CFR Working Paper NO. 17-02

Screening Discrimination in Financial Markets: Evidence from CEO-Fund Manager Dyads

S. Jaspersen • P. Limbach

centre for financial research
cologne

Screening Discrimination in Financial Markets: Evidence from CEO-Fund Manager Dyads[✧]

Stefan Jaspersen and Peter Limbach[*]

This Draft: November 2020

ABSTRACT

We find that demographic similarity to CEOs facilitates informed trading after accounting for networks and selective information distribution. Fund managers overweight firms whose CEOs resemble them in terms of age, ethnicity, and gender. Significantly higher trade performance and lower crash risk in the sub-portfolio of similar CEOs indicates that overweighting reflects informational advantage. Consistently, for similar CEOs, fund managers can better identify valuable CEO-firm matches, high-integrity CEOs, and firms with positive earnings announcement returns. The evidence supports theories of screening discrimination according to which in-group bias is a rational response to asymmetric information and has implications for fund manager diversity.

JEL classification: G11, G23, J10

Keywords: CEO-investor demographic similarity, fund manager diversity, in-group bias, informed trading, mutual fund performance, screening discrimination

---

✧ The authors would like to thank Renée Adams, Vikas Agarwal, André Betzer, Francois Brochet, Rüdiger Fahlenbrach, Alexander Kempf, David Le Bris, Daniel Metzger, Arzu Ozoguz, Raghu Rau, Anna Scherbina, Dirk Sliwka, Oscar Stolper, Roine Vestman, as well as participants at the 2018 Financial Intermediation Research Society (FIRS) annual meeting, the 2018 RBFC Research in Behavioral Finance Conference, the 2018 annual meeting of the German Finance Association, the 2017 AFFI Paris December Finance Meeting, and participants at the University of Cologne's Applied Micro seminar as well as seminars at the CFR, the University of Marburg, and the University of Wuppertal for helpful comments. We thank Tim Quigley as well as Dirk Jenter, Florian Peters, and Alexander Wagner for graciously sharing their CEO turnover data with us. We thank Kai Li for providing her data on corporate cultural values. We also thank Felix Bormann, Thorsten Greil, and Felix Weil for excellent research assistance. Jaspersen gratefully acknowledges financial support from the Center of Social and Economic Behavior (C-SEB), University of Cologne. Part of the paper was written while Limbach was visiting Rotterdam School of Management and while Limbach was with the Karlsruhe Institute of Technology.

* Jaspersen (jaspersen@wiso.uni-koeln.de) and Limbach (plimbach@wiso.uni-koeln.de) are with the University of Cologne and the Centre for Financial Research (CFR), Albertus-Magnus-Platz, 50923 Cologne, Germany.

While professional money managers play a pivotal role as delegated investors of households' wealth, the process by which they select stocks to generate fund performance is still not well understood. Not only does the literature yield mixed results as to whether investors have stock picking skills (see, e.g., Carhart (1997) vs. Daniel et al. (1997)) but it is also relatively silent about how investors detect and produce valuable information. Extant studies show that investors extract valuable information from direct connections and interaction, such as social ties and private meetings with corporate executives (e.g., Cohen, Frazzini, and Malloy (2008), Pool, Stoffman, and Yonker (2015), Solomon and Soltes (2015)). In this study, we suggest that just being similar to executives helps extract information.

We build on theories of screening discrimination and information-based homophily according to which people can extract more information about others if they are similar to themselves, even absent any connection or interaction. We argue and provide evidence that investors are better able to understand and assess demographically similar CEOs and the firms they run. We study investors' similarity to CEOs in a panel of 2.7 million distinct CEO-mutual fund manager dyads. We focus on similarity in exogenous demographics – i.e., age, ethnicity, and gender – which fund managers are plausibly aware of given that they can be inferred directly from a CEO's name and look.[1] We study the period after the adoption of Regulation Fair Disclosure (RegFD) to mitigate concerns of CEOs' selective information disclosure to similar investors.[2] Our results suggest that demographic similarity to CEOs facilitates informed trading. Specifically, we show that fund managers overweight firms whose CEOs resemble them demographically. This overweighting is associated with superior trade and overall fund performance, less stock price crash risk, and with several measures of fund managers' enhanced understanding of CEOs and their firms.

Our study assumes and suggests that the process by which fund managers make investment decisions incorporates CEO information, which is consistent with the notion that CEOs attract considerable attention and give their firms a face (Malmendier and Tate (2009), (2015)). It is

[1] Other dimensions of interpersonal similarity, such as the same educational background or political views, can be caused by similarity in age, ethnicity or gender, but not vice versa, which arguably allows us to focus on potential first-order effects of demographic similarity.

[2] RegFD prohibits selective disclosure of non-public material information. Solomon and Soltes (2015) provide evidence that since the adoption of RegFD mainly hedge funds – but not mutual funds, which we study – are still able to acquire valuable information from private meetings with corporate executives. Nevertheless, we account for investors' potential access to management and social networks.

also in line with a wealth of evidence suggesting that CEOs are major decision makers (Fama (1980)) who shape the firms they manage (Hambrick and Mason (1984)) and have significant impact on firm performance and strategy (e.g., Bertrand and Schoar (2003), Adams, Almeida, and Ferreira (2005), Bennedsen, Pérez-González, and Wolfenzon (2020)).

The theoretical underpinning of our study is developed from theories of screening discrimination (Aigner and Cain (1977), Cornell and Welch (1996)) and related information-based homophily (Kets and Sandroni (2019)). According to the former, demographic similarity to the CEO can help fund managers overcome asymmetric information because similarity between two individuals increases the precision of the signals that one individual receives about the other. Specifically, applying Cornell and Welch's (1996) model, a fund manager can evaluate noisy signals about CEOs' "qualities" and their firms – such as conference calls and presentations, interviews and meetings, strategic decisions and past performance – more precisely if both belong to the same group. The idea is that similarity facilitates the interpretation of such signals and consequently lowers the signals' noise.[3] Kets and Sandroni (2019) also argue that similarity to others reduces uncertainty about those others' future actions as it is easier to take the perspective of someone who belongs to the own group (e.g., Williams, Parker, and Turner (2007)).

We derive testable empirical predictions from the above theories. First, if demographic similarity yields informational advantage, we expect fund managers to over- or underweight firms led by similar CEOs. Second, fund managers' investments in firms with similar CEOs (for which they have a comparative advantage in processing information, in the spirit of Grossman and Stiglitz (1976) and Van Nieuwerburgh and Veldkamp (2009))[4] should outperform their investments in firms with dissimilar CEOs.

In contrast, theories of taste-based discrimination (Becker (1957)), fear of the unknown (Cao et al. (2011)), in-group favoritism (Turner, Brown, and Tajfel (1979)), or miscalibrated beliefs (Bordalo et al. (2016)) all imply that demographic (dis)similarity between fund

[3] For example, demographically similar people may find it easier to "read between the lines" and interpret their nonverbal communication, e.g., gestures, manners, and style of speech (Scheflen (1972), Mehrabian (1981)). In this regard, Mayew and Venkatachalam (2012) provide evidence that managerial vocal cues convey relevant information about firms' fundamentals.

[4] We note that investors may not be aware that their similarity to CEOs constitutes an information endowment and comparative advantage. Discrimination can be unintentional (Bertrand, Chugh, and Mullainathan, 2005).

managers and CEOs cause the former to make less informed or "prejudiced" investment decisions. These theories predict that fund managers overweight firms with similar CEOs although similarity does not yield informational advantage. Accordingly, fund managers' investments in firms with similar CEOs should exhibit an equal or even an inferior performance compared to investments in firms with dissimilar CEOs, as the latter have a higher hurdle to be included in the fund portfolio. To conclude, only theories of (or related to) screening discrimination predict that in-group bias will reflect informational advantage and ultimately yield superior performance. Thus, comparing the performance of fund managers' investments in firms with and without demographically similar CEOs allows to draw inferences about the existence of screening discrimination in financial markets.

Consistent with both information- and preference-/belief-based theories, fund managers significantly overweight firms managed by demographically similar CEOs relative to their fund's investment style. This result holds for age, ethnicity, and gender, and when we use a similarity score based on these demographics. It is robust to controlling for CEO demographics and for a variety of firm and fund variables. Furthermore, providing a first indication that the in-group bias towards similar CEOs may reflect informational advantage, firms whose CEOs resemble fund managers demographically are significantly more likely to belong to the largest 10% of a funds' investment style-adjusted excess portfolio holdings.[5]

While we study the post-RegFD period to mitigate concerns of selective disclosure, RegFD does not fully eliminate such concerns. In fact, CEOs might treat demographically similar fund managers preferentially as they share similar networks. Our results are robust to excluding (separately or at once) i) all firms that are located in a fund's geographic area, ii) all cases in which CEOs and fund managers attended the same university or universities in the same U.S. state, and iii) all Republican CEOs. Furthermore, the results are upheld for funds with arguably limited access to firm management, i.e., small funds, funds belonging to small fund families, and funds with low-tenure managers.

To address the above and other endogeneity concerns, we exploit variation in CEO-fund manager dyads that change demographic similarity. First, to take funds' endogenous selection

[5] We find only limited evidence that fund managers underweight firms with similar CEOs, consistent with Huberman (2001) who argues that „people tend to buy (and hold) the familiar stocks, not sell them." (p. 675).

of CEOs or stocks into account, we use fund-CEO and fund-stock fixed effects, respectively. Second, we exploit variation caused by CEO departures, which allows us to hold the match between fund managers and funds constant, thereby accounting for the endogenous matching between the two. Fund managers are significantly more likely to sell stocks (relative to holding or buying them) after CEO changes that decrease their demographic similarity to CEOs. For robustness, we focus on plausibly exogenous CEO departures caused by sudden and unexpected deaths. Furthermore, our results are robust to using stock-quarter fixed effects, which account for most unobserved CEO and firm heterogeneity.

Next, we provide evidence that fund managers' in-group bias towards demographically similar CEOs reflects informational advantage. To this end, we compare fund managers' trading performance in their sub-portfolio of firms managed by demographically similar CEOs to their sub-portfolio of firms managed by dissimilar CEOs. That is, we compare the performance of investments made by the same fund manager at the same time. This approach eliminates concerns of omitted variables on fund and manager level, particularly differences in managerial ability and education as well as demographics, which may drive performance.

On average, fund managers exhibit a superior next-quarter trading performance in their sub-portfolio of firms managed by demographically similar CEOs. In particular, we find that the difference in risk-adjusted returns between the stocks bought and the stocks sold is significantly higher for trades in firms with similar CEOs, even after excluding educational and local networks. For example, compared to the fund's concurrent trades in firms with dissimilar CEOs, the difference in quarterly Carhart four-factor alphas between stocks bought and stocks sold is 33 basis points higher if fund managers have a similar age, the same ethnicity, and the same gender as the CEO. The results are upheld when we adjust stock performance by the average performance of firms whose CEOs have similar demographics. Thus, even within the universe of firms with similar CEOs, fund managers select those stocks that perform better. Based on this evidence we conclude that the in-group bias towards demographically similar CEOs reflects informational advantage.

To support this prima facie evidence and to understand the potential channels through which demographic similarity enables fund managers to better understand and evaluate CEOs and their firms, we conduct further tests. First, we build on theories and evidence according to which the quality of the match between a CEO and the firm (e.g., Eisfeldt and Kuhnen (2013), Jenter, Matveyev, and Roth (2016)) as well as a CEO's integrity (e.g., Erhard, Jensen, and Zaffron (2009), Li et al. (2020)) are two pivotal CEO factors that ultimately affect firm performance. We provide evidence indicating that when CEOs are demographically similar fund managers are more capable of identifying valuable CEO-firm matches as well as CEOs with greater integrity. Actually, fund managers overweight particularly those similar CEOs who, ex post, turn out to be better matches for their firms and show more integrity. This evidence is in line with theories of screening discrimination predicting that similarity facilitates the interpretation of signals about CEO "qualities", which may help assess a CEO's fit with her firm as well as her integrity. Consistently, we provide additional evidence that the firms with similar CEOs in which fund managers invest have significantly less stock price crash risk and are less likely to face class action lawsuits.

Second, following Baker et al. (2010), we study stock returns around next-quarter earnings announcements to test whether similarity to CEOs also helps fund managers interpret and forecast earnings fundamentals and news. We find that fund managers' recent buys (sells) of firms with similar CEOs are associated with significantly higher (lower) announcement returns.

Taken together, our study provides robust evidence that demographic similarity to firms' CEOs helps fund managers overcome informational asymmetries, consistent with theories of screening discrimination. In additional tests, we find that fund managers' superior investment decisions associated with overweighting similar CEOs also translate into significantly better performance at the fund level and thus benefit fund investors. We also find a positive relation of overweighting similar CEOs with a fund's Active Share (as per Cremers and Petajisto (2009)) and industry concentration (as per Kacperczyk, Sialm, and Zheng (2005)). The stronger deviation from the benchmark and lower industry diversity of fund holdings are supportive of the informational advantage of CEO-fund manager similarity.

The above evidence has implications for fund manager allocation and diversity. When allocating fund managers to funds, fund families should consider the CEO demographics that prevail in a fund's investment style. Given the low diversity of corporate CEOs, fund manager diversity can have informational costs and it may be rational for some fund families to limit the diversity of some of their funds, depending on the net benefits of the latter. This result is consistent with and provides one potential explanation for the low fraction of women and ethnic minorities in the mutual fund industry.

This study contributes to the literature as follows. First, it provides novel insights as to the mechanisms that facilitate information production and successful stock picking by professional investors. Extant studies show that investor education and work experience (e.g., Chevalier and Ellison (1999), Cici et al. (2018)), sophisticated information acquisition (e.g., Gargano, Rossi, and Wermers (2016), Chen et al. (2020)) as well as social ties and meetings with executives or other investors (e.g., Cohen, Frazzini, and Malloy (2008), Pool, Stoffman, and Yonker (2015), Solomon and Soltes (2015), Bushee, Gerakos, and Lee (2018)) are associated with superior investor performance. All above mechanisms involve direct costs or interactions. In contrast, our study contributes to this literature by providing primary evidence for a mechanism of information production that has no direct costs and does not necessitate any interactions. Supporting theories of screening discrimination, we show that demographic similarity to CEOs facilitates informed trading after accounting for investor backgrounds, networks, and access to management. This evidence enhances our understanding of the role that soft information can play for active investment management.[6]

Thereby, this study contributes to an inconclusive literature on the informational role of familiarity for professional investors. Coval and Moskowitz (2001) and Jagannathan, Jiao, and Karolyi (2018), respectively, provide evidence that fund managers have an informational advantage when trading local stocks and stocks of firms located in countries where fund managers obtained their bachelor's degree. In contrast, Pool, Stoffman, and Yonker (2012) find that while fund managers allocate more assets to firms located in their home states, the home-state stocks do not outperform other investments. Similarly, Wintoki and Xi (2020) find no informational advantage associated with fund managers' investments in firms managed by executives and directors with whom they share a similar political partisan affiliation. Accounting for local and home-state stocks as well as CEOs' political leaning, our study contributes to this literature by suggesting that familiarity due to shared demographics, instead of shared values or proximity, is associated with informed trading.

[6] Our study also provides prima facie evidence indicating that investors' decisions incorporate information about firm executives, adding to a still limited literature on whether and how investors consider firm management.

