflect this information.

To test this idea, I use a standard calendar-time portfolio approach (see, e.g., Coval and Moskowitz (2001)) and further follow the methodology in Pool et al. (2015). For the holdings-based test, at the beginning of each fund-month observation, I assign stocks in each fund's portfolio into two subportfolios based on whether any of the fund's FB-connections also own the stock in the previous month. Stocks are placed in the "connected" subportfolio if at least one of the fund's FB-connection also holds the stock in the previous month. All other stocks in the fund's portfolio are allocated to the "unconnected" subportfolio.

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

$$R_{i,t}^C = \sum_{k \in \mathcal{C}} \left(\frac{w_{i,k,t}}{\sum_{k \in \mathcal{C}} w_{i,k,t}} \right) r_{k,t+1} \quad (11)$$

and

$$R_{i,t}^U = \sum_{k \in \mathcal{U}} \left(\frac{w_{i,k,t}}{\sum_{k \in \mathcal{U}} w_{i,k,t}} \right) r_{k,t+1}, \quad (12)$$

where $\mathcal{C}$ is the set of stocks held by at least one of fund i 's FB-connected funds and $\mathcal{U}$ is the set of unconnected stocks in fund i 's portfolio in period t . Following stock assignments into subportfolios, I keep the stocks in the subportfolios until the next reporting date, when the composition of the subportfolios is updated again, to reflect changes in holdings. Stocks are weighted by the fund's dollar holdings in the respective subportfolio. I then calculate monthly value-weighted average returns in Equation 11 and Equation 12 across funds at time t , weighting each fund's return by its TNA. This approach corresponds to a simple investment strategy of investing in the entirety of connected and unconnected portfolios in proportion to the amounts held by my sample of mutual funds.

I assess portfolio performance using simple raw returns, risk-adjusted returns, and characteristics-adjusted returns. Risk-adjusted returns are based on the four-factor model of Carhart (1997).¹⁷ Characteristics-adjusted returns are calculated as in Daniel, Grinblatt, Titman, and Wermers (1997), hereafter DGTW. I compute a stock's DGTW-adjusted return in a given month by subtracting from each stock's raw return the return on a value-weighted benchmark portfolio of all CRSP firms in the same size, book-to-market, and 1-year momentum quintile.

Table 8 presents the performance measures for the connected (R^C) and unconnected (R^U) subportfolios over the 444 months in the sample period and the difference between these averages. Results in column 3 indicate that the FB-connected subportfolio statistically outperforms the unconnected subportfolio by 0.17 (0.23) percentage points in terms of raw returns (DGTW) per month, significant at the 10% (1%) level. Outperformance in terms of four-factor alpha is positive but statistically insignificant. In columns 4 to 6, I redefine the connected portfolio to include only stocks that are held by at least one of a fund's FB-interacted funds. Results in column 6 indicate that the FB-interacted subportfolio significantly outperforms the uninteracted subportfolio across all performance measures.

¹⁷I obtain monthly Fama-French U.S. market ($Mkt-RF$), size (SMB), value (HML), and momentum (MOM) factors from Kenneth R. French's website.

Taken together, these results point into the direction that managers have an information advantage in shared portfolio holdings. Because many studies argue that trades reflect a stronger conviction than just holding a stock (e.g., Pool et al. (2015); Cohen, Coval, and Pástor (2005)), I next examine whether common trades are informative as well.

In the trade-based portfolio tests, I form four portfolios for each fund in each period based on (i) whether the fund bought (“buys” portfolio) or sold (“sells” portfolio) a stock during the previous period and (ii) whether any of the fund’s FB-connected (or FB-interacted) funds made an overlapping trade (“connected” portfolio $\mathcal{C}$) or not (“unconnected” portfolio $\mathcal{U}$). I compute average monthly portfolio returns for each fund in each month weighting each stock’s return by the dollar amount invested (in case of the “buys” portfolio) or divested (in case of the “sells” portfolio) during the previous period. I then average portfolio returns across funds, weighting each portfolio by the dollar amount invested or divested during the previous period, to produce value-weighted average monthly returns of the connected and unconnected buy and sell portfolios.

Table 9 reports the DGTW-adjusted returns of the portfolios based on trades made by connected and unconnected mutual funds.¹⁸ First turning to the full sample of fund transactions in rows 1 and 2, column 1 shows that the connected buy portfolio significantly outperforms its DGTW benchmark portfolio by an average of 0.38 percentage points per month. Column 2 reveals that, on the sell side, the connected portfolio tends to underperform its DGTW benchmark portfolio, but insignificantly so. In column 3, I report returns of a long-short strategy that buys the portfolio of stocks that connected funds buy together and sells those they sell together. This strategy yields a DGTW-adjusted return of 0.52% per month (statistically significant at the 5% level). When excluding the financial crisis (the years 2008 and 2009) from my sample period, the long-short strategy delivers a slightly larger return of 0.59% per month.

Columns 4 to 6 show the corresponding results for the unconnected buy and sell portfolios. In contrast to the connected portfolios, both unconnected buy and sell portfolio DGTW-adjusted returns are statistically indistinguishable from zero, ranging between 0.00% and 0.05% per month. Also, a long-short strategy that uses unconnected trades does not deliver abnormal returns.

Finally, column 7 reports the difference-in-difference estimates, which allow me to control for managerial skill. The difference-in-difference estimates are equal to 0.54% and 0.62% per month for the full time-series and the period excluding the financial crisis, respectively, and are statistically significant at the 5% level.

¹⁸For brevity, I only report DGTW-adjusted returns. I obtain qualitatively similar results when using the four-factor model of Carhart (1997) instead.

In rows 3 to 6, Table 9 separately shows results for extensive and intensive margin trades.¹⁹ Results suggest that the connected portfolios' outperformance is driven by extensive margin trades. The difference-in-difference estimates for extensive margin trades are equal to up to 0.91% per month (significant at the 1% level), whereas these estimates are only up to 0.38% for intensive margin trades (significant at the 10% level).

In columns 8 to 14, I repeat the above analyses and redefine the connected portfolio to include only stocks that are simultaneously traded by at least one of a fund's FB-interacted funds. Results in column 14 indicate that the FB-interacted trades significantly outperform uninteracted trades. The difference-in-difference estimates of up to 1.01% per month (significant at the 1% level) appear to be slightly larger compared to those in column 7.

Collectively, this section's results confirm the findings in Table 7 and suggest that connections and interactions among fund managers likely facilitate the transmission of value-relevant information about stocks. Put differently, managers do not just share personal sentiments and biases with one another. The fact that extensive margin trades and FB-interacted trades appear to carry additional information casts doubt on the alternative hypothesis that the observed commonalities in holdings and trades (see Table 4 and Table 5) are driven by similarities in fund managers' preferences.

¹⁹Intensive margin trades occur if a current position is either expanded (intensive margin buy) or reduced (intensive margin sell). Extensive margin trades occur if a new position is established (extensive margin buy) or if a current position is completely liquidated (extensive margin sell).

IV. Additional Tests

A. Alternative Overlap Measures

To test whether my results on portfolio choice are sensitive to a particular overlap measure, I re-estimate columns 6 to 8 from Table 4 and all columns from Table 5 using variations of *PortOverlap*, *BuyOverlap*, and *SellOverlap* as in Pool et al. (2015).

First, as an alternative measure of portfolio overlap in Table 4, I create *PortOverlapPerc*, which is the percentage of overlapping holdings (instead of the sum of minimum weights described in Equation 1) between two funds. Second, I replace *BuyOverlap* and *SellOverlap* with two alternative measures that take into account the magnitudes of portfolio weight changes—as opposed to just the direction of trades. I calculate *BuyOverlapWeight* and *SellOverlapWeight* using the minimum change in weights across two funds conditional on the trades being buys and sells, respectively. Similarly, to account for share price changes, I calculate *BuyOverlapShares* and *SellOverlapShares* using the minimum change in shares. Third, I create sell and buy overlap measures based on intensive and extensive margin trades (analogous to Table 9).

In untabulated results, coefficient estimates on *FBConnected* and *FBInteraction* remain statistically significant (at least at the 5% level) across the re-estimated specifications and regardless of the overlap measure I use.

B. Alternative Stock-Level Performance Test

In addition to the sorted-portfolio approach in Section III.C, I rely on cross-sectional Fama-MacBeth (Fama and MacBeth (1973)) regressions to evaluate the performance impact of fund managers' social connections on their common holdings. Doing so allows me to control for several other holding or trade-based measures that have been discovered to predict stock returns (e.g., Wermers, Yao, and Zhao (2012)). The dependent variable in the Fama-MacBeth regressions are stock excess returns. Following Ammann et al. (2022), I calculate the main regressor of interest, $DiffWeight_{k,t}$, for each month t and stock k as the difference between the average weight that FB-connected funds simultaneously invest in the stock (i.e., stock buys) and the average weight that all other funds invest in the stock.

I compare the return-predictive power of $DiffWeight_{k,t}$ with three other holding and trade-based measures that I include in the Fama-MacBeth regressions. Brown, Wei, and Wermers (2014) document a significant price effect by mutual fund herding behavior. To control for the impact of herding, I follow Brown et al. (2014) and construct the variable $HERD_{k,t}$. I first construct a buy-herding measure for stocks that mutual funds buy and a sell-herding measure for stocks they sell.²⁰ Buy-herded and sell-herded stocks are then separately ranked into quintiles, and finally stacked into deciles. Second, I control for the aggregate stock-picking ability of mutual funds documented in Chen et al. (2000). For each stock, I calculate aggregate

²⁰See Appendix A and Brown et al. (2014) for more details on the variable construction.

fractional mutual fund trades, $TRADE_{k,t}$, as the total dollar change in mutual fund holdings divided by the stock’s market capitalization. Third, I follow Chen, Hong, and Stein (2002) and calculate $\Delta BREADTH_{k,t}$ as the change in the number of funds that hold a stock divided by the total number of funds that exist in the period. In this way, I take into account that funds’ negative outlooks on stocks are not fully expressed in portfolio holdings as most funds face short-sale constraints.

I further control for firm- and stock-level characteristics that have been found to contain relevant pricing information. 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).

Coefficient estimates for the average risk premia are presented in Table 10. Consistent with the results in Table 8 and Table 9, stocks that are more heavily purchased simultaneously by FB-connected and FB-interacted funds, compared to unconnected funds, exhibit a significant and positive outperformance. In column 1, the coefficient estimate of $DiffWeight_{k,t}$ is 0.13, implying that a 1 percentage point increase in the weight difference predicts an increase in monthly stock returns by 0.13 percentage points (statistically significant at the 1% level). When including $HERD_{k,t}$, $TRADE_{k,t}$, and $\Delta BREADTH_{k,t}$ in column 2, the coefficient estimate of $DiffWeight_{k,t}$ decreases to 0.10 but remains statistically significant at the 5% level, suggesting that the FB-connection effect is not subsumed by other holding and trade-based return predictors documented in the literature. In column 3 and 4, I redefine $DiffWeight_{k,t}$ as the difference between the average weight that FB-interacted funds simultaneously invest in the stock (i.e., stock buys) and the average weight that all other funds invest in the stock. Coefficient estimates of $DiffWeight_{k,t}$ increase to 0.18 (column 3) and 0.16 (column 4), respectively, which also corroborate my findings in Table 8 and Table 9 regarding the additional information contained in FB-interacted trades.

C. *Alternative Explanation*

While my empirical setup allows me to distinguish the effect of managers’ social connections on portfolio choice from other local, firm, and educational effects, a potential concern may be related to reverse causality. As I cannot directly determine the point at which a Facebook connection was established, such connections between fund managers may not be capturing the likelihood of social contact over my sample period. A Facebook connection may rather be the result of similar investment choices in the past (e.g., by attending the same analyst conference calls). Similarly, more successful fund managers may be more likely to build up a larger network later in their career, impairing my inferences.

The positive stock-level performance impact of social connections (see Section III.C) is hard to reconcile with a reverse causality story. It is unlikely that the performance of simultaneously traded stocks in the past is related to forming subsequent Facebook connections. Also, the particularly pronounced outperformance of extensive margin trades (see Table 9) and the increased overlaps between FB-interacted funds (see Table 8 and Table 9) provide evidence contrary a reverse causality story.

However, to ensure that the network formation takes place *ex ante*, i.e., is independent of potential information to be shared later in the professional career, I repeat the analyses in Table 4 and Table 7 using two types of subsamples: the first subsample is restricted to fund manager FB-connections that are based on either the same hometown, same high school, or same university. In the second subsample, *FBConnected* is equal to one only in the months following the earliest “FB-connection date” I am able to identify.²¹

Compared to the *FBConnected* coefficient estimate of 1.51 in column 1 of Table 4, using the first and second subsample yields coefficient estimates of 1.37 and 1.95, respectively, both significant at the 1% level. Coefficients of *NetNorm* remain similar in magnitude and statistically significant across all three network measures and specifications in Table 7. These results suggest that most of the correlation I uncover between portfolio overlap, performance, and my FB-connection indicator, is driven by network effects, rather than the other way around.

V. Conclusion

I study how private social networks among professional investors affect portfolio choice. Although prior results are consistent with the hypothesis that professional money managers transmit investment ideas socially and trade stocks that they learn about from their peers (e.g., Pool, Stoffman, and Yonker (2012); Rossi et al. (2018); Qi et al. (2020)), they all rely on proxies for social connections among investors. This paper is the first to directly observe whether any two investors know and communicate with each other. Using Facebook, I uncover a total of 6,571 connections between U.S. mutual fund managers.

I show that fund managers who are socially connected on Facebook exhibit abnormal portfolio overlaps. Importantly, this effect remains strong within the broader categories used as proxies for social connection in prior studies (e.g., geographical location or same past employer), allowing me to rule out several alternative hypotheses that may drive similarity in portfolio holdings (e.g., being exposed to the same local media outlets or learning investment strategies at the same past employer). Portfolio overlaps are significantly more pronounced if fund managers interact with each other on Facebook, lending further support to the hypothesis that fund managers share investment ideas with one another.

²¹I identify the earliest date of a FB-connection between fund managers as the earliest date on which they like, comment, or tag each other.

My approach still raises the concern that connecting and interacting on Facebook is related to a similarity in preferences, which may in turn drive the overlap in portfolio choice. I therefore provide evidence that funds that are well-connected through their managers achieve better returns at the fund level. This support suggests that fund managers receive value-relevant information through their social networks. Positive abnormal returns of stocks that FB-connected, and especially FB-interacted, funds hold and purchase simultaneously further support this notion.

My performance analysis also has asset pricing implications. As Hong et al. (2005) note, understanding the word-of-mouth effect among fund managers is important because of its potential effect on asset prices. Theoretical work in asset pricing finds that information sharing among investors generally improves market efficiency (e.g., Han and Yang (2013)). Recent experimental evidence by Halim, Riyanto, and Roy (2019) suggests that information networks among investors enhance the ability of asset prices to reflect the available information in the market, but fail to improve price informativeness, as social communication crowds out costly information production. In this regard, the evidence provided in my paper is twofold: (i) the performance increase from accessing return-relevant signals through social networks among fund managers appears to outweigh the performance decrease from having less incentives to produce own signals; and (ii) social networks among fund managers likely facilitate the transmission of value-relevant information about stocks and do not just propagate personal sentiments and biases.

Table 1. Sample Collection and Facebook-Related Characteristics

This table describes the Facebook data collected. Panel A details the information disclosed on the 3,936 identified fund manager Facebook profiles. Variables in the ‘Information Coverage’ section present the share of profiles disclosing the respective information. Panel B provides details on the 6,571 Facebook connections between fund managers in my sample.

Panel A: Individual Fund Manager Facebook Profiles (Total = 3,936)						
	Mean	Median	Min	Max	SD	N
<i>Information Coverage</i>						
Friend List	0.56	1	0	1	0.50	2,207
Profile Picture	0.91	1	0	1	0.29	3,564
Photos	0.65	1	0	1	0.48	2,559
Family Info	0.23	0	0	1	0.42	891
Relationship	0.20	0	0	1	0.40	795
High School	0.36	0	0	1	0.48	1,424
Education	0.45	0	0	1	0.50	1,780
Workplace	0.32	0	0	1	0.47	1,276
Home Town	0.53	1	0	1	0.50	2,091
Current City	0.43	0	0	1	0.49	1,685
<i>Friends</i>						
Disclosed	247	162	1	5,265	343	938,878
Public Friends	298	208	1	5,162	402	658,129
Hidden Friends	169	111	1	2,025	200	269,602
From Friend Lists	134	93	2	1,664	150	179,655
From Photos	95	58	1	1,369	122	123,050
<i>Photos and Reactions</i>						
Photos	40	6	1	2,365	132	125,443
Reactions	482	90	1	38,646	1,732	1,431,474
Likes received	428	82	1	34,089	1,513	1,252,681
Comments received	66	13	1	6,106	254	149,959
Tags added	30	5	1	2,392	114	28,834
Panel B: Social Connections between Fund Managers (Total = 6,571)						
	N Connections		N Fund Managers			
<i>By Commonality:</i>			<i>By Network Size:</i>			
Same Hometown	142		Con > 0		1,923	
Same High School	129		Con = 1		330	
Same College	1,451		2 ≤ Con ≤ 5		905	
Same Current City	976		6 ≤ Con ≤ 10		355	
Same Employer	1,785		11 ≤ Con ≤ 20		208	
Same Fund	987		Con ≥ 21		125	
<i>By Interaction:</i>						
With Likes	1,736					
With Comments	367					
With Tags	53					

Table 2. Summary Statistics: Facebook Funds

This table presents annual coverage of Facebook-identified and connected fund managers, and the mutual funds they manage. The benchmark universe of funds consists of 418,300 fund-month observations covering the period from January 1984 to December 2020. It includes all domestic actively managed U.S. equity mutual funds from MS Direct after following the steps detailed in Section I.A. The “FB-identified” sample includes only fund-month observations for which I identify the Facebook profile of at least one of the fund’s then-current portfolio managers. The “FB-connected” sample includes only fund-month observations for which I can identify a Facebook connection between at least one of the fund’s portfolio managers and at least one of another sample fund’s portfolio managers.

	Mean	Median	Min	Max	SD
FB-identified fund managers per year					
N	888	1,102	21	1,502	584
% of all managers	.33	.36	.12	.45	.10
FB-connected fund managers per year					
N	428	540	7	762	310
% of all managers	.16	.18	.04	.23	.08
FB-identified funds per year					
N	1,110	1,475	22	1,977	750
% of funds	.52	.57	.14	.73	.19
% of total assets	.48	.51	.07	.78	.21
FB-connected funds per year					
N	547	741	9	1,072	405
% of funds	.23	.29	.06	.37	.13
% of total assets	.22	.25	.04	.39	.14

Table 3. Summary Statistics: Social Connection, Holdings, and Trades

This table reports means of the overlap measures, measures of social connection, and control variables for different samples of observations. The full sample includes all actively managed U.S. equity mutual funds from Morningstar Direct between January 1984 to December 2020, resulting in 135.3 million monthly fund-pair observations. $FBConnected_{i,j,t}$ and $FBInteraction_{i,j,t}$ are dummy variables that are one if at least one manager from fund i is connected and interacting, respectively, with at least one manager from fund j during period t . $PortOverlap_{i,j,t}$ measures the portfolio overlap in holdings (in percentage) between funds i and j during period t (see Equation 1). $BuyOverlap_{i,j,t}$ measures the overlap in stock purchases (in percentage) between fund i and j during period t (see Equation 2). $SellOverlap_{i,j,t}$ measures the overlap in stock sales (in percentage) between fund i and j during period t (see Equation 3). $SameCity_{i,j,t}$, $SamePastFirm_{i,j,t}$, and $SameEdu_{i,j,t}$ are dummy variables that are one if at least one manager from fund i resides in the same city, has a college degree from the same university, and worked at the same firm, respectively, as at least one manager from fund j in period t . $SameFundFam_{i,j,t}$ equals one if funds i and j are part of the same mutual fund family; $ManageOtherFund_{i,j,t}$ equals one if at least one pair of managers from funds i and j manage at least one other fund together. $CommonMgr_{i,j,t}$ equals one if funds i and j have at least one manager in common. $BothSmallCap$, $BothMidCap$, $BothLargeCap$, $BothValue$, $BothGrowth$, $BothBlend$ are dummy variables that are one if funds i and j match on the respective Morningstar size or value/growth categories. $TNAQuinDiff$ is the absolute value of the difference between the TNA-based quintiles of the funds in the pair, and $TNAQuinAvg$ is the average TNA quintile of the funds in the pair, where TNA quintiles are computed monthly. * denotes unconditional means.