More generally, our study complements a limited literature on informational benefits of shared backgrounds for economic decision making. Li (2017) studies peer reviews at the U.S. National Institutes of Health. She shows that evaluators have an informational advantage in assessing the quality of projects in their own area, which outweighs the potential costs of reduced objectivity resulting from personal preferences. Du, Yu, and Yu (2017) find that the forecasts on Chinese firms traded in the U.S. are more accurate when issued by U.S. analysts of Chinese ethnic origin as compared to non-Chinese analysts. Fisman, Paravisini, and Vig (2017) use unique data from an Indian bank and find that shared codes and beliefs between borrowers and lenders, measured as similarity in terms of caste and religion, increase access to credit and loan size and reduces collateral requirements and default. While Fisman, Paravisini, and Vig (2017) examine the role of value similarity for bank loans in India, one of the world's few caste systems, our study is concerned with the role of demographic similarity for investment managers in the U.S. mutual fund industry. It is important to understand this industry given its $17.7 trillion in assets under management (Investment Company Institute (2019)). Moreover, Fisman, Paravisini, and Vig (2017) study loan officers who typically meet potential borrowers before they make investment decisions and who can use loan covenants thereafter. In contrast, we study mutual fund managers who have at most limited (if any) personal contact to CEOs before and after they invest. In all, while our study is significantly different, it complements Fisman, Paravisini, and Vig (2017) by providing evidence that not only value similarity but also demographic similarity can facilitate information production.[7]

1 Theoretical background and empirical predictions

Theories in economics and social psychology predict that familiarity, i.e., demographic similarity to CEOs in our context, affects investors' processing and use of information, and ultimately their investment decisions. These theories can be classified into *information-based theories*, which predict that investment decisions will be based on (superior) information, and *preference/belief-based theories* predicting less informed or "prejudiced" decisions.

[7] In untabulated tests we examine similarity based on religious denominations and find results that support Fisman, Paravisini, and Vig's (2017) evidence. Importantly, our results remain unchanged when we additionally control for religious similarity between CEOs and fund managers.

How can similarity to firms' CEOs help investors overcome asymmetric information and facilitate informed investment decisions? According to theories of screening discrimination (e.g., Aigner and Cain (1977), Cornell and Welch (1996)), similarity between two individuals can increase the precision of the signals that one individual receives about the qualities of another individual. Hence, according to this type of statistical discrimination, in-group bias towards similar individuals can emerge as a rational response to asymmetric information.

Particularly, in Cornell and Welch's (1996) model individuals possess "qualities" that are not directly observable, such as skills and intangible characteristics, which qualify an individual for a certain position (Arrow (1972)). In case of CEOs, one can think of such qualities as the ability to make strategic decisions, innate talent as well as CEO integrity and leadership. These qualities should matter to investors in their attempts to assess the impact and value of CEOs and ultimately the firms they manage.[8] However, investors must rely on indirect assessment procedures, i.e., they have to evaluate noisy signals to measure these qualities when they make investment decisions. Signals may include conference calls, investor presentations and meetings, firms' press releases, CEO interviews and press portrayals, or prior firm performance and strategic decisions. Cornell and Welch (1996) argue that – while prior beliefs about qualities do not differ – the noise of such signals is lower when the individual being assessed is of a similar background. That is, similarities facilitate making more accurate assessments, which allow to better distinguish between high- and low-quality individuals. For example, people of the same ethnicity or gender will find it easier to interpret their verbal and nonverbal communication, while people of a similar age will use a similar language and have a joint framework for assessing each other's personal history and values as they grew up at the same time and hence experienced similar formative events and settings. Consistently, the literature suggests that people interpret various culturally intermediated signals, such as dress, gestures, manners, and style of speech (e.g., Scheflen (1972), Mehrabian (1981)) and that nonverbal cues have a considerable cultural element (e.g., Archer and Akert (1977)). Consistently, Mayew and Venkatachalam (2012) provide evidence that managerial vocal cues convey relevant information about firms' fundamentals.

[8] Indeed, theory and empirical evidence suggests that these CEO qualities matter for firm outcomes such as performance and reporting quality. For example, on the role of integrity, see Erhard, Jensen, and Zaffron (2009), Dikolli et al. (2019), and Li et al. (2020). See, e.g., Baum and Wally (2003) on CEO strategic decision making.

Consistent with Cornell and Welch (1996), Kets and Sandroni (2019) provide a theory of information-based homophily. This theory predicts that similarity to others reduces an individual's uncertainty about those others' future actions because it is easier to take other people's perspectives if they belong to one's own group (e.g., Williams, Parker, and Turner (2007), Heinke and Louis (2009)).

In terms of empirically testable predictions, the above *information-based theories* suggest that investors may over- and/or underweight firms managed by demographically similar CEOs because they have an informational advantage stemming from their similarity to these CEOs. Specifically, even if all investors receive the same noisy signals about a CEO's quality, investors may process and evaluate these signals more accurately if they are similar to the CEO. For example, if they share a similar background with a CEO, investors may find it easier to interpret the CEO's verbal and nonverbal cues, "read between the lines", and understand or envision the CEO's plans for the firm. Conversely, for dissimilar CEOs, investors have to rely on population means of dissimilar CEO groups or stereotypes. The latter can be incorrect due to miscalibrated beliefs (Bordalo et al. (2016)). Thus, for the same investor investments in firms managed by demographically similar CEOs can be expected to exhibit superior performance compared to investments in firms with dissimilar CEOs.[9]

In contrast to theories of screening discrimination, *preference/belief-based theories*, i.e., theories of taste-based discrimination (Becker (1957)), fear of the unknown (Cao et al. (2011)), in-group favoritism (e.g., Turner, Brown, and Tajfel (1979)), or miscalibrated beliefs (e.g., Bordalo et al. (2016)) all suggest that (dis)similarity between CEOs and fund managers may cause the latter to make less informed or "prejudiced" investment decisions. These theories allow for the following empirical predictions. First, investors can be expected to overweight firms led by demographically similar CEOs. Second, investors make less or uninformed investment decisions, i.e., they overweight firms led by similar CEOs not because they have superior information, but because they have preferences for in-group CEOs or prejudices against dissimilar CEOs. Specifically, even if all investors receive the same noisy signals about a CEO's quality or plans for the firm, investors may evaluate these signals overly positively

[9] Even if unaware of their informational advantage, as similarity attracts (Byrne (1971), McPherson, Smith-Lovin, and Cook (2001)) investors may simply be more aware of and may acquire more information about similar CEOs and their firms.

for in-group CEOs, whereas they may ignore or undervalue the signals if CEOs are not similar.[10] Consequently, for the same investor, investments in firms with similar CEOs can be expected to exhibit an equal or even an inferior performance compared to investments in firms with dissimilar CEOs.

To conclude, while both information- and preference/belief-based theories are consistent with an in-group bias towards demographically similar CEOs, the theories differ in terms of predicted performance. Specifically, only information-based theories predict that investments in similar CEOs outperform investments in dissimilar CEOs for the same investor. Hence, examining investor performance allows to infer which theories are likely to apply.

2 Data and variables

2.1 Data

To test the empirical predictions developed in Section 1, we combine several data sources to obtain a panel of CEOs and mutual fund managers. First, we retrieve information on fund characteristics from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP MF). Fund characteristics include, e.g., fund age and fees, fund returns, fund families, locations and investment objectives as well as total net assets under management. Information at the share-class level is aggregated at the fund level using share class total net assets as weights. We focus on actively-managed U.S. domestic equity funds and eliminate all international, sector, balanced, bond, index, and money market funds. Funds are categorized into six different styles by their dominating investment objective using CRSP style codes (Mid Cap (EDCM), Small Cap (EDCS), Micro Cap (EDCI), Growth (EDYG), Growth & Income (EDYB), and Income (EDYI)). When CRSP Style Code information is missing, we use the classifications according to Lipper, Strategic Insight, and Wiesenberger to identify a fund's dominating investment

[10] The literature (e.g., Tajfel (1978), Turner, Brown, and Tajfel (1979)) argues that people have systematically more favorable views about members of their own groups, whereas they are indifferent or have less favorable views about members of other groups. Experimental evidence by Heath and Tversky (1991) supports the view that people have confidence in the familiar and suggests that they are even willing to pay a premium to bet on their own judgements. The theory of taste-based discrimination (Becker (1957)) suggests that discrimination against others who do not belong to an individual's group results from a personal prejudice or 'taste for discrimination', which causes an individual to act as if there were a cost of associating with dissimilar people. That is, investors may be willing to forgo valuable investments in firms led by dissimilar CEOs – e.g., CEOs with a different ethnicity – putting their prejudices ahead of economic profits.

objective. We match the CRSP MF data to the Thomson Reuters Mutual Fund Holdings Database (MF Holdings) using the MFLINKS tables. We limit our analysis to holdings of common stocks (share codes 10 and 11). Additional information about these stocks is retrieved from the CRSP/Compustat Merged Database.

We obtain fund managers' names as well as their start and end dates at the respective fund from the Morningstar Direct Mutual Fund Database (MS Direct), which is more accurate in terms of fund manager information than the CRSP MF database (see, e.g., Patel and Sarkissian (2017)), and eliminate cases for which MS Direct reports anonymous management teams. We merge MS Direct with the above databases using fund CUSIPs.

Information on CEOs' names, their age and gender are from ExecuComp and Board Analyst's The Corporate Library (TCL). The latter covers a large universe of firms from 2001 onwards. Using both databases allows us to cover a broader range of common stocks held by mutual funds, which reduces the bias towards larger firms. We eliminate observations where a firm is run by more than one CEO and require the identity of the CEO to be available for at least 67% of the stocks held by a fund at a given report date. The median (mean) fraction of the stocks in a fund's portfolio for which we have CEO information is 92% (89.5%). Since mutual funds report their holdings several times throughout the year while ExecuComp and TCL provide information only as of fiscal-year end, we use information from ExecuComp and hand-collected data to identify the exact dates when CEOs took office.

Further, we follow Pool, Stoffman, and Yonker (2015) and identify the ethnicity of CEOs and fund managers using their surnames in the classification algorithm of Ambekar et al. (2009), which categorizes names into 13 different ethnic groups. For robustness, we use two alternative approaches to classify ethnic groups, which we explain in Section 3. Following Niessen-Ruenzi and Ruenzi (2019), we determine a fund manager's gender by comparing the first name to a list provided by the United States Social Security Administration (SSA) containing the most popular first male and female names. We enrich our data set with educational information for CEOs and fund managers, which we obtain primarily from Capital IQ, Marquis Who's Who, and MS Direct. In addition, we manually collected biographical data from Bloomberg, fund company websites, LinkedIn, and SEC filings. Because fund manager age frequently is unavailable, we follow Chevalier and Ellison (1999) and assume that fund managers are 21 upon receiving their bachelor's degree.

Our final sample comprises 2,487 actively managed diversified U.S. domestic equity mutual funds and 3,716 common stocks for the period 2001-2011. These funds and firms are managed by 4,862 fund managers and 5,552 CEOs, respectively, which account for 2,692,554 (1,407,801) distinct CEO-fund manager (team) dyads. Hence, parameter identification in our study results from a large number of varying CEO-fund manager combinations.

2.2 Variables

We use different measures of demographic similarity between CEOs and fund managers based on their age, ethnicity, and gender. We calculate the fraction of a fund's managers who match a firm's CEO in terms of age, ethnicity or gender, respectively (*PctMgrMatch*). Following Pool, Stoffman, and Yonker (2012), we include all observations with available information for at least one fund manager. We calculate fractions based on the number of fund managers with available information. Regarding similarity in age, we use an interval of plus or minus five years around the CEO's age as our main similarity measure. We use different age measures for robustness in Appendix B. The variable *Avg. PctMgrMatch* measures the average fraction of fund managers with the same age, ethnicity, and gender as the CEO. Alternatively, we measure similarity via indicator variables that are equal to one if all of a fund's managers, respectively, have a similar age, same ethnicity or same gender as the CEO (*AllMatch*). The variable *Similarity Score* combines demographic dimensions by summing up the aforementioned dummy variables across all three dimensions. Accordingly, the similarity score can take on values between 0 and 3.

In Section 3, we use the variable *Excess Weight* as the main dependent variable to study the relation between fund managers' investment decisions and their similarity to CEOs. *Excess Weight* is defined as the weight that a fund manager assigns to a stock in her portfolio relative to the average weight in the fund's investment style in a given quarter. Alternatively, we also use unadjusted portfolio weights (*Portfolio Weights*) as well as an indicator variable, *Top 10% Bet*, which is equal to one if a stock belongs to the largest 10% of excess weights in the fund's respective investment style.

In Section 4, we examine the performance of fund managers' investment decisions based on risk-adjusted returns. We use quarterly stock performance based on Carhart (1997) four-factor alphas (*Carhart Alpha*) as well as the stock characteristic-adjusted performance measure of Daniel et al. (1997) (*DGTW*), compounded over the three months within a quarter. We determine alphas by taking the difference of realized stock return and the expected excess stock return in the quarter. The expected return in a month is calculated using factor loading estimations from the prior 24 months and factor realizations in the current month. We compound both realized and expected returns over the quarter before taking their difference. Monthly factor returns are obtained from Kenneth French's website. For robustness, we adjust both of the above performance measures by the average performance of firms whose CEOs are demographically similar to the CEOs of firms fund managers have invested in. Thereby, we can test whether fund managers choose better performing stocks out of the universe of CEOs who share similar demographics, which speaks to informational advantage.

In the analyses presented in Sections 3 and 4, we control for a large number of stock and fund characteristics that could affect both portfolio weights and stock performance. At the stock level, we include the quarterly stock return (i.e., the compounded monthly return within the quarter), the natural logarithm of the firm's market capitalization, the natural logarithm of the firm's age (based on the first CRSP listing date), and the book-to-market ratio. Using CRSP daily stock return and trading data, we also control for stocks' quarterly turnover (i.e., the average of the daily number of shares traded divided by total shares outstanding over all trading days of a quarter), its quarterly return volatility and the quarterly mean-adjusted stock illiquidity based on a daily Amihud (2002) illiquidity measure.

At the fund level, we use an indicator variable equal to one if the fund is managed by a team (zero otherwise), the natural logarithm of the fund's total net assets under management (in $ millions), the natural logarithm of the fund's age, the fund's annual expense and turnover ratios, the fund's quarterly fund flows (i.e., the fund's percentage growth rate over the quarter as in Sirri and Tufano (1998)), and the natural logarithm of the fund family's total net assets under management (in $ millions). Finally, to account for differences in funds' portfolio styles, we include the fund's portfolio concentration (i.e., the Herfindahl index of portfolio weights in a quarter) as well as the value-weighted average size, value, and momentum scores of Daniel et al. (1997). All variables are defined in Appendix A.

2.3 Summary statistics

Table 1 reports summary statistics for our sample. While Panel A reports the number of distinct CEO-fund manager dyads, Panel B reports statistics on CEO and fund manager demographics. We find a similar distribution between CEOs and fund managers with respect to their ethnicities. However, while the average CEO is 55 years old and only 3% of all CEOs are women, fund managers are on average 45 years old and 11% are female.

Panel C reports summary statistics for our measures of CEO-fund manager demographic similarity. Mean values for *PctMgrMatch* are 0.22 for similar age, 0.27 for same ethnicity, and 0.89 for same gender. *Avg. PctMgrMatch* has a mean (median) of 0.46 (0.44). Regarding the three *AllMatch* indicator variables, for 11%, 15%, and 73% of the sample's observations, all managers of a fund manager team have a similar age, the same ethnicity, and the same gender as a firm's CEO, respectively. The variable *Similarity Score* has a mean (median) of 0.98 (1) and a minimum and maximum value of 0 and 3, respectively.

Panels D and E report key characteristics at the stock and fund level, respectively. The average firm in our sample has a market capitalization of over $3 billion, has been public for almost 19 years, and has a book-to-market ratio of 0.65. The average stock generates a quarterly return of 3.33%. These figures are consistent with prior literature (e.g., Brown, Wei, and Wermers (2014), Agarwal et al. (2015)). The average fund in our sample has a portfolio weight in a stock of 0.94%, total net assets of $1.3 billion, and is approximately 14 years old. It has a turnover ratio of 86.66% and an expense ratio of 1.28% per year.

3 Demographic similarity to CEOs and fund manager stock selection

In the following, we examine how demographic similarity between CEOs and fund managers is related to investment decisions of the latter. Sections 3.1 and 3.2 present our baseline regression results and additional robustness tests, respectively. Section 3.3 presents results from tests that exploit variation in CEO-fund manager similarity caused by changes to CEO-fund manager dyads resulting from (exogenous) CEO departures.