	(1)			(2)			(3)			(4)			N (mn.)
Avg. if $FBConnected =$	*	All		*	SameCity=1		*	SamePastFirm=1		*	SameEdu=1		
		0	1		0	1		0	1		0	1	
<i>Dependent variables:</i>													
PortOverlap (%)	5.93	5.90	13.05	7.10	6.92	14.41	7.40	7.31	14.29	7.79	7.70	11.20	135.28
BuyOverlap (%)	5.14	5.11	13.13	6.42	6.21	14.55	6.65	6.53	15.25	7.20	7.09	11.51	122.81
SellOverlap (%)	5.14	5.11	12.95	6.78	6.59	14.41	6.82	6.71	14.84	7.25	7.14	11.65	122.65
<i>Main independent variables:</i>													
FBConnected (%)	0.45			2.44			1.36			2.45			135.28
FBInteraction (%)	0.17		37.55	0.92		37.76	0.49		35.64	0.98		40.17	135.28
<i>Main control variables:</i>													
SameCity (%)	10.17	9.97	55.11				19.76	19.15	64.12	25.58	24.83	55.62	135.28
SamePastFirm (%)	10.18	10.08	30.79	19.78	19.37	35.82				25.29	25.02	36.03	135.28
SameEdu (%)	1.83	1.79	9.95	4.60	4.46	10.04	4.54	4.45	11.64				135.28

(Continued)

Table 3. Continued

	(1)			(2)			(3)			(4)			
	All			SameCity=1			SamePastFirm=1			SameEdu=1			
Avg. if <i>FBConnected</i> =	*	0	1	*	0	1	*	0	1	*	0	1	N (mn.)
<i>Baseline control variables:</i>													
SameFundFam (%)	1.41	1.23	42.69	4.74	3.72	45.50				2.45	1.74	30.66	135.28
ManageOtherFund (%)	0.18	0.12	13.14	1.17	0.72	19.25	0.89	0.65	18.44	1.30	0.95	15.38	135.28
CommonMgr (%)	0.37	0.27	21.78	1.86	1.14	30.58	1.42	1.05	28.29	1.62	1.23	17.34	135.28
BothSmallCap (%)	1.39	1.39	1.68	1.79	1.78	2.33	1.79	1.78	2.43	2.16	2.17	1.72	135.28
BothMidCap (%)	2.82	2.82	3.48	2.92	2.91	3.45	2.95	2.94	3.97	2.92	2.92	2.65	135.28
BothLargeCap (%)	11.10	11.10	11.77	11.98	11.98	11.94	11.05	11.04	11.81	12.86	12.89	11.67	135.28
BothValue (%)	0.80	0.80	1.28	0.99	0.98	1.37	1.15	1.15	1.42	1.09	1.09	1.29	135.28
BothGrowth (%)	7.64	7.62	11.44	7.54	7.47	10.47	7.84	7.77	13.06	7.45	7.46	6.85	135.28
BothBlend (%)	6.44	6.44	5.92	7.72	7.71	7.70	6.45	6.46	6.08	8.65	8.67	7.86	135.28
TNAQuinDiff	1.60	1.60	1.33	1.53	1.54	1.31	1.45	1.46	1.34	1.55	1.56	1.29	135.28
TNAQuinAvg	3.00	3.00	3.52	3.19	3.18	3.58	3.42	3.41	3.47	3.30	3.29	3.59	135.28

Table 4. Social Connections and Mutual Fund Holdings

This table reports results from an OLS estimation of various forms of the regression

$$PortOverlap_{i,j,t} = \alpha + \beta_1 FBConnected_{i,j,t} + \beta_2 FBInteraction_{i,j,t} + \gamma_1 SameCity_{i,j,t} + \gamma_2 SamePastFirm_{i,j,t} + \gamma_3 SameEdu_{i,j,t} + \Gamma' OtherControls_{i,j,t} + \epsilon_{i,j,t},$$

where *PortOverlap* is defined as in Equation 1. *FBConnected*_{*i,j,t*} and *FBInteraction*_{*i,j,t*} are dummy variables that are one if at least one manager from fund *i* is connected and interacting, respectively, with at least one manager from fund *j* during period *t*. *SameCity*_{*i,j,t*}, *SamePastFirm*_{*i,j,t*}, and *SameEdu*_{*i,j,t*} are dummy variables that are one if at least one manager from fund *i* resides in the same city, has a college degree from the same university, and worked at the same firm, respectively, as at least one manager from fund *j* in period *t*. *Controls*_{*i,j,t*} is a vector of control variables described in Table 3. The sample includes 135.3 million monthly fund-pair observations from January 1984 to December 2020. Column 6 limits the sample to fund pairs with no managers in common during period *t*; column 7 excludes fund pairs within the same fund family; and column 8 includes only funds where both funds in the pair are managed by a single manager. Standard errors in parentheses are two-way clustered by each fund in the pair. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

Sample:	Dependent Variable: <i>PortOverlap</i> _{<i>i,j,t</i>} (%)							
	Full (1)	Full (2)	Full (3)	Full (4)	Full (5)	No Common Managers (6)	Different Fund Fam (7)	Single Mgr. Pairs (8)
FBConnected	1.51*** (0.33)	0.90** (0.41)	0.72** (0.31)	0.66** (0.30)	0.55** (0.27)	0.71*** (0.27)	0.59** (0.29)	2.69*** (0.74)
FBInteraction		1.64*** (0.52)	1.65*** (0.52)	1.68*** (0.52)	1.67*** (0.52)	1.23*** (0.41)	1.10** (0.53)	1.74*** (0.53)
SameCity			0.55*** (0.11)	0.47*** (0.11)	0.45*** (0.11)	0.48*** (0.11)	0.43*** (0.11)	0.48** (0.24)
SamePastFirm				0.88*** (0.11)	0.86*** (0.11)	0.81*** (0.11)	0.82*** (0.11)	1.57*** (0.32)
SameEdu					0.84*** (0.12)	0.94*** (0.12)	0.89*** (0.12)	0.16 (0.14)
SameFundFam	0.87*** (0.22)	0.85*** (0.22)	0.77*** (0.22)	0.98*** (0.22)	0.99*** (0.22)	1.14*** (0.18)		0.88** (0.39)
MngOtherFund	1.83*** (0.25)	1.81*** (0.25)	1.72*** (0.25)	1.08*** (0.22)	1.03*** (0.22)	1.62*** (0.21)	1.40*** (0.22)	-1.06 (1.37)

(Continued)

Table 4. Continued

Sample:	Dependent Variable: $PortOverlap_{i,j,t}$ (%)							
	Full	Full	Full	Full	Full	No Common Managers	Different Fund Fam	Single Mgr. Pairs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CommonMgr	20.62*** (0.86)	20.64*** (0.86)	20.52*** (0.86)	20.28*** (0.86)	20.26*** (0.86)		22.59*** (0.89)	
BothSmallCap	2.35*** (0.29)	2.35*** (0.29)	2.34*** (0.29)	2.33*** (0.29)	2.32*** (0.29)	2.18*** (0.27)	2.21*** (0.28)	0.57 (0.37)
BothMidCap	1.57*** (0.18)	1.57*** (0.18)	1.57*** (0.18)	1.57*** (0.18)	1.57*** (0.18)	1.42*** (0.18)	1.48*** (0.18)	0.65** (0.29)
BothLargeCap	14.17*** (0.31)	14.17*** (0.31)	14.17*** (0.31)	14.18*** (0.31)	14.18*** (0.31)	14.09*** (0.31)	14.07*** (0.31)	13.26*** (0.58)
BothValue	0.32 (0.19)	0.32 (0.19)	0.33 (0.20)	0.35 (0.22)	0.35 (0.22)	0.50* (0.28)	0.41 (0.28)	0.08 (0.23)
BothGrowth	2.28*** (0.22)	2.28*** (0.22)	2.28*** (0.21)	2.28*** (0.21)	2.28*** (0.21)	2.22*** (0.21)	2.20*** (0.21)	3.40*** (0.46)
BothBlend	-0.32 (0.28)	-0.32 (0.29)	-0.32 (0.28)	-0.32 (0.28)	-0.32 (0.28)	-0.34 (0.27)	-0.34 (0.27)	-0.47 (0.32)
TNAQuinDiff	-0.13*** (0.02)	-0.13*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)	-0.12*** (0.02)	-0.18*** (0.04)
TNAQuinAvg	0.91*** (0.06)	0.91*** (0.06)	0.90*** (0.06)	0.86*** (0.06)	0.86*** (0.06)	0.84*** (0.06)	0.84*** (0.06)	1.01*** (0.10)
Constant	1.51*** (0.16)	1.51*** (0.16)	1.48*** (0.16)	1.49*** (0.16)	1.49*** (0.16)	1.56*** (0.16)	1.56*** (0.16)	1.15*** (0.254)
Adj. R-squared	31.36	31.37	31.40	31.48	31.50	30.48	30.98	32.39
N (thousands)	135'276	135'276	135'276	135'276	135'276	134'776	133'365	6'619

Table 5. Social Connections and Mutual Fund Trades

This table reports results from an OLS estimation of various forms of the regression of purchase (Equation 5) and sale (Equation 6) overlap on *FBConnected* and *FBInteraction*, and the control variables as defined in Table IV. In columns 1 through 3 (4 through 6), the dependent variable is *BuyOverlap_{i,j,t}* (*SellOverlap_{i,j,t}*), i.e., the percentage of overlapping stock purchases (sales) between a given pair of funds during period t , as defined in Equation 2 and Equation 3, respectively. The total sample includes 135.3 million monthly fund-pair observations from January 1984 to December 2020. In columns 1 and 4, the sample is restricted to fund pairs with no managers in common during period t . In columns 2 and 5, fund pairs within the same fund family are excluded. Columns 3 and 6 limit the sample to fund pairs in which both funds are managed by a single manager. Standard errors in parentheses are two-way clustered by each fund in the pair. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

Sample:	Dependent Variable: <i>BuyOverlap_{i,j,t}</i> (%)			Dependent Variable: <i>SellOverlap_{i,j,t}</i> (%)		
	No Common Managers (1)	Different Fund Fam (2)	Single Mgr. Pairs (3)	No Common Managers (4)	Different Fund Fam (5)	Single Mgr. Pairs (6)
FBConnected	0.78*** (0.30)	0.82** (0.41)	1.96*** (0.62)	0.82*** (0.28)	0.85** (0.40)	1.92*** (0.60)
FBInteraction	1.40*** (0.39)	1.67*** (0.65)	2.38*** (0.93)	1.15*** (0.36)	1.36** (0.61)	1.71** (0.83)
SameCity	0.60*** (0.10)	0.53*** (0.10)	-0.02 (0.22)	1.01*** (0.10)	0.97*** (0.10)	0.20 (0.22)
SamePastFirm	0.85*** (0.09)	0.87*** (0.09)	0.97*** (0.23)	1.01*** (0.10)	1.02*** (0.10)	1.05*** (0.22)
SameEdu	1.18*** (0.11)	1.13*** (0.11)	0.58** (0.29)	1.15*** (0.11)	1.10*** (0.11)	0.68** (0.29)
SameFundFam	1.33*** (0.18)		2.09*** (0.41)	1.06*** (0.17)		2.05*** (0.41)
MngOtherFund	2.21*** (0.20)	1.90*** (0.21)	-1.32 (1.18)	2.19*** (0.19)	1.88*** (0.21)	-1.21 (1.07)
CommonMgr		27.42*** (1.12)			25.59*** (1.04)	

(Continued)

Table 5. Continued

Sample:	Dependent Variable: $BuyOverlap_{i,j,t}$ (%)			Dependent Variable: $SellOverlap_{i,j,t}$ (%)		
	No Common	Different	Single Mgr.	No Common	Different	Single Mgr.
	Managers	Fund Fam	Pairs	Managers	Fund Fam	Pairs
	(1)	(2)	(3)	(4)	(5)	(6)
BothSmallCap	3.02*** (0.33)	3.09*** (0.33)	1.70*** (0.53)	2.80*** (0.27)	2.86*** (0.28)	1.28*** (0.37)
BothMidCap	1.42*** (0.16)	1.51*** (0.16)	0.75*** (0.24)	1.29*** (0.16)	1.36*** (0.16)	0.38* (0.22)
BothLargeCap	9.07*** (0.24)	9.06*** (0.24)	8.86*** (0.43)	9.31*** (0.26)	9.31*** (0.27)	7.81*** (0.39)
BothValue	0.10 (0.24)	0.00 (0.25)	0.08 (0.41)	0.16 (0.17)	0.07 (0.17)	0.18 (0.19)
BothGrowth	1.25*** (0.19)	1.25*** (0.19)	1.90*** (0.38)	1.43*** (0.21)	1.43*** (0.21)	2.63*** (0.37)
BothBlend	0.40 (0.15)	0.40 (0.15)	0.26 (0.29)	0.21 (0.14)	0.20 (0.14)	0.32 (0.20)
TNAQuinDiff	0.09*** (0.02)	0.09*** (0.02)	0.07** (0.04)	0.00 (0.02)	0.00 (0.02)	0.02 (0.03)
TNAQuinAvg	0.73*** (0.06)	0.74*** (0.06)	0.84*** (0.09)	0.72*** (0.06)	0.73*** (0.06)	0.80*** (0.08)
Constant	1.25*** (0.16)	1.25*** (0.16)	1.00*** (0.26)	1.35*** (0.16)	1.35*** (0.16)	0.80*** (0.23)
Adj. R-squared	7.86	8.76	9.32	8.39	9.19	9.27
N (thousands)	122'340	121'012	6'040	122'150	120'813	6'021

Table 6. Summary Statistics: Social Connections and Performance

This table reports summary statistics for fund performance, network centrality measures, and various fund-level control variables. The sample includes all actively managed U.S. equity mutual funds from Morningstar Direct between January 1984 to December 2020, resulting in 216,864 fund-month observations. *FundAlpha* is the fund's four-factor alpha from a Carhart (1997) model using monthly fund net returns over a 24-month look-back period requiring at least 12 available return observations. The network centrality measures, *DegreeCen*, *PrestigeCen*, and *BetweenCen*, are calculated for all funds each month according to Equations 7, 8, and 9, respectively. *FundSize* is the fund's TNA (in USD bn.). *FamSize* is the TNA of all active equity funds in the fund family (in USD bn.). *TeamSize* is the number of portfolio managers on the fund. *FundAge* is the fund's age since inception (in years). *FundFlow* is the monthly net percentage fund flow, computed as $[TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})]/TNA_{i,t-1}$, where $TNA_{i,t}$ is fund i 's TNA in month t and $r_{i,t}$ stands for fund i 's net return in month t . *ExpenseRatio* and *TurnoverRatio* come from CRSP. *MgrMBA* is a dummy variable equal to one if the manager has an MBA degree. *MgrIvy* is a dummy variable equal to one if a manager has any degree from an Ivy League school. *MgrTenure* is the number of years that the manager has been managing the respective fund. *MgrAge* is the fund manager's age. *MgrMBA*, *MgrIvy*, *MgrTenure*, and *MgrAge* are averaged at the fund-level if the fund is managed by multiple managers.

	Mean	Std.	Median	10th	90th	N
<i>Dependent variable</i>						
FundAlpha (%)	-0.111	1.551	-0.093	-1.871	1.632	216'864
<i>Main independent variables</i>						
DegreeCen	0.008	0.012	0.004	0.001	0.022	216'864
PrestigeCen	0.001	0.006	0.000	0.000	0.002	211'384
BetweenCen	0.002	0.007	0.000	0.000	0.006	216'864
<i>Control variables</i>						
FundSize (USD bn.)	2.282	9.307	0.343	0.017	4.221	216'392
FamSize (USD bn.)	83.647	238.195	14.941	0.243	127.744	215'779
TeamSize	3.629	3.596	3.000	1.000	6.000	216'864
FundAge (years)	12.036	8.847	10.500	1.750	24.667	216'864
FundFlow (%)	0.517	6.358	-0.31	-2.928	4.273	216'864
ExpenseRatio (%)	0.112	0.148	0.106	0.078	0.175	216'386
TurnoverRatio	0.873	1.181	0.657	0.186	1.669	216'191
MgrMBA	0.54	0.43	0.50	0.000	1.000	216'386
MgrIvy	0.385	0.361	0.333	0.000	1.000	216'864
MgrTenure (years)	4.906	3.904	3.917	1.000	10.056	216'864
MgrAge (years)	48.862	9.138	47.029	38.817	60.174	216'864

Table 7. Network Centrality and Fund Performance

This table reports results from an OLS estimation of various forms of the regression

$$FundAlpha_{i,t+1} = \alpha + \beta NetNorm_{i,t} + \gamma Controls_{i,t} + \epsilon_{i,t},$$

where $FundAlpha_{i,t+1}$ is fund i 's four-factor alpha in period $t+1$. Alphas are computed using monthly net returns over a 24-month look-back period requiring at least 12 observations. $NetNorm_{i,t}$ is the respective network centrality measure (*DegreeCen* in columns 1–3, *PrestigeCen* in columns 4–6, and *BetweenCen* in columns 7–9) of fund i in month t , normalized by the cross-sectional average in month t . $Controls_{i,t}$ is a vector of control variables described in Table 7. Standard errors in parentheses are two-way clustered by fund and month. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

Network measure =	Dependent Variable: $FundAlpha_{i,t+1}$ (in bps)								
	DegreeCen			PrestigeCen			BetweenCen		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NetNorm	1.83** (0.81)	1.76** (0.78)	1.61** (0.69)	4.97*** (1.28)	4.12*** (1.21)	2.57** (1.15)	1.84** (0.88)	2.16** (1.01)	2.33** (1.09)
Log(FundSize)	-1.30** (0.60)	-1.41** (0.67)	-2.13*** (0.79)	-1.36** (0.57)	-1.44** (0.65)	-2.28*** (0.87)	-1.29** (0.59)	-1.28** (0.56)	-2.08*** (0.77)
Log(FamSize)	1.87*** (0.34)	1.79*** (0.32)	2.15*** (0.48)	1.89*** (0.35)	1.93*** (0.37)	2.18*** (0.49)	1.86*** (0.34)	1.72*** (0.32)	2.04*** (0.47)
TeamSize	-0.20* (0.11)	-0.22* (0.11)	-0.42* (0.24)	-0.24** (0.12)	-0.23* (0.12)	-0.47** (0.24)	-0.20* (0.11)	-0.23** (0.11)	-0.51** (0.19)
Log(FundAge)	-1.24 (1.12)	-1.46 (0.96)	-1.54 (1.16)	-1.02 (1.12)	-1.24 (0.95)	-1.36 (1.17)	-1.25 (1.13)	-1.45 (0.96)	-1.50 (1.16)
FundFlow	0.18* (0.11)	0.17* (0.10)	0.18 (0.13)	0.19* (0.11)	0.17* (0.10)	0.19* (0.10)	0.18* (0.10)	0.17* (0.10)	0.18* (0.10)
ExpenseRatio	-0.05* (0.03)	-0.05* (0.03)	-0.04 (0.04)	-0.05* (0.03)	-0.04* (0.03)	-0.04 (0.04)	-0.05* (0.03)	-0.05* (0.03)	-0.04 (0.04)
Turnover	-0.30*** (0.05)	-0.21*** (0.04)	-0.15** (0.07)	-0.29*** (0.05)	-0.20*** (0.04)	-0.14** (0.07)	-0.30*** (0.05)	-0.22*** (0.04)	-0.15** (0.07)
Manager Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style Fixed Effects	No	Yes	No	No	Yes	No	No	Yes	No
Family Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
N	215'677	214'577	214'577	209'171	209'171	209'171	214'577	214'577	214'577