3.1 Baseline regression results

To capture a fund manager's preference for a stock, we use the *Excess weight* as our primary dependent variable. That is, we examine the weights fund managers assign to stocks in their portfolios relative to the average weight in their fund's investment style in a given quarter. Using style-adjusted weights ensures that funds do not just overweight certain groups of CEOs because the firms in their investment style are mainly managed by CEOs with specific demographics. We conduct regressions according to equation (1):

$$ExcessWeight_{i,j,t} = \alpha + \beta\ Similarity_{i,j,t} + \gamma' X_{i,j,t-1} + \varepsilon_{i,j,t} \quad (1)$$

$ExcessWeight_{i,j,t}$ is the portfolio weight of fund *i* in stock *j* at the end of quarter *t* in percent relative to the average weight in stock *j* across all funds in the same investment style as fund *i*. $Similarity_{i,j,t}$ is a placeholder for the different similarity measures described in Section 2.2. It either stands for the variable *Similarity Score*, or for one of the three separate *AllMatch* indicator variables, or for the fraction of a fund's managers who are similar to a CEO in terms of age, ethnicity or gender (i.e., *PctMgrMatch*) at the end of quarter *t*. $X_{i,j,t-1}$ is a vector of control variables at the fund and stock level. All controls, except for the *Team* dummy, enter the regression with one (quarterly) lag. To control for unobservable heterogeneity, the regressions also include style as well as industry-time fixed effects, with time fixed effects corresponding to the year quarters (denoted quarter fixed effects). Industry fixed effects eliminate the concern that funds in a given investment style simply differ in their preference for particular industries in which specific CEO characteristics might be more or less prevalent. We define industries based on the Fama and French (1997) 48-industry classification. In all regressions, we cluster standard errors at the fund-stock level.

Table 2 reports the regression results. Panel A shows the results when we use the variable *Similarity Score* and its components, i.e., the separate *AllMatch* indicator variables, as our variables of interest. Panel B shows the results when we instead use *Avg. PctMgrMatch* and the three separate *PctMgrMatch* variables as our variables of interest. The evidence in both Panel A and Panel B indicates that fund managers place significantly larger weights on stocks of firms that are managed by CEOs who resemble them demographically. Irrespective of the similarity measure we use, the effect of CEO-fund manager similarity is always positive and statistically significant. In fact, the coefficients on all variables of interest are significant at the 1% level, except for the coefficient on $PctMgrMatch^{Age}$, which is significant at the 10% level.

The levels of statistical significance do not hinge on whether we examine the *AllMatch* indicator variables or the *PctMgrMatch* variables separately or together in one regression.[11]

The results are also economically significant. For example, the coefficient on *Similarity Score* in column (1) of Panel A suggests that, all else equal, for each one demographic dimension that fund managers share with CEOs the excess portfolio weight of a stock increases by 6.1 basis points. That is, compared to a fund manager without any demographic similarity to a firm's CEO, a fund manager who is similar to the CEO in age, ethnicity, and gender, overweights the respective stock by more than 18 basis points. Given that the average portfolio weight in our sample amounts to 94 basis points, the economic magnitude of this effect – an increase of almost 20% relative to the average portfolio weight – is meaningful.

Panel C presents results from regressions similar to that shown in equation (1) but with different dependent variables. Specifically, we use *Portfolio Weight*, i.e., the unadjusted weight of a stock in the fund's portfolio, and *Top 10% Bet*, which is an indicator variable that equals one if a stock belongs to the largest 10% of excess weights within the fund's investment style. The coefficients on both *Similarity Score* and *Avg. PctMgrMatch* are positive and statistically significant at the 1% level, irrespective of the dependent variable we use. In untabulated regressions, we find the coefficients on the *AllMatch* indicator variables as well as the *PctMgrMatch* variables also remain statistically significant. The results for *Top 10% Bet* provide a first indication that the in-group bias towards demographically similar CEOs is likely to reflect informational advantage, given that fund managers will more likely take the risk of large bets if they are informed (e.g., due to career concerns).[12]

[11] In untabulated regressions, we use the weights of sub-portfolios for different age cohorts, female CEOs, and different ethnicities. This approach follows Pool, Stoffman, and Yonker (2012) who analyze sub-portfolio weights in managers' home states. The results corroborate our findings, independent of whether we use OLS or Fama and MacBeth (1973) regressions.

[12] In untabulated tests, we further investigate whether demographic similarity to CEOs is also associated with the probability that fund managers hold a specific stock in the first place. To this end, we regress the dependent variable *Hold*, which equals one if the fund holds a stock (and zero otherwise) on the variable *Similarity Score* along with the control variables used in Table 2 as well as the average weight of a stock in the investment style. We define a fund's investment universe as all stocks that are currently held by at least one fund in the fund's investment style. We find that the coefficient on *Similarity Score* amounts to -0.0028, statistically significant at the 1% level. This finding suggests that a fund manager who resembles a firm's CEO in terms of age, ethnicity, and gender has a 0.84 basis points lower probability to hold the stock of that firm. The effect is economically meaningful as the average likelihood to hold the stock, i.e., the average value of *Hold*, is 4.4 basis points. This result provides further support for the informational advantage associated with demographic similarity.

Regarding the control variables, our results are consistent with extant literature. In particular, we find the funds in our sample to assign larger portfolio weights to smaller and less frequently traded firms, and those with higher last-quarter returns. These findings are consistent with, e.g., Chan, Chen, and Lakonishok (2002) and Jiang, Verbeek, and Wang (2014) who find that active funds expect to find more investment opportunities in the less efficient small-cap segment and have a preference for past winner stocks. At the fund level, we find that team-managed funds, larger funds, and funds from larger fund families exhibit smaller excess weights. This evidence is in line with, e.g., Bär, Kempf, and Ruenzi (2011) and Huang et al. (2016) who document that teams and larger funds and fund families tend to hold more diversified portfolios. Lastly, as expected, stock concentration in the fund portfolio has a significantly positive relation with excess weights in particular stocks.

3.2 Robustness tests and alternative explanations

Table 3 presents the results from several robustness tests. For brevity, we do not show any control variables. The results shown in Panel A address the concern that the in-group bias towards similar CEOs reflects CEOs' selective distribution of information to fund managers. In fact, demographic similarity may proxy for CEO-fund manager ties resulting from shared educational, geographic or political networks. For example Cohen, Frazzini, and Malloy (2008) document that fund managers place larger bets on those firms to which they have school ties, while Coval and Moskowitz (2001), among others, show that fund managers invest more in geographically proximate firms. This concern is mitigated as our sample starts in 2001, i.e., after the introduction of RegFD (in October 2000), which prohibits selective disclosure of material information. Yet, RegFD cannot rule out that CEOs provide demographically similar fund managers with valuable non-public information.

To address this concern beyond our focus on the post-RegFD period, we remove stocks with potential educational, geographic or political ties between CEOs and fund managers and re-estimate our baseline regressions shown in Table 2. That is, we remove from our sample all stocks of firms whose CEOs attended the same university as at least one fund manager (which equals the CONNECTED1 measure in Cohen, Frazzini, and Malloy (2008)) or attended their

---

Particularly, fund managers are less likely to invest in firms whose CEOs resemble them demographically – i.e., they are more selective – but upon deciding to buy such firms they significantly overweight their stocks.

bachelor university in the same U.S. state and hence may share the same home state. We also remove the stocks of all firms that are located within a distance of 100 kilometers from funds' management company headquarters (Coval and Moskowitz (2001)).[13] To account for potential political ties, we remove all observations from Republican-leaning CEOs, using the variable *Republican* CEO (as provided by Hutton, Jiang, and Kumar (2014)) in the previous year, which is based on contributions to Republican-affiliated candidates or party committees.. Our results are robust to excluding educational, geographic, and political ties, either separately or all at once. For brevity, we tabulate the results only for the variable *Similarity Score*. However, results are qualitatively similar for single demographic dimensions. We also find similar results when we use the variable *Residual Similarity Score* instead of *Similarity Score*. It is obtained from regressing the latter on the variable *Republican CEO* as well as on three indicator variables that equal one, respectively, if a CEO and a fund manager attended the same university, a (bachelor) university in the same state, and for firms located within 100 kilometers of fund headquarters.

Panel B reports results from re-estimating our baseline regression model excluding all firms whose CEOs belong to the most frequent demographic groups. Our results remain qualitatively similar when we exclude all firms whose CEOs are i) British, ii) male, or iii) between 49 and 60 years old (corresponding to the 25th and 75th percentiles of CEO age), or when we exclude all firms led by CEOs who are British, male, and between 49 and 60 years of age. Hence, the in-group bias for demographically similar CEOs is not driven by and does not only apply to the most frequent CEO and fund manager demographics.

Next, Panel C presents results from tests that account for unobserved heterogeneity, which might explain our results discussed in Section 3.1. First, we re-estimate our baseline regressions with stock-quarter fixed effects, i.e., we compare all fund managers invested in the same stock and quarter. This approach accounts for most unobserved firm and CEO heterogeneity. Second, we replace stock-quarter fixed effects with fund-CEO fixed effects or, alternatively, fund-stock fixed effects to account for any unobserved time-invariant heterogeneity at the CEO or firm

[13] We obtain the location of the fund's management company from the CRSP MF database. Information on firm headquarters is obtained from Compustat. The results are qualitatively the same if, alternatively, we eliminate all stocks from the same state as the fund company. We eliminate observations for which local or educational information is missing.

level as well as for funds' endogenous selection of CEOs or stocks. The results remain qualitatively similar. The coefficient on *Similarity Score* is lower when we use fund-CEO or fund-stock fixed effects because the (within) variation in the dependent variable *Excess Weight* is much lower per fund-CEO or fund-stock pair.

We provide additional robustness tests in Appendix B. Table B.1 shows results for several alternative measures of CEO-fund manager demographic similarity, which all support our previous results. With respect to age similarity, we calculate *PctMgrMatch* based on a maximum gap of three (instead of five) years between CEOs and fund managers. We also calculate the fraction of the fund's managers who are in the same age cohort (e.g., 40s, 50s, 60s) as the CEO and we use the average age gap between CEOs and fund managers, i.e., the simple difference in years of age. As higher values of this age gap indicate less CEO-fund manager similarity, we expect a negative relation with *Excess Weight*. Regarding ethnicity, we present results for two alternative classifications. First, we use the dominating ethnicity of surnames from the ethnicity classification of the 2000 U.S. Census (from the U.S. Census Bureau). We require that the dominating ethnicity covers at least 75% of the population with a given surname. Instead of the 13 groups from the Ambekar et al. (2009) algorithm, in this case we classify CEOs and fund managers into only four groups (Asian, Black, Hispanic, and White). Second, we use an alternative algorithm from Onolytics (formerly OnoMap) that has already been used in existing academic studies, such as Ellahie, Tahoun, and Tuna (2017). This algorithm derives the origin of a name from both the first and last name instead of just the surname.[14] Lastly, we construct alternative versions of the *Similarity Score*, which are each based on two of the three demographic dimensions.

Importantly, Table B.2 of Appendix B presents results from re-estimating the regressions shown in Panel A of Table 2 for sub-samples of funds with arguably limited access to firm management, i.e., small funds and funds that belong to small fund families (both with below-median size) as well as funds whose managers have a below-median tenure in the fund industry. In all three regressions, the coefficient on *Similarity Score* remains significant at the 1% level,

[14] We also obtain information from Onolytics on the likely religion for a given first and last name. In untabulated tests, we calculate the similarity between CEOs and fund managers based on whether they have the same religion. We again find a significantly positive relation between the variable *Excess Weight* and CEO-fund manager similarity. All tests based on Onolytics exclude cases in which ethnicity is identified as "International".

indicating that fund managers' in-group bias towards firms led by demographically similar CEOs is unlikely to reflect enhanced access to firm management.

Finally, following Altonji and Pierret's (2001) test for statistical discrimination, we analyze whether screening discrimination becomes less important, i.e., if the coefficient on *Similarity Score* declines, as fund managers learn about firms' CEOs over time. For example, fund managers may get to know CEOs personally as their tenure increases. We re-estimate our baseline regression additionally including the variable *Joint Tenure*, which equals the average number of quarters that a funds' managers have an investment connection with the firm's CEO, and the interaction term, *Similarity Score* x *Joint Tenure*. The latter is our variable of interest in this test and we expect it to show a negative coefficient, indicating that the importance and impact of demographic similarity declines as fund managers learn about CEOs. The results in column (1) of Table B.3 corroborate our expectation and support the notion that our results indeed reflect screening discrimination.

3.3 Evidence from (exogenous) CEO departures

In the following, we provide a more direct test of whether fund managers incorporate CEOs in their information production process and whether demographic similarity to CEOs indeed affects fund managers' investment decisions. In particular, we exploit variation in CEO-fund manager dyads resulting from CEO departures, which lead to changes in CEO-fund manager similarity. This test allows to hold fund manager-fund pairs constant, whereby we account for the endogenous matching between funds and managers.

We test whether a change in fund managers' demographic similarity to a firm's CEO, as caused by the change of the CEO, is associated with the likelihood of fund managers selling the firm's stock. The identifying assumption of this test is that CEO departures and changes in firm fundamentals due to these departures are unrelated to demographic similarity between CEOs and fund managers. We focus on fund trades in the quarter of CEO departure to minimize concerns that fund managers trade because firm fundamentals change materially. Consistent with theory and our previous results, we expect fund managers to be more (less) likely to sell a stock if the firm's new CEO is less (more) similar to them.

We identify 1,890 CEO departures during our sample period. To analyze how these departures relate to fund manager trades, we calculate the similarity of fund managers to both the former and the new CEOs in terms of age, ethnicity, and gender. We eliminate cases where the composition of the fund manager team or the fund manager changes around the quarter of a CEO departure. That is, holding the firm and the fund manager-fund match constant, we compare the demographic similarity of two CEO-fund manager dyads that differ only because CEO demographics differ.

As the dependent variable, we use the indicator variable *Sell*, which is equal to one if the fund sells shares of the stock of a firm that experiences a CEO departure (as compared to holding or buying the stock). We relate the sell decision to several independent variables that measure changes in demographic similarity around CEO departures. These variables are *Similarity Increase*^{Score}, *Similarity Increase*^{Age}, *Similarity Increase*^{Ethnicity} and *Similarity Increase*^{Gender}. All four variables are indicator variables, which are equal to one if either the variable *Similarity Score* or the respective *AllMatch* indicator variables increase. That is, the variables capture instances in which fund managers become demographically more similar to a firm's (new) CEO. Our regressions include stock-quarter fixed effects to mitigate concerns that fund managers simply trade in reaction to CEO departures coinciding with considerable changes in firm characteristics.[15]

We report the regression results in Table 4. Panel A shows results that are based on all CEO departures. However, one might argue that some mutual funds have an impact on the likelihood of CEOs being replaced (see, e.g., Parrino, Sias, and Starks (2003)). To address this concern, we perform two additional analyses. First, we re-estimate the regressions in Panel A using only those turnovers that are neither classified as forced nor as unclassified turnovers according to Jenter and Kanaan (2015) whose turnover data we use. The results are shown in Panel B. Second, we focus only on those CEO turnovers, which are caused by sudden and unexpected CEO deaths (excluding murders or suicides). Because sudden CEO deaths occur randomly and are arguably exogenous to current firm and market conditions (see Jenter, Matveyev, and Roth (2016), Nguyen and Nielsen (2014), Quigley, Crossland, and Campbell (2017)), they provide variation in CEO-fund manager similarity, which is plausibly exogenous

[15] In untabulated regressions, we find that our results are upheld when we compare fund managers' trading behavior within the same stock in the same investment style (using stock-style-quarter fixed effects). The results are also upheld when we use a matched sample based on a propensity score matching approach, which explains the dependent variable *Similarity Increase*^{Score} by fund characteristics and investment style fixed effects.

to mutual funds' impact on CEO turnover decisions. Data on sudden CEO deaths for the years 2001-2007 is provided by Timothy Quigley and corresponds to the data used in Quigley, Crossland, and Campbell (2017). For the years 2008-2011, we hand-collect sudden CEO deaths following the procedures described in Nguyen and Nielsen (2014) and Quigley, Crossland, and Campbell (2017). We show the results for sudden CEO deaths in Panel C.