Table 8. Stock-Level Performance and Social Connections: Holdings

This table reports returns for “connected” (C) and “unconnected” (U) holdings of funds. The connected portfolio of fund i contains those stocks in the fund’s portfolio that are also held by at least one of fund i ’s FB-connected (columns 1 to 3) or FB-interacted (columns 4 to 6) funds. Holdings that do not meet this criterion comprise the unconnected portfolio. I compute connected and unconnected portfolio returns for each fund i in each period t as

$$R_{i,t}^C = \sum_{k \in \mathcal{C}} \left(\frac{w_{i,k,t}}{\sum_{k \in \mathcal{C}} w_{i,k,t}} \right) r_{k,t+1}$$

and

$$R_{i,t}^U = \sum_{k \in \mathcal{U}} \left(\frac{w_{i,k,t}}{\sum_{k \in \mathcal{U}} w_{i,k,t}} \right) r_{k,t+1}$$

and then average across funds for each period t , weighting each fund’s portfolio return by its respective TNA, to produce value-weighted average monthly returns of the connected and unconnected holdings portfolios. $\mathcal{C}$ denotes the set of connected stocks, $\mathcal{U}$ the set of unconnected stocks, and $w_{i,k,t}$ is stock k ’s weight in fund i ’s portfolio during period t . The table presents average raw and risk-adjusted monthly returns for the connected and unconnected portfolios for the sample period from January 1984 to December 2020. Risk adjustment is based on the four-factor Carhart (1997) model and DGTW benchmark returns. In columns 1 to 3, the sample comprises all FB-connected funds. In columns 4 to 6, the sample is restricted to FB-interacted funds. Columns 3 and 6 report the difference in returns between the connected and unconnected portfolios. Standard errors are reported in parentheses. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	FB-Connected Funds			FB-Interacted Funds		
	R^C	R^U	$R^C - R^U$	R^C	R^U	$R^C - R^U$
	(1)	(2)	(3)	(4)	(5)	(6)
Raw return	1.13*** (0.26)	0.96*** (0.23)	0.17* (0.09)	1.17*** (0.26)	0.99*** (0.24)	0.19** (0.08)
4-factor alpha	0.10 (0.08)	-0.00 (0.03)	0.11 (0.08)	0.15** (0.07)	-0.01 (0.03)	0.16** (0.07)
DGTW	0.21*** (0.08)	-0.01 (0.04)	0.23*** (0.08)	0.24*** (0.08)	-0.00 (0.04)	0.25*** (0.08)

Table 9. Stock-Level Performance and Social Connections: Trades

This table reports the performance of portfolios based on trades made by connected and unconnected mutual funds. For each fund, I form four portfolios in each period based on (i) whether the fund bought (“buys” portfolio) or sold (“sells” portfolio) a stock during the previous period and (ii) whether any of the fund’s FB-connected (columns 1 to 7) or FB-interacted (columns 8 to 14) funds made an overlapping trade (“connected” portfolio $\mathcal{C}$) or not (“unconnected” portfolio $\mathcal{U}$). I compute average monthly portfolio returns for each fund in each month weighting each stock’s return by the dollar amount invested (“buys” portfolio) or divested (“sells” portfolio) during the previous period. I then average portfolio returns across funds, weighting each portfolio by the dollar amount invested or divested during the previous period, to produce value-weighted average monthly returns of the connected and unconnected buy and sell portfolios. Risk adjustment is based on DGTW benchmark returns. Columns 3, 6, 10, and 13 describe return differences of the buy and sell portfolios for the connected and unconnected stocks, respectively, and columns 7 and 14 show difference-in-difference estimates. Returns are reported for the full sample period and the sample period excluding the financial crisis, as well as for all fund trades, extensive margin trades, and intensive margin trades. Standard errors are reported in parentheses. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	FB-Connected Funds							FB-Interacted Funds						
	DGTW ^C			DGTW ^U			D.-D.	DGTW ^C			DGTW ^U			D.-D.
	Buys	Sells	Diff.	Buys	Sells	Diff.		Buys	Sells	Diff.	Buys	Sells	Diff.	
<i>All trades:</i>														
Full time-series	0.38** (0.15)	-0.14 (0.22)	0.52** (0.24)	0.02 (0.08)	0.04 (0.06)	-0.02 (0.07)	0.54** (0.24)	0.48** (0.19)	-0.18 (0.22)	0.67*** (0.25)	0.01 (0.08)	0.00 (0.06)	0.01 (0.10)	0.66** (0.26)
Excl. fin. crisis	0.42** (0.17)	-0.17 (0.23)	0.59*** (0.22)	0.03 (0.09)	0.05 (0.06)	-0.02 (0.08)	0.62** (0.24)	0.51** (0.21)	-0.19 (0.23)	0.70*** (0.26)	0.02 (0.09)	0.05 (0.06)	-0.03 (0.08)	0.72*** (0.27)
<i>Extensive margin:</i>														
Full time-series	0.52** (0.24)	-0.16 (0.27)	0.69** (0.29)	0.01 (0.09)	0.06 (0.07)	-0.05 (0.10)	0.74** (0.32)	0.60** (0.29)	-0.20 (0.19)	0.80** (0.31)	-0.02 (0.10)	0.07 (0.07)	-0.09 (0.11)	0.88*** (0.33)
Excl. fin. crisis	0.57** (0.26)	-0.30* (0.18)	0.87*** (0.33)	-0.00 (0.10)	0.05 (0.07)	-0.05 (0.09)	0.91*** (0.35)	0.66** (0.32)	-0.31* (0.16)	0.96*** (0.35)	-0.00 (0.11)	0.06 (0.08)	-0.06 (0.10)	1.01*** (0.37)
<i>Intensive margin:</i>														
Full time-series	0.21 (0.14)	-0.13 (0.22)	0.33* (0.19)	0.01 (0.06)	0.04 (0.06)	-0.03 (0.07)	0.36* (0.20)	0.36** (0.17)	-0.16 (0.20)	0.51** (0.25)	0.02 (0.06)	-0.03 (0.06)	0.04 (0.08)	0.47** (0.24)
Excl. fin. crisis	0.21 (0.16)	-0.15 (0.23)	0.36* (0.22)	0.03 (0.07)	0.05 (0.06)	-0.02 (0.06)	0.38* (0.23)	0.39** (0.19)	-0.16 (0.21)	0.54** (0.26)	0.03 (0.07)	-0.03 (0.06)	0.03 (0.07)	0.51** (0.21)

Table 10. Stock-Level Performance and Social Connections: Holdings

This table reports risk premium estimates from monthly cross-sectional Fama and MacBeth (1973) regressions across the period from January 1984 to December 2020. The main independent variable of interest is $DiffWeight_{k,t}$, the difference between the average weight that FB-connected (columns 2 to 3) or FB-interacted (columns 3 to 4) funds simultaneously invest in the stock (i.e., stock buys) and the average weight that all other funds invest in the stock. Control variables include other holding or trade-based measures, i.e., $HERD_{k,t}$ (calculated as in Brown et al. (2014)), $TRADE_{k,t}$ (calculated as in Chen et al. (2000)), and $\Delta BREADTH_{k,t}$ (calculated as in Chen et al. (2002)). Other independent variables are 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 is next month's stock excess return, calculated as raw return minus the risk-free rate. All dependent and independent variables are in each month winsorized at the 1st and 99th percentile. Standard errors are reported in parentheses. 10%, 5%, and 1% significance levels are denoted by *, **, and ***, respectively.

	Dependent Variable: $StockRet_{k,t+1} - RiskFree_{t+1}$ (%)			
	FB-Connected vs.		FB-Interacted vs.	
	Unconnected Buys		Uninteracted Buys	
DiffWeight	0.13*** (0.04)	0.10** (0.04)	0.18*** (0.06)	0.16*** (0.06)
HERD		0.06*** (0.02)		0.05*** (0.02)
TRADE		0.09*** (0.02)		0.10*** (0.02)
$\Delta BREADTH$		0.17* (0.10)		0.19* (0.11)
ME	-0.08* (0.05)	-0.08* (0.05)	-0.10** (0.05)	-0.10** (0.05)
BM	0.10 (0.10)	0.10 (0.09)	0.07 (0.09)	0.06 (0.09)
MOM	0.17 (0.20)	0.17 (0.20)	0.16 (0.21)	0.16 (0.20)
STR	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.01)	-0.02*** (0.01)
IMOM	0.07*** (0.02)	0.07*** (0.02)	0.06*** (0.02)	0.06*** (0.02)
SUE	0.13 (0.91)	-0.15 (0.92)	0.61 (0.79)	0.59 (0.81)
Constant	1.23*** (0.50)	0.91* (0.55)	1.22*** (0.50)	0.90* (0.53)
Adj. R-squared	4.93	5.25	5.18	5.70
N	884'795	882'484	869'321	867'168
N Months	330	330	315	315