Because sudden CEO deaths are unexpected shocks to both firms, it is not immediately clear in many cases who will (finally) succeed the deceased CEO and firms typically need a considerable amount of time to find a successor (see Rivolta (2018) on delayed successions). Moreover, fund managers first have to learn about the death, its consequences, and who will be the successor. Hence, we focus on a longer period of time after the event and compare the weight that a fund held in the stock at the beginning of the quarter during which the CEO died with the average portfolio weight in the stock in the year after the death. Accordingly, we define the indicator variable *Sell* as being equal to one if the average portfolio weight in the stock in the year after the CEO death is lower than before the death (and zero otherwise). We have 35 cases of sudden CEO deaths in our sample period, which still leaves us with a sample size of more than 1,300 observations as each death event affects several mutual funds.

The results in all three panels of Table 4 support our expectation that an increase in demographic similarity due to a CEO change makes a fund manager less likely to sell the stock of the affected firm. The coefficient on the variable *Similarity Increase*^{Score} is negative and statistically significant, at the 1% level in Panels A and B and at the 5% level in Panel C. Furthermore, across all three panels, the coefficients on *Similarity Increase*^{Age}, *Similarity Increase*^{Ethnicity} and *Similarity Increase*^{Gender} are always negative and statistically significant in seven out of nine regressions. In terms of economic magnitude, column (1) of Panel A, suggests that, all else equal, an increase in overall demographic similarity between a CEO and a fund manager is associated with a decrease in the probability that the firm's stock will be sold by that fund manager of 2.8 percentage points. This difference accounts for almost 8% of the average likelihood to sell a stock (which is 35.8%).

The above results provide additional evidence that changes in demographic similarity to CEOs bring about economically meaningful changes in the portfolios of fund managers. We conclude that fund managers indeed react to who is leading a firm, and whether that person resembles them demographically, instead of just trading on basic firm characteristics.

4 Does the in-group bias towards similar CEOs reflect informational advantage?

As fund managers' in-group bias towards demographically similar CEOs is consistent with both information-based and preference/belief-based theories, we conduct several analyses in this section to test whether the in-group bias reflects informational advantage. In Section 4.1, we compare the performance of fund managers' trades in firms led by demographically similar and dissimilar CEOs. Section 4.2 provides evidence on potential channels through which demographic similarity to CEOs can facilitate informed fund manager trading. Finally, in Section 4.3 we examine performance consequences and trading behavior at the fund level.

4.1 Evidence from fund managers' trades in similar and dissimilar CEOs

In the following, we consider the performance of fund managers' investments as a direct test of whether overweighting demographically similar CEOs reflects informational advantage. If so, we should find that fund managers' investments in firms with demographically similar CEOs outperform their investments in firms with dissimilar CEOs. However, in case fund managers invest more in similar CEOs because of preferences or miscalibrated beliefs, we would expect to find either a negative relative performance or no performance differences. To test our empirical expectations, we analyze whether the next-quarter performance of fund manager trades is related to their demographic similarity to CEOs. In this regard, several studies argue that trades are more appropriate to identify informational advantage (and biases) of fund managers than stock holdings because they better capture active investment decisions (see, e.g., Chen, Jegadeesh, and Wermers (2000), Pool, Stoffman, and Yonker (2015)). Accordingly, we examine trading returns, i.e., the performance of buys over sells.

To study trade performance, we use an approach similar to Kempf, Manconi, and Spalt (2017) and define a trade as a buy (sell) if the fund increases (decreases) the number of shares in the stock. Since we are interested in the success of a trading-based strategy, we eliminate observations for which the number of shares does not change. We then conduct the following regression at the fund-stock level (see equation (2)):

$$Perf_{i,j,t+1} = \alpha + \beta_1 Similarity_{i,j,t} + \beta_2 Buy_{i,j,t} + \beta_3 Similarity_{i,j,t} \times Buy_{i,j,t} + \gamma' X_{j,t} + \varepsilon_{i,j,t+1} \quad (2)$$

Perf$_{i,j,t+1}$ denotes the stock performance in the quarter following the trade. We examine risk-adjusted trading returns using both the stock characteristic-adjusted performance measure of Daniel et al. (1997) (*DGTW*) and quarterly stock performance based on Carhart (1997) four-factor alphas (*Carhart Alpha*). *Similarity*$_{i,j,t}$ represents the measure of demographic similarity between the manager(s) of fund *i* and the CEO of stock *j*. To capture similarity, we use the same variables as in Section 3, but again focus on the variable *Similarity Score* for brevity. *Buy*$_{i,j,t}$ is an indicator variable, which equals one for buys and zero for sells. In regression equation (2), β_2 captures the performance differences of buys and sells in case fund managers are not demographically similar to a CEO, while the sum of β_2 and β_3 measures the same performance difference but now for funds whose managers are similar to the CEO. Thus, β_3 represents a difference-in-differences-like estimator for the comparison of buy-sell performance differences between fund managers' trades in firms with similar and firms with dissimilar CEOs. $X_{j,t-1}$ is a vector of the same stock-level control variables as in equation (1), which refer to the quarter preceding the stock performance calculation. We do not report these controls for brevity. As before, we add industry-quarter fixed effects and cluster standard errors at the fund-stock level.

To better identify whether demographic similarity to CEOs results in informational advantage, we additionally include fund-quarter fixed effects in the regressions. This way, we compare the relation between trade performance and demographic similarity to CEOs for the same fund manager(s) at the same time, which eliminates concerns of omitted variables on fund and fund manager level. Importantly, this approach allows us to account for differences in fund managers' ability and skills, demographics, and networks. Nevertheless, our results are qualitatively similar if we omit fund-quarter fixed effects and instead control for the same fund-level variables as used in Table 2.

Table 5 presents the regression results. In Panels A, B, C, and E the dependent variables are *DGTW* and *Carhart Alpha*. Panel A presents our baseline regression results. Panel B shows results from regressions that exclude fund managers' potential educational, local, and political networks (analogous to Panel A of Table 3). The results in Panel C are from regressions that additionally control for fund-stock fixed effects, which account for unobserved time-invariant heterogeneity at both the fund and stock level as well as for funds' endogenous selection of stocks. In Panel D, we adjust the two performance measures by the average performance of firms whose CEOs are demographically similar to the CEOs managing the firms that fund managers have invested in. This adjustment allows us to test whether fund managers are able to select better performing stocks even within the universe of firms whose CEOs are demographically similar, which speaks even more to informational advantage. Finally, Panel E shows results from re-estimating the baseline regressions shown in Panel A for fund manager trades at the extensive margin, i.e., newly-established positions and liquidated positions only. The results in all five panels indicate that demographic similarity to the CEO is associated with significantly higher performance of fund manager's trades. In particular, the coefficient on the interaction term *Similarity* × *Buy*, our variable of interest, is positive and statistically significant at the 1% level in all regression specifications. This evidence suggests that fund managers' in-group bias towards demographically similar CEOs, on average, reflects informational advantage, supporting information-based theories.

The performance effect is economically meaningful. For example, column (2) of Panel A suggests that a buy-sell strategy of the same fund in the same quarter delivers a 33 (= 3 × 11) basis points higher performance per quarter for trades in firms led by CEOs who resemble fund managers in terms of age, ethnicity, and gender. This difference is even larger (53 bp) when we examine only trades at the extensive margin, and it is sizeable given that the average difference in quarterly Carhart alphas of stocks bought and stocks sold in the sample is -22 basis points. In this regard, we note that the general underperformance of stocks bought relative to stocks sold is in line with Dyakov, Jiang, and Verbeek (2017) who find that mutual funds' sells have outperformed their buys since the beginning of the millennium.

Table B.2 of Appendix B presents the results from re-estimating the regressions shown in Panel A of Table 5 for sub-samples of funds with limited access to firm management. The coefficient on *Similarity Score x Buy* remains significant at the 1% level for small funds and those that belong to small fund families and at the 5% level for funds with low-tenure managers.

We conclude that fund managers' superior trade performance in firms led by demographically similar CEOs is unlikely to reflect enhanced access to firm management.[16]

We separately consider the three dimensions of the similarity score in Table B.4 of Appendix B. We find the positive performance effect of demographic similarity between CEOs and fund managers to be driven by age and gender similarity, which are associated with Carhart alphas of 13.5 and 21.9 basis points, respectively. The results are significant for both the *PctMgrMatch* variables and the *AllMatch* indicator variables. The variables provide no indication that ethnic similarity to CEOs is associated with superior performance. Hence, fund managers' overweighting of CEOs with whom they share the same ethnicity likely does not reflect informational advantage but rather preferences (or stereotypes), comparable to the home-state bias in Pool, Stoffman, and Yonker (2012). This result is in line with McPherson, Smith-Lovin, and Cook (2001) who point out that differences in ethnicities (still) cause the strongest divide in society. They argue that people of different age and gender are less prejudiced against each other than people of different ethnic groups because the former interact significantly more often (e.g., in households and neighborhoods).

4.2 Channels of informed fund manager trading

The previous section provides prima facie evidence suggesting that fund managers' in-group bias towards demographically similar CEOs reflects informed trading. In this section, we conduct additional tests to provide further support for this conclusion and to understand potential channels through which similarity to CEOs facilitates informed trading.

As a first test, we study whether demographic similarity to CEOs enables fund managers to more accurately understand and assess two CEO-related factors that, according to theory and empirical evidence, are pivotal for firm performance. The first factor is the quality of the match between that CEO and the firm she manages (see, e.g., Hermalin and Weisbach (1998), Eisfeldt and Kuhnen (2013), Jenter, Matveyev, and Roth (2016)). In order to evaluate the CEO-firm match, fund managers do not only have to understand the firm's current and future managerial skill needs but also the skill set or, more generally, the "qualities" of the CEO (in

[16] In Table B.3 of Appendix B, we show that the positive trade performance associated with demographic similarity to CEOs declines over the time that fund managers have an investment connection with a firm's CEO (denoted as *Joint Tenure*), which is consistent with the declining importance of screening discrimination – as reflected by the declining overweighting of similar CEOs – as fund managers know CEOs better over time.

the spirit of Cornell and Welch (1996)). The second factor is the CEO's integrity, which can affect firm performance and reporting quality (see, e.g., Erhard, Jensen, and Zaffron (2009), Dikolli et al. (2019), Li et al. (2020)). Theories of screening discrimination predict that demographic similarity facilitates the interpretation of noisy signals about such CEO qualities. Hence, if CEO are similar to fund managers, we expect the latter to be more capable of identifying valuable CEO-firm matches and high-integrity CEOs.

To test our expectation regarding the quality of the CEO-firm match, we again use the CEO turnover data provided by Jenter and Kanaan (2015) and Peters and Wagner (2014). Following the empirical literature (e.g., Nguyen and Nielsen (2014), Jenter, Matveyev, and Roth (2016)), we interpret stock returns in reaction to announcements of CEO departures as the market's assessment of the departing CEO's contribution to future firm value (net of the expected successor), and hence as indicative of the quality of the CEO-firm match. Accordingly, we define a CEO-firm match as a high-quality match – ex post – if the stock return in the three-day event window (-1,+1) around the announcement of a CEO's departure, i.e., *CAR (-1,+1)*, is in the bottom quartile of the distribution of all CEO turnover events in the turnover sample, and zero otherwise. Mean *CAR (-1,+1)* in the bottom quartile is -3%, i.e., shareholder value declines indicating that the CEO-firm match was valuable. Alternatively, we directly use the variable *CAR (-1,+1)*, for which higher values indicate lower CEO-firm match quality. To test whether fund managers overweight those demographically similar CEOs who are valuable matches for the firms they manage, we regress *Excess Weight* on the interaction term *Similarity Score x CEO-firm Match Quality* and its baseline effects, along with the same controls as used in Table 2. *CEO-firm Match Quality* is a placeholder variable equaling either *CAR (-1,+1) < p25* or *CAR (-1,+1)*.

Panel A of Table 6 reports the regression results. The first two columns show the results from regressions that are based on all observations. The third and fourth columns show results from regressions that are based on a restricted sample, which excludes all observations in the year prior to CEO departure to rule that events or firm performance causing the CEO's departure drive our results. The coefficients on *Similarity Score x CEO-firm Match Quality* and *Similarity Score* are positive and statistically significant, indicating that fund managers overweight particularly those firms led by demographically similar CEOs who later turn out to be valuable matches for their firms. This result indicates that similarity to CEOs allows fund managers to better assess a CEO's fit with the firm she manages and hence identify valuable CEO-firm matches.[17]

To test our expectation regarding the integrity of CEOs, we rely on data provided by Li et al. (2020) who derive corporate cultural values, including integrity, from earnings call transcripts using a machine learning approach. As earnings calls mostly involve CEOs, their data is a proxy for (hard-to-observe) CEO integrity. We obtain the annual integrity score for a given CEO-firm combination from Li et al. (2020), which we use to calculate the variable *Avg. Integrity Score*, defined as the average integrity score over all CEO-firm-years. We require that the CEO manages the firm throughout the whole year when assigning the firm's integrity score. We also calculate the indicator variable *Avg. Integrity Score > p50*, which equals one if the variable *Avg. Integrity Score* is larger than its sample median. In a next step, we re-estimate the regressions in Panel A of Table 6 replacing the interaction variables for CEO-firm match quality with the two aforementioned variables for a CEO's integrity, which we denote *Similarity Score x CEO Integrity*.

The regression results are shown in Panel B of Table 6. We find the coefficients on the variables *Similarity Score x CEO Integrity* and *Similarity Score* to be positive and statistically significant in both columns.[18] The results suggest that while funds managers generally overweight demographically similar CEOs, they particularly do so for CEOs who turn out to show a high level of integrity (as inferred from their spoken language in earnings calls). Hence, demographic similarity appears to help fund managers assess CEO integrity.

In Table 7, we present the results from an additional test of whether fund managers are better able to assess the qualities of demographically similar CEO, such as their integrity. Specifically, we examine whether investments of fund managers in similar CEOs predict lower stock price crash risk and a lower likelihood of facing class action lawsuits. Both crash risk and law suits against firms arguably relate to CEO integrity and both matter considerably to

[17] Complementing the results in Panel A of Table 6, we find in untabulated regressions that fund managers particularly overweight firms whose CEOs have significant decision-making power (as per Adams, Almeida, and Ferreira (2005)), e.g., CEOs who simultaneously hold the position of chairman of the board, and thus have considerable impact on firm value.

[18] In untabulated regressions, we find qualitatively similar results when we use only the current year's integrity score (instead of the average) and when we additionally control for variable *Fund Integrity*, which is the investment style-adjusted value-weighted integrity score in the fund portfolio in the previous quarter based on integrity scores used from the previous year. It accounts for funds' preferences to invest in high-integrity firms.

investors. Following Callen and Fang (2015), we use three measures of crash risk: *NCSKEW* is the negative coefficient of skewness of a firm's residual daily returns; *DUVOL* represents the down-to-up volatility of a firm's residual daily returns; *CRASH COUNT* is the difference between number of days with extreme negative residual daily returns and extreme positive residual daily returns. *Class Action Lawsuit* is an indicator variable that equals one if a class action lawsuit is filed against the company in a given quarter, and zero otherwise. Data on class action lawsuits is obtained from the Stanford Securities Class Action Clearinghouse database.

We estimate the regression model described in equation (2) using the above measures of stock price crash risk and the indicator *Class Action Lawsuit* as dependent variables, all valid as of the quarter following the trade decision. The coefficient on our variable of interest, *Similarity Score x Buy*, is negative and significant at the 1% level in all four columns of Table 7. Hence, the buy decisions of fund managers in firms with similar CEOs predict significantly lower stock price crash risk and a significantly lower likelihood of facing class action lawsuits.

As another test on whether demographic similarity to CEOs facilitates informed trading, we follow Baker et al. (2010) as well as Kempf, Manconi, and Spalt (2017) and study stock returns to next-quarter earnings announcements. Returns to earnings announcements are useful for detecting informed trading (Baker et al. (2010)) as they contain significant information about firms' future earnings prospects. Hence, they allow to test whether fund managers are better able to assess and forecast earnings fundamentals, as well as interpret and act upon news in advance of earnings announcements, if they are demographically similar to firms' CEOs.

We retrieve earnings announcement dates for our sample firms from IBES. For each firm and quarter, we use the first earnings announcement date after the fund manager's trading decision. For the event windows (-1,+1) and (-2,+2) around these events, we calculate abnormal stock returns, i.e., *CAR (-1,+1)* and *CAR (-2,+2)*. We regress these returns on the interaction term *Similarity Score x Buy* and its two baseline effects, along with controls for CEO demographics and last-quarter stock characteristics (those used in previous analyses). To mitigate endogeneity concerns, we additionally include fund-quarter fixed effects as well as industry-quarter fixed effects. That is, we compare investments in firms from the same industry made by the same fund (manager) at the same time. Table 8 reports the results.

We find that fund managers' recent buys (sells) of firms with demographically similar CEOs are associated with significantly higher (lower) announcement returns. In fact, the coefficient on *Similarity Score* × *Buy* is positive and statistically significant at the 1% level in both regression specifications, while the coefficient on *Similarity Score* (i.e., sells of firms with similar CEOs) is negative and significant at the 10% and 5% level in specifications (1) and (2), respectively. Thus, in case fund managers resemble CEOs demographically, their trades are more accurate predictors for stock returns to firms' earnings announcements. Consistent with the results for trade performance, we find in untabulated regressions that the results for earnings announcement returns are driven by similarity in age and gender.

Taken together, the tests presented in this section support our previous results and provide evidence on the potential channels through which fund managers' demographic similarity to CEOs facilitates informed trading.

4.3 Performance and trading behavior at the fund level

In this last section, we test whether the superior performance associated with investing in demographically similar CEOs also translates into superior performance at the overall fund level. This question is of particular interest to fund investors. Even if fund managers have informational advantage due to their similarity to firms' CEOs, they still manage diversified funds and their own demographics might not be sufficiently covered by the CEOs of firms in their investment universe. So, their portfolio will also consist of a significant fraction of less similar CEOs and it is not clear ex ante whether better performance in the sub-portfolio of demographically similar CEOs will ultimately translate into overall fund performance.

We measure a fund's probability to invest in CEOs who resemble fund managers demographically via the variable *Similarity Overweighting*. It is defined as the deviation of the fund's weight in the fund manager's age cohort, ethnicity, or gender from the average weight of the respective demographic in the fund's investment style. To take into account that portfolio weights in some fund manager demographics (e.g., female gender) are smaller due to a smaller number of CEOs sharing the respective demographic, we divide the deviation by the average weight of the fund manager's demographic in the fund's investment style.[19] For funds with

[19] This measure is conceptually similar to the $bias_{state}$ measure in Giannetti and Laeven (2016). Furthermore, note that using the five-year age difference as before is not feasible at the sub-portfolio level as we cannot compare the

multiple managers, we use the average relative deviation across all managers. To capture a fund's overall tendency to invest in similar CEOs, we use the simple average of *Similarity Overweighting* for the measures of age cohort, ethnicity, and gender.

We regress fund performance in quarter t on the value of *Similarity Overweighting* in quarter t-1 and the same lagged fund-level control variables as used in Table 2. We measure fund performance via Carhart (1997) alphas. We use fund performance based on gross-of-fee returns, i.e., the net-of-fee return plus one twelfth of the annual total expense ratio, because gross-of-fee returns more accurately capture differences in fund managers' investment decisions and skills. However, we repeat the analysis using net-of-fee returns to identify costs and benefits for fund investors. The regressions include style and quarter fixed effects. Standard errors are clustered at the fund level. The regression results are shown in the first two columns of Table 9.

The results suggest that the likelihood of fund managers investing in firms managed by demographically similar CEOs has performance consequences also at the overall fund level. Specifically, we find a positive coefficient on *Similarity Overweighting*, which is statistically significant at the 1% level, irrespective of whether we measure fund performance via gross-of-fee returns or net-of-fee returns. In terms of economic significance, column (1) of Table 9 suggests that an increase in *Similarity Overweighting* by one standard deviation relates to an increase in next-quarter Carhart alphas of 4.1 (0.47×0.087) basis points. This effect is sizeable given that the average (median) Carhart alpha for funds in our sample is only 8 (4) basis points. We thus conclude that fund manager investments in firms with demographically similar CEOs benefit overall fund performance and impact the wealth of fund investors.

Importantly, our results are robust to controls for fund manager diversity, namely the coefficient of variation of manager ages and Teachman's entropy indices for ethnic and gender diversity. They are also robust to controls for educational and local tie biases.[20] Hence, the

weights across different funds with different manager ages. We instead focus on portfolio weights in age cohorts as in the robustness section.

[20] The variable *School tie bias* is the difference between the fund's portfolio weight in stocks with educational ties to firms' CEOs relative to the market capitalization weight of the fund's school ties (i.e., all firms for which the fund's managers have educational ties), divided by the market capitalization weight of fund's educational ties. *Local bias* is the fund's difference between the fund's weight in stocks of firms located the same U.S. state as the fund's headquarter and the market capitalization weight of the state, divided by the market capitalization weight of the fund's state.

superior fund performance associated with the variable *Similarity Overweighting* is unlikely to just reflect potential positive effects of fund manager diversity or informational advantage due to educational or local networks.

To provide additional evidence in support of the informational advantage of investing in demographically similar CEOs, we also consider trading behavior. Following Jagannathan, Jiao, and Karolyi (2018), we examine a fund's Active Share and diversity of fund holdings. The variable *Active Share*, defined as per Cremers and Petajisto (2009), measures the extent to which fund manager stock holdings deviate from their respective weights in a benchmark index. The variable *ICI*, defined as per Kacperczyk, Sialm, and Zheng (2005), measures the diversity of fund holdings in terms of industry concentration. We regress the two measures of trading behavior in quarter *t* on *Similarity Overweighting* in quarter *t-1* and the same set of lagged fund-level controls as before. The results are shown in the third and fourth column of Table 9. The coefficient on *Similarity Overweighting* is positive and statistically significant at the 1% level in both regressions. This evidence indicates that as fund managers invest more in firms led by demographically similar CEOs they deviate more from their benchmark and exhibit a lower industry diversity of their holdings, which is supportive of informational advantage. Further, the latter result also supports the model of Cornell and Welch (1996), which predicts that similarity to CEOs can increase the variance of investee firms per industry because fund managers receive more precise signals about CEOs and their firms.

5 Conclusion

This study provides evidence that investors' demographic similarity to CEOs facilitates informed trading. We find that fund managers overweight firms whose CEOs resemble them in terms of age, ethnicity, and gender. This in-group bias towards similar CEOs is supported by variation in CEO-fund manager dyads resulting from (exogenous) CEO departures. We show that overweighting demographically similar CEOs reflects informational advantage, in line with theories of screening discrimination according to which in-group bias emerges as a rational response to asymmetric information. Specifically, fund managers' trade performance is significantly higher in the sub-portfolio of demographically similar CEOs, while stock price crash risk is lower. Regarding potential channels of informed trading, we show that when firms are managed by demographically similar CEOs, fund managers invest more in firms with valuable CEO-firm matches and high-integrity CEOs, and their buys (sells) of these firms are associated with higher (lower) next-quarter earnings announcement returns. The informed trading decisions appear to translate into better overall fund performance.

The evidence provided in this study fosters our understanding of the process by which investors produce information and sheds additional light on their stock picking abilities. It points to the value of costless soft information in professional asset management and suggests that investors' decisions incorporate firm management.

Finally, our study has novel implications for mutual fund families and their investors. Both should take fund manager demographics into account. Investors should do so when they select funds that tend to invest in industries or specific types of firms that are associated with certain CEO demographics. Fund families should do so when they allocate fund managers to funds or fund teams. In this regard, our evidence implies that it can be rational for some fund families to limit the demographic diversity of some of their fund manager teams.

REFERENCES

Adams, Renée B., Heitor Almeida, and Daniel Ferreira, 2005, Powerful CEOs and Their Impact on Corporate Performance, *Review of Financial Studies* 18, 1403-1432.

Agarwal, Vikas, Kevin A. Mullally, Yuehua Tang, and Baozhong Yang, 2015, Mandatory Portfolio Disclosure, Stock Liquidity, and Mutual Fund Performance, *Journal of Finance* 70, 2733-2776.

Aigner, Dennis J., and Glen G. Cain, 1977, Statistical Theories of Discrimination in Labor Markets, *Industrial and Labor Relations Review* 30, 175-87.

Altonji, Joseph G., and Charles R. Pierret, 2001, Employer Learning and Statistical Discrimination, *Quarterly Journal of Economics* 116, 313-350.

Ambekar, Anurag, Charles Ward, Jahangir Mohammed, Swapna Male, and Steven Skiena, 2009, Name-ethnicity Classification from Open Sources, Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining Paris, France.

Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5, 31-56.

Archer, Dennis, and Robert M. Akert, 1977, Words and Everything Else: Verbal and Nonverbal Cues in Social Interpretation, *Journal of Personality and Social Psychology* 35, 443-449.

Arrow, Kenneth J., 1972, Models of Job Discrimination, in Anthony H. Pascal, ed.: *Racial Discrimination in Economic Life* (Heath, Lexington, Mass.).

Bär, Michaela, Alexander Kempf, and Stefan Ruenzi, 2011, Is a Team Different from the Sum of its Parts? Evidence from Mutual Fund Managers, *Review of Finance* 15, 359-396.

Baker, Malcom, Lubomir Litov, Jessica A. Wachter, and Jeffrey Wurgler, 2010, Can Mutual Fund Managers Pick Stocks? Evidence from Their Trades Prior to Earnings Announcements, *Journal of Financial and Quantitative Analysis* 45, 1111-1131.

Baum, J. Robert, and Stefan Wally, 2003, Strategic Decision Speed and Firm Performance, *Strategic Management Journal* 24, 1107-1129.

Becker, Gary S., 1957. *The Economics of Discrimination*, University of Chicago Press, Chicago.

Bennedsen, Morten, Francisco Pérez-González, and Daniel Wolfenzon, 2020, Do CEOs Matter? Evidence from CEO Hospitalization Events, *Journal of Finance* 75, 1877-1911.

Bertrand, Marianne, Dolly Chugh, and Sendhil Mullainathan, 2005, Implicit Discrimination, *American Economic Review Papers and Proceedings* 95, 94-98.

Bertrand, Marianne, and Antoinette Schoar, 2003, Managing with Style: The Effect of Managers on Firm Policies, *Quarterly Journal of Economics* 118, 1169-1208.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer, 2016, Stereotypes, *Quarterly Journal of Economics* 131, 1753-1794.

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.

Bushee, Brian J., Joseph Gerakos, and Lian F. Lee, 2018, Corporate Jets and Private Meetings with Investors, *Journal of Accounting and Economics* 65, 358-379.

Byrne, Donn E., 1971, *The Attraction Paradigm* (Academic Press, N.Y.).

Callen, Jeffrey L., and Xiaohua Fang, 2015, Religion and Stock Price Crash Risk, *Journal of Financial and Quantitative Analysis* 50, 169-195.

Cao, H. Henry, Bing Han, David Hirshleifer, and Harold H. Zhang, 2011, Fear of the Unknown: Familiarity and Economic Decisions, *Review of Finance* 15, 173-206.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57-82.

Chan, Louis K. C., Hsiu-Lang Chen, and Josef Lakonishok, 2002, On Mutual Fund Investment Styles, *Review of Financial Studies* 15, 1407-1437.

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, 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, Are Some Mutual Fund Managers Better than Others? Cross-Sectional Patterns in Behavior and Performance, *Journal of Finance* 54, 875-899.

Cici, Gjergji, Monika Gehde-Trapp, Marc-André Goericke, and Alexander Kempf, 2018, The Investment Value of Mutual Fund Managers' Experience Outside the Financial Sector, *Review of Financial Studies* 31, 3821-53.

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.

Cornell, Bradford, and Ivo Welch, 1996, Culture, Information, and Screening Discrimination, *Journal of Political Economy* 104, 542-571.

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, K.J. Martijn, and Antti Petajisto, 2009, How Active Is Your Fund Manager? A New Measure That Predicts Performance, *Review of Financial Studies* 22, 3329-3365.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance* 52, 1035-1058.

Dikolli, Shane S., Thomas Keusch, William J. Mayew, and Thomas D. Steffen, 2019, CEO Behavioral Integrity, Auditor Responses, and Firm Outcomes, Working Paper, Duke University.

Du, Qianqian, Frank Yu, and Xiaoyun Yu, 2017, Cultural Proximity and the Processing of Financial Information, *Journal of Financial and Quantitative Analysis* 52, 2703-2726.

Dyakov, Teodor, Hao Jiang, and Marno Verbeek, 2017, Losing Money Through Trading, Working Paper, VU University Amsterdam.

Ellahie, Atif, Ahmed Tahoun, and Irem Tuna, 2017, Do Common Inherited Beliefs and Values Influence CEO Pay?, *Journal of Accounting and Economics* 64, 346-367.

Eisfeldt, Andrea L., and Camelia M. Kuhnen, 2013, CEO Turnover in a Competitive Assignment Framework, *Journal of Financial Economics* 109, 351-372.

Erhard, Werner H., Michael C. Jensen, and Steve Zaffron, 2009, Integrity: A Positive Model That Incorporates the Normative Phenomena of Morality, Ethics, and Legality, Working Paper, Harvard University.

Fama, Eugene, F., 1980, Agency problems and the theory of the firm, *Journal of Political Economy* 88, 288-307.

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.

Fisman, Raymond, Daniel Paravisini, and Vikrant Vig, 2017, Cultural Proximity and Loan Outcomes, *American Economic Review* 107, 457-492.

Gargano, Antonio, Alberto G. Rossi, and Russ Wermers, 2016, The Freedom of Information Act and the Race Toward Information Acquisition, *Review of Financial Studies* 30, 2179-2228.

Giannetti, Mariassunta, and Luc Laeven, 2016, Local Ownership, Crises, and Asset Prices: Evidence from US Mutual Funds, *Review of Finance* 20, 947-978.

Grossman, Sanford J., and Joseph E. Stiglitz, 1976, Information and Competitive Price Systems, *American Economic Review Papers and Proceedings* 66, 246-253.

Hambrick, Donald C., and Phyllis A. Mason, 1984, Upper Echelons: The Organization as a Reflection of Its Top Management, *Academy of Management Review* 9, 193-206.

Heath, Chip, and Amos Tversky, 1991, Preference and Belief: Ambiguity and Competence in Choice Under Uncertainty, *Journal of Risk and Uncertainty* 4, 5-28.

Heinke, Miriam S., and Winnifred R. Louis, 2009, Cultural Background and Individualistic-collectivistic Values in Relation to Similarity, Perspective Taking, and Empathy, *Journal of Applied Social Psychology* 39, 2570-2590.

Hermalin, Benjamin E., and Michael S. Weisbach, 1998, Endogenously Chosen Boards of Directors and Their Monitoring of the CEO, *American Economic Review* 88, 96-118.

Huang, Jennifer, Zhigang Qiu, Yuehua Tang, and Xiaoyu Xu, 2016, Scale, Skill, and Team Management: Organizational Structure of Mutual Fund Families, Working Paper, Cheung Kong Graduate School of Business.

Huberman, Gur, 2001, Familiarity Breeds Investment, *Review of Financial Studies* 14, 659-680.

Hutton, Irena, Danling Jiang, and Alok Kumar, 2014, Corporate Policies of Republican Managers, *Journal of Financial and Quantitative Analysis* 49, 1279-1310.

Investment Company Institute, 2019, Investment Company Fact Book 2019, https://www.ici.org/pdf/2019_factbook.pdf.

Jagannathan, Murali, Wei Jiao, and G. Andrew Karolyi, 2018, Is There a Home Field Advantage in Global Markets? Working Paper, Cornell University.

Jenter, Dirk, and Fadi Kanaan, 2015, CEO Turnover and Relative Performance Evaluation, *Journal of Finance* 70, 2155-2184.

Jenter, Dirk, Egor Matveyev, and Lukas Roth, 2016, Good and Bad CEOs, Working Paper, London School of Economics.