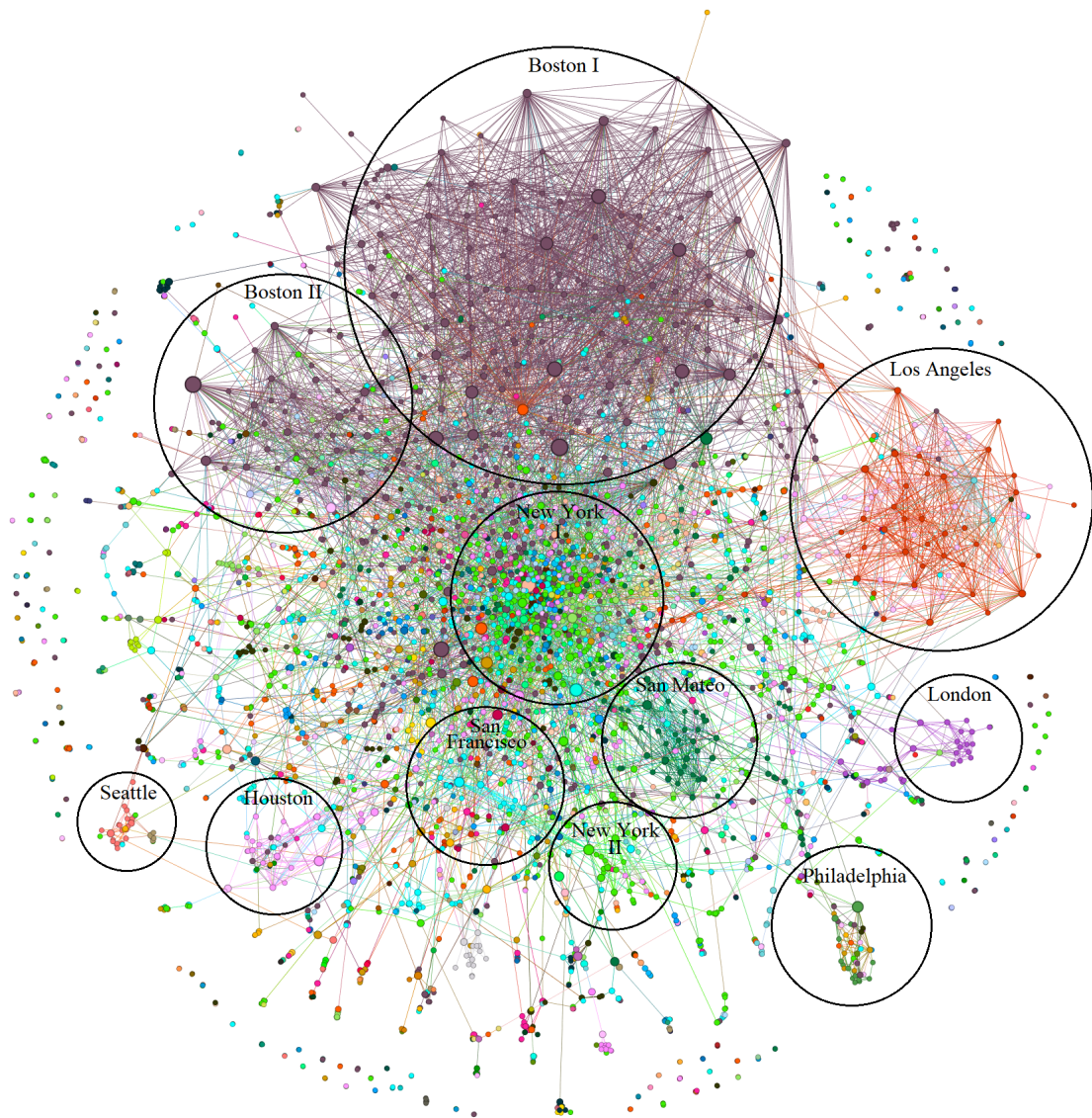


Fig. 1. Facebook connections among U.S. mutual fund managers by place of residence. This figure displays 6,571 Facebook connections among the sample of 3,936 FB-identified U.S. mutual fund managers. Every node represents a fund manager, and edges are indicated by lines connecting two nodes. Node size is based on the number of edges. Nodes are colored according to the fund manager's place of residence. Circles in black highlight the most prominent location-based networks.

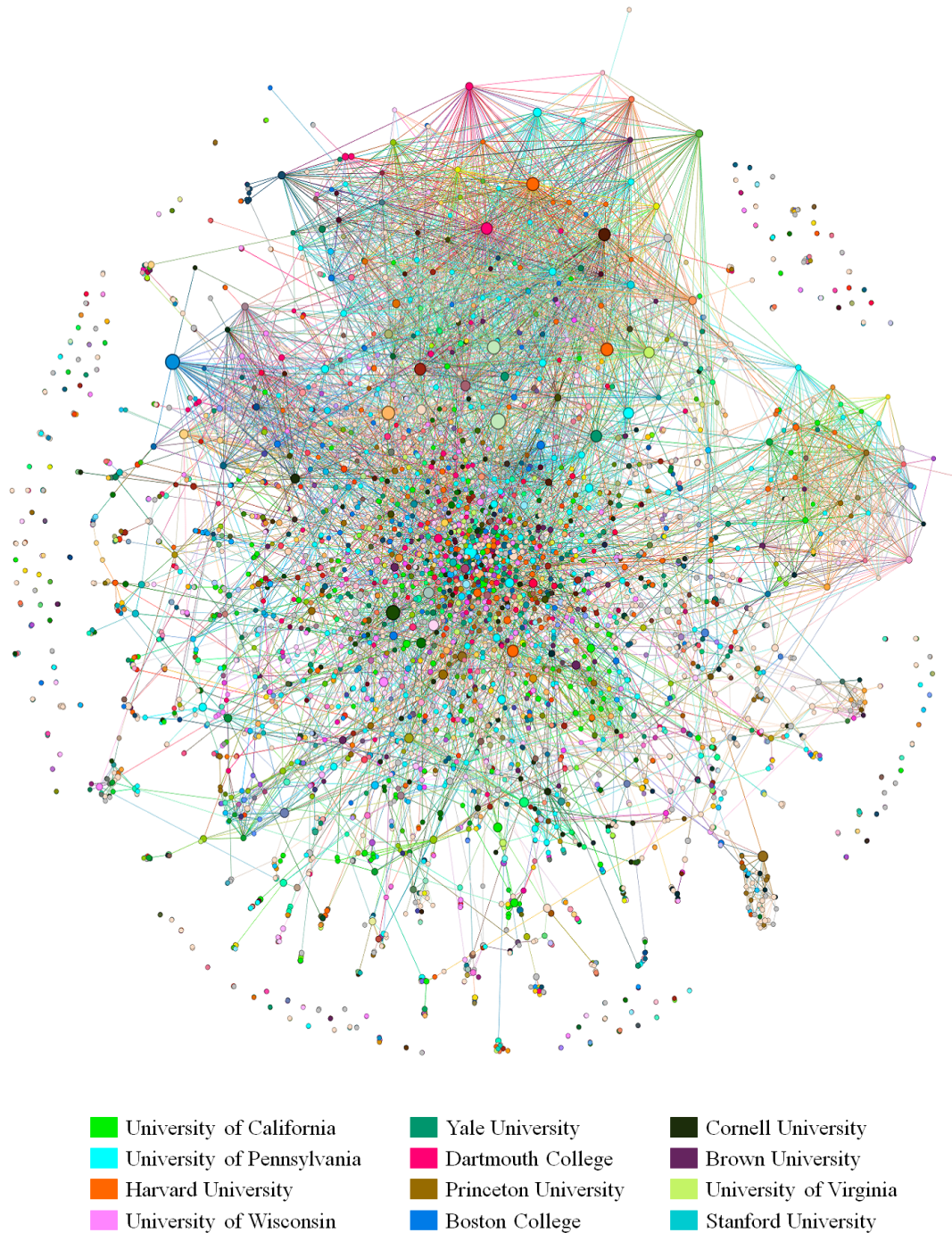


Fig. 2. Facebook connections among U.S. mutual fund managers by educational institution. This figure displays 6,571 Facebook connections among the sample of 3,936 FB-identified U.S. mutual fund managers. Every node represents a fund manager, and edges are indicated by lines connecting two nodes. Node size is based on the number of edges. Nodes are colored according to the fund manager's educational institution. Legend entries include the 12 most prominent education-based networks.

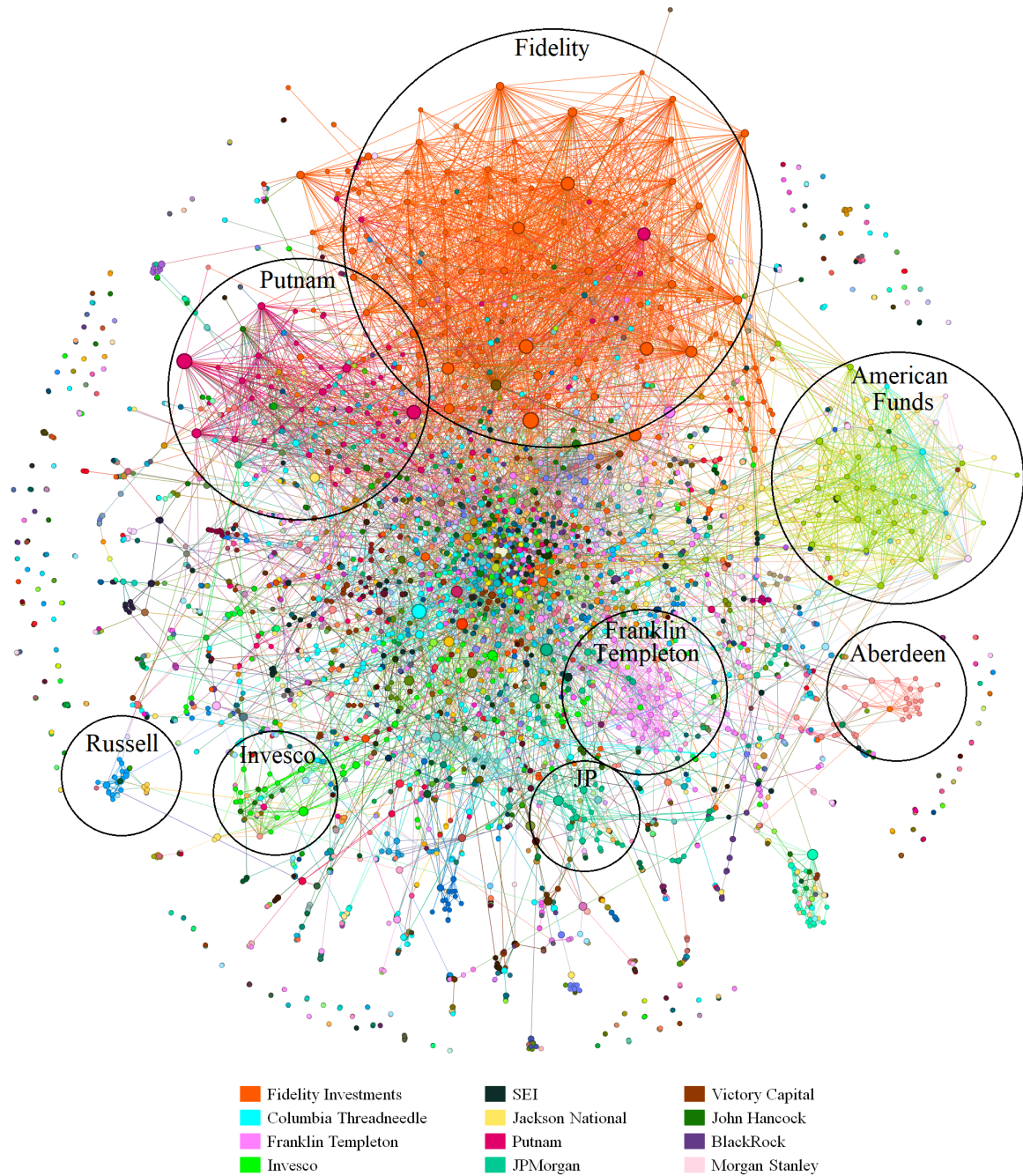


Fig. 3. Facebook connections among U.S. mutual fund managers by fund firm. This figure displays 6,571 Facebook connections among the sample of 3,936 FB-identified U.S. mutual fund managers. Every node represents a fund manager, and edges are indicated by lines connecting two nodes. Node size is based on the number of edges. Nodes are colored according to the fund manager's fund firm. Legend entries include the 12 most prominent education-based networks.