Jiang, Hao, Marno Verbeek, and Yu Wang, 2014, Information Content When Mutual Funds Deviate from Benchmarks, *Management Science* 60, 2038-2053.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005, On the Industry Concentration of Actively Managed Equity Mutual Funds, *Journal of Finance* 60, 1983-2011.

Kempf, Elisabeth, Alberto Manconi, and Oliver G. Spalt, 2017, Learning by Doing: The Value of Experience and the Origins of Skill for Mutual Fund Managers, Working Paper, University of Chicago.

Kets, Willemien, and Alvaro Sandroni, 2019, A Belief-based Theory of Homophily, *Games and Economic Behavior* 115, 410-435.

Li, Danielle, 2017, Expertise versus Bias in Evaluation: Evidence from the NIH, *American Economic Journal: Applied Economics* 9, 60-92.

Li, Kai, Feng Mai, Rui Shen, and Xinyan Yan, 2020, Measuring Corporate Culture Using Maching Learning, *Review of Financial Studies*, forthcoming.

Malmendier, Ulrike, and Geoffrey Tate, 2015, Behavioral CEOs: The Role of Managerial Overconfidence, *Journal of Economic Perspectives* 29, 37-60.

Malmendier, Ulrike, and Geoffrey Tate, 2009, Superstar CEOs, *Quarterly Journal of Economics* 124, 1593-1638.

Mayew, William J., and Mohan Venkatachalam, 2012, The Power of Voice: Managerial Affective States and Future Firm Performance, *Journal of Finance* 67, 1-43.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook, 2001, Birds of a Feather: Homophily in Social Networks, *Annual Review of Sociology* 27, 415-444.

Mehrabian, Albert, 1981, *Silent Messages: Implicit Communication of Emotions and Attitudes*, 2nd ed. (Wadsworth Belmont, Calif.).

Nguyen, Bang Dang, and Kaspar Meisner Nielsen, 2014, What Death Can Tell: Are Executives Paid for Their Contributions to Firm Value?, *Management Science* 60, 2994-3010.

Niessen-Ruenzi, Alexandra, and Stefan Ruenzi, 2019, Sex Matters: Gender Bias in the Mutual Fund Industry, *Management Science* 65, 3001-3025.

Parrino, Robert, Richard W. Sias, and Laura T. Starks, 2003, Voting With Their Feet: Institutional Ownership Changes Around Forced CEO Turnover, *Journal of Financial Economics* 68, 3-46.

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.

Peters, Florian S., and Alexander F. Wagner, 2014, The Executive Turnover Risk Premium, *Journal of Finance* 69, 1529-1563.

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.

Quigley, Timothy J., Craig Crossland, and Robert J. Campbell, 2017, Shareholder Perceptions of the Changing Impact of CEOs: Market Reactions to Unexpected CEO Death, 1950–2009. *Strategic Management Journal* 38, 939-949.

Rivolta, Mia L., 2018, Worth the Wait? Delay in CEO Succession after Unplanned CEO Departures, *Journal of Corporate Finance* 49, 225-251.

Scheflen, Albert E., 1972, *Body Language and the Social Order: Communication as Behavioral Control* (Prentice-Hall, Englewood Cliffs, N.J.).

Sirri, Erik R., and Peter Tufano, 1998, Costly Search and Mutual Fund Flows, *Journal of Finance* 53, 1589-1622.

Solomon, David H., and Eugene Soltes, 2015, What Are We Meeting For? The Consequences of Private Meetings with Investors, *Journal of Law and Economics* 58, 325-355.

Tajfel, Henri, 1978, *Differentiation Between Social Groups: Studies in the Social Psychology of Intergroup Relations* (Academic Press, Cambridge, MA.).

Turner, John C., Rupert J. Brown, and Henri Tajfel, 1979, Social Comparison and Group Interest in Ingroup Favouritism, *European Journal of Social Psychology* 9, 187-204.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2009, Information Immobility and the Home Bias Puzzle, *Journal of Finance* 64, 1187-1215.

Williams, Helen, M., Sharon K. Parker, and Nick Turner, 2007, Perceived Dissimilarity and Perspective Taking within Work Teams, *Group and Organization Management* 32, 569-597.

Wintoki, M. Babajide, and Yaoyi Xi, 2020, Partisan Bias in Fund Portfolios, *Journal of Financial and Quantitative Analysis* 55, 1717-1754.

Table 1 – Summary statistics

This table reports summary statistics for the CEO-fund manager panel used in this study. Panel A reports the number of CEO-fund manager (team) dyads, i.e., the number of distinct combinations of CEOs and fund managers (or fund manager teams). Panel B reports mean values for CEO and fund manager demographics. *Age* is shown in years. *Female* represents the fraction of CEOs and fund managers who are female. The remaining rows in Panel B report the distribution of the 13 distinct CEO and fund manager ethnicities, which we derive from the surname-based name classification algorithm of Ambekar et al. (2009). Panel C reports summary statistics for measures of demographic similarity between CEOs and fund managers. The variables *AllMatch* are indicator variables that equal one if all of the fund's managers have the same age, ethnicity or gender as the CEO, respectively (and zero otherwise). *Similarity Score* is the sum of the three *AllMatch* indicator variables. The variables *PctMgrMatch* are defined as the fractions of fund managers per fund with the same age (i.e., with an age difference ≤ 5 years), ethnicity or gender as the CEO, respectively. *Avg. PctMgrMatch* is the average fraction of fund managers with similar age, same ethnicity, and same gender as the CEO. Panel D reports summary statistics for stock characteristics at the firm-quarter level. Panel E reports fund characteristics at the fund-quarter level. All variables are defined in Appendix A.

Panel A: Number of distinct CEO-fund manager (team) dyads

CEO-fund manager dyads	2,692,554
CEO-fund manager team dyads	1,407,801

Panel B: CEO and fund managers demographics

	CEOs (N=5,552)	**Fund managers (N=4,862)**
Age	55	45
Female (%)	2.70	11.33
African (%)	2.00	2.24
British (%)	49.42	46.95
East Asian (%)	2.61	3.46
East European (%)	3.49	4.18
French (%)	5.28	3.62
German (%)	3.21	2.86
Hispanic (%)	3.73	2.70
Indian (%)	3.40	3.54
Italian (%)	6.54	5.62
Japanese (%)	1.51	1.93
Jewish (%)	14.09	18.44
Muslim (%)	2.68	2.39
Nordic (%)	2.04	2.06

Panel C: Measures of CEO-fund manager demographic similarity

	Mean	Median	SD
PctMgrMatch^{Age}	0.22	0.00	0.33
PctMgrMatch^{Ethnicity}	0.27	0.00	0.37
PctMgrMatch^{Gender}	0.89	1.00	0.24
Avg. PctMgrMatch	0.46	0.44	0.19
AllMatch^{Age} (0/1)	0.11	0.00	0.31
AllMatch^{Ethnicity} (0/1)	0.15	0.00	0.36
AllMatch^{Gender} (0/1)	0.73	1.00	0.45
Similarity Score	0.98	1.00	0.72

Panel D: Stock characteristics (N=3,716)

	Mean	Median	SD
Firm Size	3,233	702	6,241
Firm Age	18.89	14.00	17.07
Book-to-market Ratio	0.65	0.51	0.69
Quarterly Return (%)	3.33	2.08	25.01
Quarterly Stock Turnover (*100)	0.95	0.68	1.08
Quarterly Volatility (*100)	44.22	39.32	22.54
Amihud Illiquidity (*100)	4.73	0.08	114.03

Panel E: Fund characteristics (N=2,487)

	Mean	Median	SD
Portfolio Weight (%)	0.94	0.58	1.15
Excess Weight (%)	0.00	-0.15	0.98
Top 10% Bet (0/1)	0.10	0.00	0.30
Team (0/1)	0.65	1.00	0.47
Fund Size	1,282.78	194.90	5,432.45
Fund Age	13.83	10.00	13.36
Turnover Ratio (%)	86.66	67.00	73.00
Expense Ratio (%)	1.28	1.23	0.52
Quarterly Fund Flows (%)	6.27	-0.92	51.45
Stock Concentration (*100)	2.35	2.00	2.37
Size Score	4.08	4.49	0.98
Value Score	2.93	2.91	0.36
Momentum Score	3.09	3.07	0.46
Family Size	25,088.62	4,139.00	70,563.63

Table 2 – CEO-fund manager demographic similarity and portfolio choice

This table presents results from regressions of stock selection measures, mainly the excess portfolio weight in a stock, on variables measuring the demographic similarity between fund managers and firms' CEOs along with controls for fund and stock characteristics and several fixed effects. The dependent variable in Panel A and B is *Excess Weight*, which is defined as the portfolio weight of the stock in the fund portfolio (in percent) in quarter t minus the average weight of the stock in portfolios of the fund's investment style. In Panel A, the independent variables are the three *AllMatch* indicator variables, which equal one if all of the fund's managers have a similar age, the same ethnicity, and the same gender as the CEO, respectively (and zero otherwise). The variable *Similarity Score* is the sum of the three *AllMatch* indicator variables. In Panel B, the independent variables are three *PctMgrMatch* variables defined as the fraction of fund managers per fund who have similar age (i.e., age difference ≤ 5 years), the same ethnicity or the same gender as the CEO. *Avg. PctMgrMatch* is the average fraction of fund managers with the same age, ethnicity, and gender as the CEO. All similarity measures refer to quarter t. All control variables, except for *Team*, enter the regressions with one lag. In Panel C, the dependent variable is either *Portfolio Weight*, i.e., the portfolio weight of the stock in the fund portfolio (in percent) or *Top 10% Bet,* which is an indicator variable that equals one if the stock belongs to the largest 10% of a fund's holdings in the fund's investment style. All variables are defined in Appendix A. A constant is included in all regressions but not reported for brevity. All regressions include CEO ethnicity, industry-time (i.e., year-quarter), and style fixed effects. t-statistics (in parentheses) are based on standard errors clustered at the fund-stock level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Complete demographic matches between CEOs and fund managers

Dependent variable:			*Excess Weight*		
Similarity Score	**0.061 *****				
	(31.47)				
AllMatch^{Age}		**0.027 *****			**0.024 *****
		(7.26)			**(6.50)**
AllMatch^{Ethnicity}			**0.048 *****		**0.041 *****
			(13.73)		**(11.44)**
AllMatch^{Gender}				**0.090 *****	**0.091 *****
				(28.94)	**(28.52)**
Firm Size	-0.054 ***	-0.054 ***	-0.054 ***	-0.054 ***	-0.054 ***
	(-29.92)	(-30.24)	(-30.62)	(-30.81)	(-30.15)
Firm Age	0.011 ***	0.011 ***	0.011 ***	0.011 ***	0.011 ***
	(8.68)	(8.66)	(8.86)	(8.75)	(8.63)
Book-to-market Ratio	0.006 ***	0.005 ***	0.005 ***	0.005 ***	0.006 ***
	(3.80)	(3.49)	(3.57)	(3.63)	(3.84)
Quarterly Return	0.040 ***	0.041 ***	0.042 ***	0.042 ***	0.041 ***
	(17.09)	(17.37)	(18.09)	(18.26)	(17.17)
Quarterly Stock Turnover	-0.474 ***	-0.492 ***	-0.447 ***	-0.445 ***	-0.476 ***
	(-4.10)	(-4.26)	(-3.96)	(-3.94)	(-4.12)
Quarterly Volatility	-0.002	-0.000	-0.005	-0.006	-0.002
	(-0.21)	(-0.00)	(-0.74)	(-0.91)	(-0.33)
Amihud Illiquidity	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.51)	(-0.37)	(-0.44)	(-0.52)	(-0.55)
Team	-0.004	-0.041 ***	-0.029 ***	-0.018 ***	-0.008 ***
	(-1.45)	(-14.96)	(-10.53)	(-7.14)	(-2.73)
Fund Size	-0.041 ***	-0.042 ***	-0.041 ***	-0.041 ***	-0.041 ***
	(-31.70)	(-32.04)	(-31.96)	(-31.94)	(-31.71)
Fund Age	0.040 ***	0.041 ***	0.039 ***	0.037 ***	0.040 ***
	(14.07)	(14.38)	(14.08)	(13.65)	(14.17)
Turnover Ratio	-0.051 ***	-0.053 ***	-0.054 ***	-0.054 ***	-0.051 ***

	(1)	(2)	(3)	(4)	(5)
	(-18.74)	(-19.56)	(-20.05)	(-20.45)	(-18.79)
Expense Ratio	13.104 ***	12.569 ***	12.658 ***	13.115 ***	13.330 ***
	(18.50)	(17.96)	(18.41)	(18.65)	(18.75)
Quarterly Fund Flows	0.022 ***	0.022 ***	0.021 ***	0.020 ***	0.022 ***
	(6.66)	(6.64)	(6.41)	(6.28)	(6.77)
Stock Concentration	33.000 ***	33.132 ***	33.658 ***	33.440 ***	32.935 ***
	(24.90)	(25.05)	(25.81)	(25.53)	(24.78)
Size Score	-0.155 ***	-0.158 ***	-0.164 ***	-0.160 ***	-0.154 ***
	(-32.64)	(-33.41)	(-36.10)	(-34.69)	(-32.02)
Value Score	-0.052 ***	-0.054 ***	-0.051 ***	-0.051 ***	-0.052 ***
	(-10.25)	(-10.61)	(-10.31)	(-10.25)	(-10.31)
Momentum Score	-0.084 ***	-0.082 ***	-0.075 ***	-0.074 ***	-0.084 ***
	(-19.79)	(-19.43)	(-18.31)	(-18.13)	(-19.74)
Family Size	-0.033 ***	-0.034 ***	-0.031 ***	-0.031 ***	-0.033 ***
	(-36.56)	(-36.94)	(-36.05)	(-36.25)	(-36.53)
CEO Age	0.034 ***	0.015 *	0.002	0.003	0.015 *
	(3.95)	(1.75)	(0.22)	(0.36)	(1.69)
CEO Female	0.052 ***	0.008	0.006	0.072 ***	0.075 ***
	(8.26)	(1.34)	(1.00)	(11.12)	(11.32)
CEO ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-time fixed effects	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	4,322,245	4,323,383	4,433,235	4,434,723	4,322,245
Adj. R-Squared	0.258	0.257	0.257	0.259	0.258

Panel B: Fraction of fund managers similar to the CEO

Dependent variable:			***Excess Weight***		
Avg. PctMgrMatch	**0.067** ***				
	(9.87)				
PctMgrMatch^{Age}		**0.007** *			**0.006** *
		(1.84)			**(1.74)**
PctMgrMatch^{Ethnicity}			**0.032** ***		**0.032** ***
			(8.85)		**(8.59)**
PctMgrMatch^{Gender}				**0.037** ***	**0.039** ***
				(8.01)	**(8.02)**
Controls as in Panel A	Yes	Yes	Yes	Yes	Yes
Observations	4,322,245	4,323,383	4,433,235	4,434,723	4,322,245
Adj. R-Squared	0.257	0.257	0.257	0.257	0.257

Panel C: Alternative dependent variables

Dependent variable:	***Portfolio Weight***		***Top 10% Bet***	
Similarity Score	**0.069** ***		**0.012** ***	
	(33.48)		**(21.45)**	
Avg. PctMgrMatch		**0.089** ***		**0.019** ***
		(12.18)		**(9.48)**
Controls as in Panel A	Yes	Yes	Yes	Yes
Observations	4,322,245	4,322,245	4,322,245	4,322,245
Adj. R-Squared	0.409	0.407	0.165	0.165

Table 3 – Addressing alternative explanations

This table presents robustness tests for the regressions in Table 2. For brevity, we only report coefficients for the main variable of interest, *Similarity Score*, and omit control variables. The dependent variable is *Excess Weight*, defined as in Table 2. The regressions are similar to those in Table 2. Panel A reports results from regressions of the baseline regression model in Table 2 after eliminating stocks with potential school ties or home state ties between CEOs and fund managers, local stocks, or stocks of firms managed by Republican CEOs (i.e., firms for which the variable *Republican CEO* is > 0 in the previous year), or all four. School ties exist if at least one fund manager attended the same university as the CEO (which corresponds to the CONNECTED1 measure in Cohen, Frazzini, and Malloy (2008)). A home state connection exists if at least one fund manager and the CEO obtained their bachelor degree in the same U.S. state (consistent with Jagannathan, Jiao, and Karolyi (2018)). Local stocks are defined as stocks of companies headquartered in a distance of less than 100 kilometers from the fund's management company (as per Coval and Moskowitz (2001)). We exclude observations with missing network information. The variable *Republican CEO* is based on manager's political contributions to Republican-affiliated candidates or party committees and is taken from Hutton, Jiang, and Kumar (2014). To mitigate the bias towards Execucomp firms due to the sample selection of Hutton, Jiang, and Kumar (2014), we do not drop observations where *Republican CEO* is missing, but add an indicator variable that equals to one if this information is missing, and zero otherwise. We further conduct a regression in which we replace *Similarity Score* by the variable *Residual Similarity Score*, which we obtain from regressing the variable *Similarity Score* for a given fund-firm-quarter combination on three indicator variables which are, respectively, equal to one for school ties, home state ties, and local stocks as well as on the variable *Republican CEO* (for which we set missing values to zero and adding an indicator variable for missing values, in order not to lose too many observations). Panel B reports results from regressions of the baseline regression model shown in Table 2, excluding all observations for CEOs with the most frequent demographics, i.e., age between the 25th and 75th percentiles of the age distribution (49-60 years), British CEOs, and male CEOs. Panel C reports results from regressions that account for unobserved heterogeneity and endogenous selection of CEOs or stocks by including either stock-time fixed effects, fund-CEO fixed effects or fund-stock fixed effects. The reported t-statistics are based on standard errors clustered at the fund-stock level.

Panel A: Exclude potential network connections

	Coefficient on *Similarity Score*	**t-statistic**	**Obs**
(1): w/o school ties	0.056	26.41	3,623,975
(2): w/o same home state	0.056	24.48	2,613,235
(3): w/o local stocks (within 100km)	0.062	32.93	3,753,822
(4): w/o Republican CEOs	0.061	28.31	3,362,985
W/o (1), (2), (3) and (4)	0.054	20.06	1,670,354
Residual Similarity Score	0.065	28.96	2,754,550

Panel B: Exclude most frequent demographics

	Coefficient on *Similarity Score*	t-statistic	Obs
W/o male CEOs	0.060	3.91	94,724
W/o British CEOs	0.060	14.81	2,145,275
W/o CEOs aged 49-60 years	0.061	23.11	1,677,396
W/o British male CEOs aged 49-60 years	0.060	23.39	2,997,265

Panel C: Accounting for endogenous matching/unobserved heterogeneity

	Coefficient on *Similarity Score*	t-statistic	Obs
Stock-time fixed effects	0.063	31.53	4,322,643
Fund-CEO fixed effects	0.015	5.63	4,135,877
Fund-stock fixed effects	0.013	6.25	4,176,391

Table 4 – Changes in demographic similarity caused by (exogenous) CEO departures

This table presents results from regressions of the variable *Sell* on measures of increasing similarity between the fund manager(s) and the CEO, which result from changes to CEO-fund manager dyads caused by CEO departures. All analyses are based on only those funds whose managers do not change in the quarter of CEO departure, i.e., the fund manager-fund match remains constant. The dependent variable in Panel A and B is *Sell*, which is an indicator variable that equals one if the fund has decreased its number of shares in the stock in the quarter during which the CEO departure occurred (and zero otherwise). *Similarity Increase* is a placeholder for four indicator variables, which equal one, respectively, if the variable *Similarity Score* or the individual *AllMatch* indicator variables (for age, ethnicity, and gender) increase (and zero otherwise). In Panel B, CEO departures classified as "forced" or "unclassified" turnovers based on Jenter and Kanaan (2015) and Peters and Wagner (2014) are excluded. The regression results in Panel C are based only on CEO departures caused by sudden and unexpected CEO deaths for which the CEO successor is announced within six months. In Panel C, the dependent variable *Sell* is an indicator variable, which equals one if the fund has decreased its portfolio weight in the stock in the year after the death compared to the portfolio weight right before the event (and zero otherwise). All regressions include stock-time (i.e., year-quarter) fixed effects. A constant is included in all regressions but not reported for brevity. t-statistics (in parentheses) are based on standard errors clustered at the fund-stock level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: All CEO departures

Dependent variable:	*Sell*			
	Similarity Score	*Age*	*Ethnicity*	*Gender*
Similarity Increase	**-0.028 *****	-0.021 ***	-0.053 ***	-0.043 *
	(-6.69)	(-4.59)	(-8.97)	(-1.67)
Stock-time fixed effects	Yes	Yes	Yes	Yes
Observations	102,725	102,789	109,176	109,198
Adj. R-Squared	0.032	0.031	0.032	0.031

Panel B: Exclude forced and unclassified turnovers

Dependent variable:	*Sell*			
	Similarity Score	*Age*	*Ethnicity*	*Gender*
Similarity Increase	**-0.020 *****	-0.020 ***	-0.035 ***	-0.024
	(-3.72)	(-3.47)	(-4.56)	(-0.54)
Stock-time fixed effects	Yes	Yes	Yes	Yes
Observations	59,150	59,180	62,688	62,718
Adj. R-Squared	0.023	0.023	0.024	0.024

Panel C: Sudden CEO deaths only

Dependent variable:	*Sell*			
	Similarity Score	*Age*	*Ethnicity*	*Gender*
Similarity Increase	**-0.066 ****	-0.029	-0.128 ***	-0.357 ***
	(-2.06)	(-0.85)	(-3.05)	(-3.90)
Stock-time fixed effects	Yes	Yes	Yes	Yes
Observations	1,341	1,341	1,378	1,378
Adj. R-Squared	0.085	0.082	0.088	0.082

Table 5 – CEO-fund manager demographic similarity and trade performance

This table presents results from regressions of measures of fund manager trade performance in the next quarter on the interaction term *Similarity Score x Buy* and its baseline effects, along with controls for CEO demographics and lagged stock characteristics (similar to those used in Table 2). The dependent variables capturing next-quarter stock performance are the compounded stock characteristic-adjusted stock return within the quarter, as per Daniel et al. (1997) (*DGTW*), or the Carhart (1997) four-factor alpha of the stock (*Carhart Alpha*). To determine the Carhart alpha, the difference between realized and expected returns is used, where the expected excess return of the stock is calculated as the sum of the products of estimated factor loadings and current factor values. Factor loadings are estimated over the prior 24 months. *Buy* is an indicator variable equal to one if the fund has increased the number of shares in a stock during the quarter, and zero if the fund has decreased the number of shares. Panel B shows regressions similar to those in Panel A but based on a restricted sample that excludes all observations with potential network connections between fund managers and CEOs, as defined in Panel A of Table 3 (i.e., school ties, same home state, local stocks, and Republican CEOs). Panel C shows the results from re-estimating the regressions shown in Panel A with additional controls for fund-stock fixed effects. In Panel D, performance measures are adjusted for the average performance of CEOs with similar demographics instead of controlling for CEO demographics. The dependent variable is the next-quarter stock performance (as defined above) relative to the value-weighted performance of stocks managed by CEOs in the same age cohort, and with the same ethnicity and gender. Panel E shows results from re-estimating the regressions in Panel A when focusing on trades at the extensive margin, i.e., newly-established positions and liquidated positions, in which case the indicator variable *Buy* is equal to one for newly-established positions and zero for liquidated positions. All regressions include fund-time and industry-time fixed effects (with time fixed effects corresponding to year-quarter fixed effects). t-statistics (in parentheses) are based on standard errors clustered at the fund-stock level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Baseline regressions

Dependent variable:	***DGTW***		***Carhart Alpha***	
Similarity Score × Buy	**0.114**	***	**0.110**	***
	(5.16)		**(4.34)**	
Similarity Score	-0.041	*	-0.045	
	(-1.70)		(-1.61)	
Buy	-0.163	***	-0.144	***
	(-6.29)		(-4.81)	
Stock and CEO controls	Yes		Yes	
Fund-time fixed effects	Yes		Yes	
Industry-time fixed effects	Yes		Yes	
Observations	4,731,250		4,671,220	
Adj. R-Squared	0.133		0.138	

Panel B: Trade performance w/o network connections

Dependent variable:	***DGTW***		***Carhart Alpha***	
Similarity Score × Buy	**0.105**	***	**0.115**	***
	(2.85)		**(2.73)**	
Similarity Score	-0.084	**	-0.126	***
	(-2.17)		(-2.81)	
Buy	-0.148	***	-0.138	***
	(-3.31)		(-2.68)	
Controls as in Panel A	Yes		Yes	
Observations	1,670,481		1,643,836	
Adj. R-Squared	0.160		0.162	

Panel C: Additional controls for fund-stock fixed effects

Dependent variable:	*DGTW*		*Carhart Alpha*	
Similarity Score × Buy	**0.091**	***	**0.097**	***
	(3.93)		**(3.60)**	
Similarity Score	0.019		0.001	
	(0.43)		(0.01)	
Buy	0.108	***	0.076	**
	(3.96)		(2.41)	
Stock and CEO controls	Yes		Yes	
Fund-stock fixed effects	Yes		Yes	
Fund-time fixed effects	Yes		Yes	
Industry-time fixed effects	Yes		Yes	
Observations	4,634,295		4,576,347	
Adj. R-Squared	0.222		0.214	

Panel D: Trade performance adjusted for CEO demographics

Dependent variable:	*DGTW*		*Carhart Alpha*	
Similarity Score × Buy	**0.105**	***	**0.102**	***
	(4.80)		**(4.06)**	
Similarity Score	0.008		-0.022	
	(0.37)		(-0.85)	
Buy	-0.159	***	-0.154	***
	(-6.17)		(-5.17)	
Controls as in Panel A (w/o CEO controls)	Yes		Yes	
Observations	4,731,250		4,671,220	
Adj. R-Squared	0.121		0.128	

Panel E: Extensive margin buys and sells only

Dependent variable:	*DGTW*		*Carhart Alpha*	
Similarity Score × Buy	**0.167**	***	**0.176**	***
	(4.32)		**(3.98)**	
Similarity Score	-0.065		-0.084	*
	(-1.55)		(-1.74)	
Buy	-0.235	***	-0.254	***
	(-5.13)		(-4.81)	
Controls as in Panel A	Yes		Yes	
Observations	1,736,996		1,707,732	
Adj. R-Squared	0.132		0.139	

Table 6 – CEO-fund manager demographic similarity, CEO-firm match quality, and CEO integrity

Panel A of this table presents results from regressions of the dependent variable *Excess Weight* (defined as in Table 2) on the interaction term *Similarity Score x CEO-firm Match Quality* and its baseline effects, along with the same control variables as used in Table 2. *Similarity Score* is defined as in Table 2. *CEO-firm Match Quality* is a proxy variable that captures the quality of the match between a CEO and the firm he or she manages. In the first and third row, this proxy variable for CEO-firm match quality, i.e., *CAR (-1,+1) < p25*, is an indicator variable that equals one if the cumulative Carhart four-factor adjusted abnormal stock return in the three-day event window (-1,+1) around the announcement of the CEO leaving the firm is in the bottom quartile across all turnover events in the CEO turnover sample (Jenter and Kanaan (2015), Peters and Wagner (2014)), and zero otherwise. Mean *CAR (-1,+1)* in the bottom quartile of the CEO turnover sample is -0.0298, which indicates a decline in shareholder value reflecting the loss of a valuable CEO-firm match. In the second and fourth column, the proxy variable, i.e., *CAR (-1,+1)*, is the cumulative Carhart four-factor adjusted abnormal stock return in the three-day event window (-1,+1) around the announcement of the CEO leaving the firm. In this regard, lower stock returns in reaction to CEO turnovers indicate that the respective CEO is associated with a significant positive contribution to future firm value and hence that the CEO-firm match was of relatively high quality. The regression results shown in the first two columns of Panel A of Table 6 are based on all observations in the fund holdings for a given CEO-firm combination. The regression results shown in the last two columns are based on only those observations prior to the year preceding the quarter during which CEO turnover was announced. In Panel B, we replace the interaction variable for CEO-firm match quality with a proxy variable for the CEO's integrity in a given firm. We obtain the annual integrity score for a given CEO-firm combination from Li et al. (2020) and calculate the average score across all available CEO-firm-year combinations (denoted *Avg. Integrity Score*). We require that the CEO manages the firm throughout the whole year when assigning the firm's integrity score. In columns 1 Panel B, we use *Avg. Integrity Score* as our interaction variable, while in columns 2 we replace the average score with an indicator variable equal to one if the average integrity of a CEO-firm combination is above the sample median, and zero otherwise. All regressions include industry-time (i.e., year-quarter) and style fixed effects. A constant is included in all regressions but not reported for brevity. t-statistics (in parentheses) are based on standard errors clustered at the fund-stock level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: CEO-firm match quality

Dependent variable:	*Excess weight*							
	All observations				W/o observations in the year prior to the quarter of CEO turnover announcement			
	Stock market reaction to CEO turnover announcements							
Proxy for CEO-firm match quality:	CAR (-1,+1)		CAR (-1,+1) < p25		CAR (-1,+1)		CAR (-1,+1) < p25	
Similarity Score × CEO-firm Match Quality	**-0.266**	***	**0.025**	*	**-0.310**	***	**0.034**	**
	(-2.95)		**(1.94)**		**(-2.86)**		**(2.20)**	
Similarity Score	0.049	***	0.043	***	0.048	***	0.039	***
	(7.45)		(5.80)		(6.05)		(4.44)	
CEO-firm Match Quality	0.235	**	-0.023		0.309	**	-0.035	*
	(2.06)		(-1.36)		(2.19)		(-1.69)	
Fund and stock controls	Yes		Yes		Yes		Yes	
Industry-time fixed effects	Yes		Yes		Yes		Yes	
Style fixed effects	Yes		Yes		Yes		Yes	
Number of observations	235,850		235,850		157,081		157,081	
Adj. R-Squared	0.244		0.244		0.243		0.243	

Panel B: CEO integrity

Dependent variable:	*Excess weight*			
Proxy for CEO integrity:	Avg. Integrity Score		Avg. Integrity Score > p50	
Similarity Score × CEO Integrity	**0.017**	*******	**0.010**	*******
	(3.03)		**(3.20)**	
Similarity Score	0.053	***	0.057	***
	(14.65)		(21.75)	
CEO Integrity	-0.023	***	-0.011	***
	(-3.41)		(-2.81)	
Fund and stock controls	Yes		Yes	
Industry-time fixed effects	Yes		Yes	
Style fixed effects	Yes		Yes	
Number of observations	3,623,717		3,623,717	
Adj. R-Squared	0.258		0.258	

Table 7 – CEO-fund manager demographic similarity, stock price crash risks, and lawsuits

This table presents results from regressions of next-quarter stock price crash risk measures and a class action lawsuit indicator on the interaction term *Similarity Score x Buy* and its baseline effects, along with controls for CEO demographics and lagged stock characteristics (similar to those used in Table 2). The dependent variable is either *NCSKEW, DUVOL, CRASH COUNT* (as per Callen and Fang, 2015) or *Class action lawsuit*, all defined in Appendix A and measured in the quarter following the trading decision. *NCSKEW* is the negative coefficient of skewness of a firm's residual daily returns; *DUVOL* represents the down-to-up volatility of a firm's residual daily returns; *CRASH COUNT* is the difference between number of days with extreme negative residual daily returns and extreme positive residual daily returns. *Class action lawsuit* is an indicator variable that is equal to one if a class action lawsuit is filed against the company in a given quarter, and zero otherwise. *Buy* is an indicator variable that equals one if the fund has increased the number of shares in a stock during the quarter, and zero if the fund has decreased the number of shares. *Similarity Score* is defined as in Table 2. All regressions include fund-time and industry-time fixed effects (with time fixed effects corresponding to year-quarter fixed effects). t-statistics (in parentheses) are based on standard errors clustered at the fund-stock level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Stock price crash risk							
Dependent variable:	***NCSKEW***		***DUVOL***		***CRASH COUNT***		***Class action lawsuit***	
Similarity Score × Buy	**-0.005**	***	**-0.002**	***	**-0.003**	***	**-0.038**	***
	(-2.73)		**(-2.74)**		**(-3.59)**		**(-3.19)**	
Similarity Score	0.002		0.001		0.003	***	0.008	
	(1.05)		(1.00)		(3.41)		(0.61)	
Buy	0.009	***	0.004	***	0.004	***	0.002	
	(4.56)		(4.26)		(3.75)		(0.14)	
Stock and CEO controls	Yes		Yes		Yes		Yes	
Fund-time fixed effects	Yes		Yes		Yes		Yes	
Industry-time fixed effects	Yes		Yes		Yes		Yes	
Observations	4,653,767		4,653,767		4,653,767		4,820,201	
Adj. R-Squared	0.036		0.059		0.030		0.059	