REFERENCES

- Abreu, Dilip, and Markus K Brunnermeier, 2002, Synchronization risk and delayed arbitrage, *Journal of Financial Economics* 66, 341–360.
- Ammann, Manuel, Alexander Cochardt, Lauren Cohen, and Stephan Heller, 2022, Hidden alpha.
- Bayer, Patrick, Stephen L Ross, and Giorgio Topa, 2008, Place of work and place of residence: Informal hiring networks and labor market outcomes, *Journal of Political Economy* 116, 1150–1196.
- Billio, Monica, Mila Getmansky, Andrew W Lo, and Loriana Pelizzon, 2012, Econometric measures of connectedness and systemic risk in the finance and insurance sectors, *Journal of Financial Economics* 104, 535–559.
- Brown, Nerissa C, Kelsey D Wei, and Russ Wermers, 2014, Analyst recommendations, mutual fund herding, and overreaction in stock prices, *Management Science* 60, 1–20.
- Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.
- Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers, 2000, The value of active mutual fund management: An examination of the stockholdings and trades of fund managers, *Journal of Financial and Quantitative Analysis* 35, 343–368.
- Chen, Joseph, Harrison Hong, and Jeremy C Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66, 171–205.
- Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008, The small world of investing: Board connections and mutual fund returns, *Journal of Political Economy* 116, 951–979.
- Cohen, Randolph B., Joshua D. Coval, and Lubos Pástor, 2005, Judging fund managers by the company they keep, *Journal of Finance* 60, 1057–1096.

- Coval, Joshua D, and Tobias J Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811–841.
- Crawford, Steven S, Wesley R Gray, and Andrew E Kern, 2017, Why do fund managers identify and share profitable ideas?, *Journal of Financial and Quantitative Analysis* 52, 1903–1926.
- Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.
- Ellison, Glenn, and Drew Fudenberg, 1993, Rules of thumb for social learning, *Journal of Political Economy* 101, 612–643.
- Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2011, Holdings data, security returns, and the selection of superior mutual funds, *Journal of Financial and Quantitative Analysis* 46, 341–367.
- Fama, Eugene F, and James D MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.
- Gerritzen, Marc, Jens Carsten Jackwerth, and Alberto Plazzi, 2020, Birds of a feather – Do hedge fund managers flock together?, Swiss Finance Institute Research Paper 16–10.
- Grinblatt, Mark, Matti Keloharju, and Seppo Ikäheimo, 2008, Social influence and consumption: Evidence from the automobile purchases of neighbors, *Review of Economics and Statistics* 90, 735–753.
- Halim, Edward, Yohanes E Riyanto, and Nilanjan Roy, 2019, Costly information acquisition, social networks, and asset prices: Experimental evidence, *Journal of Finance* 74, 1975–2010.
- Han, Bing, and Liyan Yang, 2013, Social networks, information acquisition, and asset prices, *Management Science* 59, 1444–1457.
- Hartup, Willard W, and Nan Stevens, 1999, Friendships and adaptation across the life span, *Current Directions in Psychological Science* 8, 76–79.

- Hochberg, Yael V, Alexander Ljungqvist, and Yang Lu, 2007, Whom you know matters: Venture capital networks and investment performance, *Journal of Finance* 62, 251–301.
- Hong, Harrison, Jeffrey D Kubik, and Jeremy C Stein, 2005, Thy neighbor’s portfolio: Word-of-mouth effects in the holdings and trades of money managers, *Journal of Finance* 60, 2801–2824.
- Hvide, Hans K, and Per Östberg, 2015, Social interaction at work, *Journal of Financial Economics* 117, 628–652.
- Jackson, Matthew O, 2010, *Social and economic networks* (Princeton University press).
- Kacperczyk, Marcin, and Amit Seru, 2007, Fund manager use of public information: New evidence on managerial skills, *Journal of Finance* 62, 485–528.
- Livnat, Joshua, and Richard R Mendenhall, 2006, Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts, *Journal of Accounting Research* 44, 177–205.
- Massa, Massimo, Jonathan Reuter, and Eric Zitzewitz, 2010, When should firms share credit with employees? Evidence from anonymously managed mutual funds, *Journal of Financial Economics* 95, 400–424.
- Patel, Saurin, and Sergei Sarkissian, 2017, To group or not to group? Evidence from mutual fund databases, *Journal of Financial and Quantitative Analysis* 52, 1989–2021.
- Perry-Smith, Jill E, and Christina E Shalley, 2003, The social side of creativity: A static and dynamic social network perspective, *Academy of Management Review* 28, 89–106.
- Pool, Veronika K, Noah Stoffman, and Scott E Yonker, 2012, No place like home: Familiarity in mutual fund manager portfolio choice, *Review of Financial Studies* 25, 2563–2599.
- Pool, Veronika K, Noah Stoffman, and Scott E Yonker, 2015, The people in your neighborhood: Social interactions and mutual fund portfolios, *Journal of Finance* 70, 2679–2732.

- Qi, Tong, Jian Li, Wenjing Xie, and Haoyuan Ding, 2020, Alumni networks and investment strategy: Evidence from chinese mutual funds, *Emerging Markets Finance and Trade* 56, 2639–2655.
- Rossi, Alberto G, David Blake, Allan Timmermann, Ian Tonks, and Russ Wermers, 2018, Network centrality and delegated investment performance, *Journal of Financial Economics* 128, 183–206.
- Shiller, Robert J, and John Pound, 1989, Survey evidence on diffusion of interest and information among investors, *Journal of Economic Behavior & Organization* 12, 47–66.
- Stein, Jeremy C, 2008, Conversations among competitors, *American Economic Review* 98, 2150–62.
- Tesch, Stephanie A, 1983, Review of friendship development across the life span, *Human Development* 26, 266–276.
- Wermers, Russ, Tong Yao, and Jane Zhao, 2012, Forecasting stock returns through an efficient aggregation of mutual fund holdings, *Review of Financial Studies* 25, 3490–3529.

Appendix A.

Table A.1. Descriptions of Main Variables and Sources.

This table provides descriptions and sources of variables used in my study. The following abbreviations are used: MS - Morningstar Direct Database; FB - Facebook.com; BL - Bloomberg; MQ - Marquis Who's Who Database; FINRA - BrokerCheck; LI - LinkedIn.com; ANC - Ancestry.com; LEG - Legacy.com; FW - Fund Firm Websites; LN - LexisNexis; NP - Newspapers.com; CRSP - CRSP Survivorship Bias Free Mutual Fund Database; CS - Compustat; KF - Kenneth R. French's website; AE - Author's estimations; MC - Manually collected.

Variables	Description	Source
Panel A: Dependent Variables		
PortOverlap _{<i>i,j,t</i>}	Monthly portfolio overlap between two funds <i>i</i> and <i>j</i> , computed as $\sum_{k \in H_t} \min\{w_{i,k,t}, w_{j,k,t}\}$, where $w_{i,k,t}$ is fund <i>i</i> 's portfolio weight in stock <i>k</i> during period <i>t</i> , and H_t is the set of all stocks held by funds <i>i</i> and <i>j</i> as reported at the end of period <i>t</i> .	MS, AE
BuyOverlap _{<i>i,j,t</i>}	Monthly overlap in stock buys between two funds <i>i</i> and <i>j</i> , computed as $\frac{\sum_{k \in T_t} \min\{I_{i,k,t}^+, I_{j,k,t}^+\}}{\min\{\sum_{k \in T_t} I_{i,k,t}^+, \sum_{k \in T_t} I_{j,k,t}^+\}}$, where $I_{i,k,t}^+$ is one if fund <i>i</i> increases the number of shares in stock <i>k</i> between period <i>t</i> − 1 and <i>t</i> , and zero otherwise. T_t is the union of all stocks traded by funds <i>i</i> and <i>j</i> .	MS, AE
SellOverlap _{<i>i,j,t</i>}	Monthly overlap in stock sell between two funds <i>i</i> and <i>j</i> , computed as $\frac{\sum_{k \in T_t} \min\{I_{i,k,t}^-, I_{j,k,t}^-\}}{\min\{\sum_{k \in T_t} I_{i,k,t}^-, \sum_{k \in T_t} I_{j,k,t}^-\}}$, where $I_{i,k,t}^-$ is one if fund <i>i</i> decreases the number of shares in stock <i>k</i> between period <i>t</i> − 1 and <i>t</i> , and zero otherwise. T_t is the union of all stocks traded by funds <i>i</i> and <i>j</i> .	MS, AE
FundAlpha _{<i>i,t</i>}	Fund <i>i</i> 's four-factor alpha in period <i>t</i> from a Carhart (1997) model using monthly fund net returns over a 24-month look-back period requiring at least 12 available return observations.	MS, AE

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Table A.1 – continued from previous page.

Variables	Description	Source
$StockRet_{k,t}$ - $RiskFree_t$	Stock k 's excess return in period t . $StockRet_{k,t}$ is stock k 's raw return in period t obtained from CRSP. $RiskFree_t$ is the U.S. risk free rate in period t obtained from Kenneth R. French's website.	CRSP, KF, AE
Panel B: Main Independent Variables		
FBConnected $_{i,j,t}$	A dummy variable that is one if at least one manager from fund i is connected with at least one manager from fund j during period t .	MS, FB, BL, MQ, FINRA, LI, ANC, LEG, FW, LN, NP, MC
FBInteraction $_{i,j,t}$	A dummy variable that is one if at least one manager from fund i is interacting with at least one manager from fund j during period t .	MS, FB, BL, MQ, FINRA, LI, ANC, LEG, FW, LN, NP, MC
DegreeCen $_{i,t}$	Fund i 's degree centrality in period t , computed as $\frac{d_{i,t}}{N_t-1}$, where $d_{i,t}$ is the number of fund i 's FB-connected funds (through its fund manager(s)) in period t and N_t is the total number of nodes in the network in period t .	MS, FB, AE
PrestigeCen $_{i,t}$	Fund i 's value-weighted prestige centrality in period t , computed as $\sum_{i \neq j} g_{i,j,t} \frac{P_{j,t}}{d_{j,t}}$, where $g_{i,j,t}$ is the (i, j) entry of the weighted connection matrix in period t ; i and j refer to funds; and $d_{j,t}$ is the number of j 's connected nodes in period t . Each network connection is weighted by the sum of the involved funds' TNA in period t .	MS, FB, AE
BetweenCen $_{i,t}$	Fund i 's betweenness centrality in period t , computed as $\frac{\sum_{k \neq j; i \neq k; i \neq j} \frac{P_i(k,j)}{P(k,j)}}{(N_t-1)(N_t-2)/2}$, where $P_i(k, j)$ is the number of geodesics between nodes k and j that pass through i and $P(k, j)$ is the total number of geodesics between k and j .	MS, FB, AE

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Variables	Description	Source
DiffWeight $_{k,t}$	The difference between the average weight that FB-connected (or FB-interacted, depending on the specification) funds in period t simultaneously invest in stock k (i.e., stock buys) and the average weight that all other funds invest in stock k in period t .	MS, FB, AE
Panel C: Other Variables		
SameCity $_{i,j,t}$	A dummy variable that is one if at least one manager from fund i resides in the same city as at least one manager from fund j during period t .	MS, FB, BL, MQ, FINRA, LI, ANC, LEG, FW, LN, NP, MC
SamePastFirm $_{i,j,t}$	A dummy variable that is one if at least one manager from fund i worked at the same fund firm in the past as at least one manager from fund j during period t .	MS, FB, BL, MQ, FINRA, LI, ANC, LEG, FW, LN, NP, MC
SameEdu $_{i,j,t}$	A dummy variable that is one if at least one manager from fund i has a degree from the same university as at least one manager from fund j during period t .	MS, FB, BL, MQ, FINRA, LI, ANC, LEG, FW, LN, NP, MC
SameFundFam $_{i,j,t}$	A dummy variable that is one if funds i and j are part of the same mutual fund family.	MS
ManageOtherFund $_{i,j,t}$	A dummy variable that is one if at least one pair of managers from funds i and j manage at least one other fund together during period t .	MS, AE
CommonMgr $_{i,j,t}$	A dummy variable that is one if funds i and j have at least one manager in common during period t .	MS, AE
BothSmallCap $_{i,j,t}$	A dummy variable that is one if funds i and j are both categorized as small-cap funds according to Morningstar's 3x3 style box.	MS

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Variables	Description	Source
$\text{BothMidCap}_{i,j,t}$	A dummy variable that is one if funds i and j are both categorized as mid-cap funds according to Morningstar's 3x3 style box.	MS
$\text{BothLargeCap}_{i,j,t}$	A dummy variable that is one if funds i and j are both categorized as large-cap funds according to Morningstar's 3x3 style box.	MS
$\text{BothValue}_{i,j,t}$	A dummy variable that is one if funds i and j are both categorized as value funds according to Morningstar's 3x3 style box.	MS
$\text{BothGrowth}_{i,j,t}$	A dummy variable that is one if funds i and j are both categorized as growth funds according to Morningstar's 3x3 style box.	MS
$\text{BothBlend}_{i,j,t}$	A dummy variable that is one if funds i and j are both categorized as blend funds according to Morningstar's 3x3 style box.	MS
$\text{TNAQuinDiff}_{i,j,t}$	The absolute value of the difference between the TNA-based quintiles of funds i and j . Fund TNA is calculated as the sum of the fund's share class TNA. TNA quintiles are computed monthly.	MS, AE
$\text{TNAQuinAvg}_{i,j,t}$	The average TNA quintile of funds i and j . Fund TNA is calculated as the sum of the fund's share class TNA. TNA quintiles are computed monthly.	MS, AE
$\text{FundSize}_{i,t}$	Fund i 's monthly TNA (in USD bn.) in period t . Fund TNA is calculated as the sum of the fund's share class TNA. $\log(\text{FundSize}_{i,t})$ is the natural logarithm of $\text{FundSize}_{i,t}$.	MS, AE
$\text{FamSize}_{i,t}$	Monthly TNA of all active equity funds in the fund i fund family (in USD bn.) in period t . Fund TNA is calculated as the sum of the fund's share class TNA. $\log(\text{FamSize}_{i,t})$ is the natural logarithm of $\text{FamSize}_{i,t}$.	MS, AE

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Variables	Description	Source
TeamSize _{<i>i,t</i>}	The number of portfolio managers managing fund <i>i</i> in period <i>t</i>	MS, AE
FundAge _{<i>i,t</i>}	Fund <i>i</i> 's age in years that the fund has been active at the current time period <i>t</i> . Calculated using the Inception Date variable from MS Direct.	MS, AE
FundFlow _{<i>i,t</i>}	Fund <i>i</i> 's monthly net percentage fund flows in period <i>t</i> , computed as $[TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})]/TNA_{i,t-1}$, where $TNA_{i,t}$ is fund <i>i</i> 's total net assets in month <i>t</i> and $r_{i,t}$ stands for the net return in period <i>t</i> .	MS, AE
ExpenseRatio _{<i>i,t</i>}	Fund <i>i</i> 's expense ratio.	MS, CRSP
TurnoverRatio _{<i>i,t</i>}	Fund <i>i</i> 's turnover ratio.	MS, CRSP
MgrMBA _{<i>i,t</i>}	A dummy variable equal to one if a manager on fund <i>i</i> has an MBA degree. $MgrMBA_{i,t}$ is averaged at the fund-level if fund <i>i</i> is managed by multiple managers in period <i>t</i> .	MS, FB, BL, MQ, LI, FW, LN, NP, MC
MgrIvy _{<i>i,t</i>}	A dummy variable equal to one if a manager on fund <i>i</i> has any degree from an Ivy league school. $MgrIvy_{i,t}$ is averaged at the fund-level if fund <i>i</i> is managed by multiple managers in period <i>t</i> .	MS, FB, BL, MQ, LI, FW, LN, NP, MC
MgrTenure _{<i>i,t</i>}	The number of years that a manager has been managing the fund <i>i</i> . $MgrTenure_{i,t}$ is averaged at the fund-level if fund <i>i</i> is managed by multiple managers in period <i>t</i> .	MS, AE
MgrAge _{<i>i,t</i>}	Biological age of a manager on fund <i>t</i> in years in a given period <i>t</i> . $MgrAge_{i,t}$ is averaged at the fund-level if fund <i>i</i> is managed by multiple managers in period <i>t</i> .	MS, FB, BL, MQ, LI, ANC, LEG, FW, NP, MC, AE

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Variables	Description	Source
$HERD_{k,t}$	Stock k 's <i>HERD</i> decile in period t . For each stock k and period t , I construct the buy-herding measure ($BHM_{k,t}$) and sell-herding measure ($SHM_{k,t}$) according to Brown et al. (2014). Stocks are then separately ranked into quintiles based on $BHM_{k,t}$ and $SHM_{k,t}$, respectively, and then stacked into deciles (with the 10th decile representing stocks that funds herd most in period t).	MS, CRSP, AE
$TRADE_{k,t}$	Aggregate fractional mutual fund trades in stock k in period t , calculated following Chen et al. (2000) as the total dollar change in mutual fund holdings of stock k divided by the stock's market capitalization in period t .	MS, CRSP, AE
$\Delta BREADTH_{k,t}$	Stock k 's $\Delta BREADTH$ measure in period t , calculated following Chen et al. (2002) as the change in the number of funds that hold stock k in period t divided by the total number of funds that exist in the period t .	MS, CRSP, AE
$ME_{k,t}$	Stock k 's market equity in month t , calculated as stock k 's price at the end of month t times its shares outstanding at the end of month t . If $ME_{k,t}$ is non-positive, the observation is considered to be missing. The variable is log-transformed.	CRSP, AE
$BM_{k,t}$	Stock k 's book-to-market ratio at the end of month t , calculated as the firm's book equity from the last fiscal year (ending at least six months and less than 18 months ago) divided by stock k 's ME at the end of the month of the last fiscal year ending. If either book equity or ME is non-positive, the observation is considered to be missing. The variable is log-transformed.	CRSP, CS, AE
$MOM_{k,t}$	Stock k 's momentum at the end of month t , calculated as stock k 's return from the end of month $t-12$ to the end of month $t-1$.	CRSP, AE

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Variables	Description	Source
$\text{STR}_{k,t}$	Stock k 's short-term reversal at the end of month t , calculated as stock k 's return from the end of month $t-1$ to the end of month t .	CRSP, AE
$\text{IMOM}_{k,t}$	Stock k 's industry momentum at the end of month t , calculated as the value-weighted return of stock k 's Fama-French-48 industry from the end of month $t-1$ to the end of month t .	CRSP, CS, KF, AE
$\text{SUE}_{k,t}$	Stock k 's standardized unexpected earnings measure at the end of month t , calculated as in Livnat and Mendenhall (2006).	CRSP, CS, AE

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