Table 8 – CEO-fund manager demographic similarity and earnings announcement returns

This table presents results from regressions of abnormal stock returns around corporate earnings announcements in the next quarter on the interaction term *Similarity Score x Buy* and its baseline effects, along with controls for CEO demographics and lagged stock characteristics (similar to those used in Table 2). Earnings announcement dates are from IBES and refer to the first earnings announcement date in the quarter following the trading decision in the respective stock. The dependent variables are the cumulative Carhart four-factor adjusted abnormal stock returns (in percent) over the three-day (-1,+1) or five-day (-2,+2) event window around the earnings announcement dates, denoted *CAR (-1,+1)* and *CAR (-2,+2)*. *Buy* is an indicator variable that equals one if the fund has increased the number of shares in a stock during the quarter, and zero if the fund has decreased the number of shares. *Similarity Score* is defined as in Table 2. All regressions include fund-time and industry-time (i.e., year-quarter) fixed effects. t-statistics (in parentheses) are based on standard errors clustered at the fund-stock level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Dependent variable:	***CAR (-1,+1)***		***CAR (-2,+2)***	
Similarity Score × Buy	**0.025**	*******	**0.035**	*******
	(2.90)		**(3.62)**	
Similarity Score	-0.016	*	-0.023	**
	(-1.74)		(-2.27)	
Buy	-0.052	***	-0.093	***
	(-5.14)		(-8.15)	
Stock and CEO controls	Yes		Yes	
Fund-time fixed effects	Yes		Yes	
Industry-time fixed effects	Yes		Yes	
Observations	4,706,347		4,706,216	
Adj. R-Squared	0.044		0.052	

Table 9 – Performance and trading behavior at the fund level

This table presents results from regressions of quarterly mutual fund performance, or alternatively measures of trading behavior, on a fund's lagged probability to invest in CEOs who are demographically similar to the fund manager(s) as well as fund controls. The dependent variable in the first two columns are the Carhart (1997) four-factor alphas (i.e., *Carhart Alpha*) based on either gross-of-fee returns (in column 1) or net-of-fee returns (in column 2). The performance measures are in percent. In the third column, the dependent variable is the *Active Share* measure as per Cremers and Petajisto (2009). In the fourth column, the dependent variable is the Industry Concentration Index (*ICI*) as per Kacperczyk, Sialm, and Zheng (2005). The variable *Similarity Overweighting* measures a fund's probability to invest in CEOs who are demographically similar to the fund's manager(s). The variable is calculated as the average of the deviations of the fund's weight in its manager's age cohort, ethnicity, and gender from the average weight of the respective demographic in the fund's investment style, divided by the average weight of the demographic in the investment style. Additional fund-level control variables include *Age Diversity*, which is the coefficient of variation of the fund managers' ages, *Ethnic Diversity*, which is the Teachman's entropy index across the ethnicities of a fund's managers, and *Gender Diversity*, which is the Teachman's entropy index across the genders of a fund's managers. We also control for *School Tie Bias* and *Local Bias*. *School Tie Bias* is the difference between the fund's portfolio weight in stocks with educational ties to the firm's CEOs relative to the market capitalization weight of the fund's educational ties (i.e., all firms for which the fund's managers have educational ties), divided by the market capitalization weight of fund's educational ties. *Local Bias* is the fund's difference between the fund's weight in stocks from the same state as the fund's headquarter and the market capitalization weight of the state, divided by the market capitalization weight of the fund's state. Remaining fund-level control variables are the same as in Table 2. All variables are described in Appendix A. All independent variables are valid as of the end of the quarter preceding the fund performance, active share, and industry concentration calculation. All regressions include investment style and time (i.e., year-quarter) fixed effects. t-statistics (in parentheses) are based on standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Dependent variable:	Carhart Alpha				Active Share		ICI	
	Gross-of-fees		Net-of-fees					
Similarity Overweighting	**0.079**	**	**0.079**	**	**0.012**	***	**0.008**	***
	(2.36)		**(2.36)**		**(3.73)**		**(4.33)**	
Age Diversity	-0.002		-0.002		0.000		-0.000	
	(-1.14)		(-1.12)		(0.26)		(-1.06)	
Ethnic Diversity	-0.011		-0.010		-0.032	***	-0.002	
	(-0.28)		(-0.27)		(-4.42)		(-1.25)	
Gender Diversity	-0.106		-0.107		-0.039	***	-0.005	
	(-1.63)		(-1.64)		(-3.23)		(-1.47)	
School Tie Bias	-0.003		-0.003		0.000		-0.000	
	(-0.89)		(-0.90)		(1.45)		(-1.31)	
Local Bias	0.018	**	0.018	**	0.001		0.000	
	(2.48)		(2.48)		(1.15)		(0.05)	
Team	-0.024		-0.024		0.022	***	0.001	
	(-0.45)		(-0.45)		(2.79)		(0.64)	
Fund Size	-0.034	***	-0.034	***	0.001		0.002	***
	(-3.19)		(-3.21)		(0.49)		(3.19)	
Fund Age	0.092	***	0.090	***	0.009	**	-0.000	
	(3.74)		(3.66)		(2.29)		(-0.19)	
Turnover Ratio	-0.059	**	-0.058	**	-0.007		0.002	
	(-1.99)		(-1.98)		(-1.58)		(1.11)	
Expense Ratio	-7.584		-30.819	***	4.852	***	0.896	***
	(-1.29)		(-5.40)		(5.62)		(3.80)	
Quarterly Fund Flows	-0.048		-0.043		0.015	***	-0.003	***
	(-0.51)		(-0.45)		(3.26)		(-2.72)	
Stock Concentration	0.447		0.434		3.154	***	0.963	***
	(0.98)		(0.95)		(4.96)		(10.03)	
Size Score	-0.058		-0.057		-0.090	***	-0.009	***
	(-1.55)		(-1.51)		(-17.27)		(-4.67)	
Value Score	-0.216	***	-0.217	***	0.012	*	-0.009	***
	(-4.68)		(-4.71)		(1.85)		(-4.27)	
Momentum Score	-0.105	**	-0.106	**	0.009		0.003	*
	(-2.34)		(-2.36)		(1.62)		(1.81)	
Family Size	0.010	*	0.011	*	-0.005	***	-0.001	***
	(1.85)		(1.92)		(-4.44)		(-3.01)	
Style fixed effects	Yes		Yes		Yes		Yes	
Time fixed effects	Yes		Yes		Yes		Yes	
Number of observations	44,511		44,511		23,224		39,650	
Adj. R-Squared	0.083		0.084		0.533		0.285	

Appendix A: Variable definitions

Variable	Definition
CEO characteristics	
CEO Age	Natural logarithm of the CEO's age in years.
CEO Ethnicity	Indicator variables for the thirteen different ethnicities reported in Panel B of Table 1.
CEO Female	Indicator variable equal to one if the CEO is female, and zero otherwise.
CEO-firm Match Quality	Proxy variable that captures the quality of the CEO-firm match. It is either the cumulative Carhart four-factor adjusted abnormal stock return in the three-day event window (-1,+1) around the announcement of the CEO leaving the firm or an indicator variable equal to one if the cumulative Carhart four-factor adjusted abnormal stock return in the three-day event window (-1,+1) around the announcement of the CEO leaving the firm is in the bottom quartile of all turnover events in the sample, and zero otherwise.
CEO Integrity	Proxy variable that captures the integrity of a CEO-firm pair. It is either the average integrity score of Li et al. (2020), measured over all CEO-firm years, or an indicator variable equal to one for CEO-firm combinations with above-median average integrity score, and zero otherwise.
Republican CEO	Follows Hutton, Jiang, and Kumar (2014). Firm-level CEO Republican index, which is the REPMGR of the CEOs of a firm. When there is more than one CEO during a fiscal year, it is the average REPMGR of the CEOs. Missing values exist for CEOs who are unidentified in ExecuComp. REPMGR is the manager-level Republican index, which is the mean REPDUMMGR across all election cycles in which the manager makes political contributions, with REPDUMMGR being a dummy variable that takes a value of one if a manager's political contributions in a given election cycle all go to Republican-affiliated candidates or party committees, and zero otherwise.
CEO-fund manager demographic similarity measures	
$AllMatch^{Age}$	Indicator variable equal to one if the fund's managers all have a similar age (+/- 5 years) as the CEO, and zero otherwise.
$AllMatch^{Ethnicity}$	Indicator variable equal to one if the fund's managers all have the same ethnicity as the CEO, and zero otherwise.
$AllMatch^{Gender}$	Indicator variable equal to one if the fund's managers all have the same gender as the CEO, and zero otherwise.
Avg. PctMgrMatch	Average of $PctMgrMatch^{Age}$, $PctMgrMatch^{Ethnicity}$, and $PctMgrMatch^{Gender}$.
$PctMgrMatch^{Age}$	Fraction of the fund's managers with similar age (+/- 5 years) as the CEO.
$PctMgrMatch^{Ethnicity}$	Fraction of the fund's managers with the same ethnicity as the CEO.
$PctMgrMatch^{Gender}$	Fraction of the fund's managers with the same gender as the CEO.

Residual Similarity	The residual from a regression of the variable Similarity Score on indicator variables for educational networks and local stocks.
Similarity Increase	Indicator variable equal to one if the Similarity Score or the individual AllMatch dummies, respectively, increase around the quarter of CEO departure, and zero otherwise.
Similarity Score	Sum of $\text{AllMatch}^{\text{Age}}$, $\text{AllMatch}^{\text{Ethnicity}}$, and $\text{AllMatch}^{\text{Gender}}$.
Stock characteristics	
Amihud Illiquidity	Mean-adjusted quarterly illiquidity of a stock based on a daily Amihud (2002) illiquidity measure.
Book-to-market Ratio	Ratio of book value of shareholder equity and market capitalization of equity.
Carhart Alpha	Quarterly Carhart (1997) four-factor alpha of a stock, measured as the difference between realized and expected excess stock returns. The expected excess return is calculated as the product of realized factor values and factor loadings, which were estimated using the stock's return over the previous 24 months.
CAR (+1,-1)	Cumulative Carhart 4-factor adjusted abnormal return of the stock over a three-day (-1,+1) window around the first earnings announcement date in the quarter following the trading decision.
CAR (+2,-2)	Cumulative Carhart 4-factor adjusted abnormal return of the stock over a five-day (-2,+2) window around the first earnings announcement date in the quarter following the trading decision.
Class Action Lawsuit	Indicator variable equal to one if a class action lawsuit has been filed against the firm in a quarter (obtained from the Stanford Securities Class Action Clearinghouse (SCAC) database), and zero otherwise.
CRASH COUNT	Difference between number of days with extreme negative residual daily returns and extreme positive daily returns. Extreme daily returns are daily returns exceeding 3.09 standard deviations above and below the mean firm-specific daily return in the quarter.
DGTW	Compounded monthly stock-characteristic adjusted return of a stock within a quarter, as in Daniel et al. (1997).
DUVOL	Down-to-up volatility of firm-specific residual daily returns within a quarter.
Firm Age	Natural logarithm of the age of the company in years, measured as the difference between the current year and the first CRSP listing date.
Firm Size	Natural logarithm of the market capitalization of the company at the end of a quarter in millions of dollars.
NCSKEW	Negative coefficient of skewness of firm-specific residual daily returns within a quarter.

Quarterly Return	Compounded monthly stock return within a quarter. Monthly returns are winsorized at the 1st and 99th percentiles.
Quarterly Stock Turnover	Average daily turnover ratio of the stock within a quarter, where turnover is the daily number of shares traded divided by total shares outstanding.
Quarterly Volatility	Annualized standard deviation of daily returns of a stock within a quarter.

Fund and fund-stock characteristics

Active Share	A fund's quarterly Active Share measure as per Cremers and Petajisto (2009).
Age Diversity	*C*oefficient of variation of the ages of a fund's managers.
Buy	Indicator variable equal to one if the fund has increased its number of shares in the stock in a given quarter, and zero if it has decreased its number of shares.
Ethnic Diversity	Teachman's entropy index across the ethnicities of a fund's managers.
Excess Weight	Portfolio weight of the stock in the fund's portfolio minus the average weight of the stock across funds in the same investment style in the respective quarter.
Expense Ratio	The funds' fees charged for total services.
Family Size	Natural logarithm of the total net assets under management of the fund's family at the end of a quarter in millions of dollars.
Fund Age	Natural logarithm the fund's age in years, measured as the current year minus the year of fund inception.
Fund Size	Natural logarithm of total net assets under management in millions of dollars at the end of a quarter.
Gender Diversity	Teachman's entropy index across the genders of a fund's managers.
ICI	A fund's quarterly industry concentration index (ICI) as per Kacperczyk, Sialm, and Zheng (2005).
Local Bias	Difference between the fund's weight in stocks located in the same U.S. state as the fund's headquarter and the market capitalization weight of the state, divided by the market capitalization weight of the fund's state.
Portfolio Weight	Percentage of the total portfolio value that the fund holds in the stock at a report date.
Quarterly Fund Flows	The fund's percentage growth rate over a quarter adjusted for the internal growth of the fund as in Sirri and Tufano (1998).
School Tie Bias	Difference between the fund's weight in stocks with educational ties to the firm's CEOs relative to the market capitalization weight of the fund's

	educational ties (i.e., all firms for which the fund's managers have educational ties), divided by the market capitalization weight of fund's educational ties.
Sell	Indicator variable equal to one if the fund has decreased its number of shares in the stock in the quarter of the CEO departure event, and zero otherwise.
Similarity Overweighting	Average of the deviations of the fund's weights in its managers' age cohort, ethnicity, and gender from the average weight of the respective characteristic in the investment style relative to the average weight of the characteristic in the investment style.
Size, Value, Momentum Score	Value-weighted average quintile scores of the stocks in the fund's portfolio at a report date along the respective dimension following Daniel et al. (1997).
Stock Concentration	Herfindahl index of portfolio weights for a fund at a report date.
Team	Indicator variable equal to one if the fund is managed by a team, and zero otherwise.
Top 10% Bet	Indicator variable equal to one, if the fund's chosen excess weight is in the largest decile across all excess weights in the same investment style in the respective quarter, and zero otherwise.
Turnover Ratio	Minimum of the fund's security purchases and sales divided by the average total net assets under management during the calendar year.

Appendix B: Additional results

Table B.1 – Alternative measures of CEO-fund manager demographic similarity

This table reports results from re-estimating the baseline regression in Panel A of Table 2 using alternative measures of demographic similarity between CEOs and fund managers. For brevity, only the coefficients of interest are shown. The dependent variable is *Excess Weight*, defined as in Table 2. The variable *Avg. Age Gap* is defined as the average age difference between the fund managers and the CEO in years. $PctMgrMatch^{AgeGap3}$ is the fraction of a fund's managers with an age difference to the CEO 3 or less years. $PctMgrMatch^{SameAgeCohort}$ is the fraction of a fund's managers in the same age cohort (i.e., 30-39, 40-49, 50-59, 60-69, etc.) as the CEO. $PctMgrMatch^{Census\_Ethnicity}$ is the fraction of fund managers with the same ethnicity (White, Black, Asian, or Hispanic) based on the 2000 U.S. Census ethnicity classification of surnames. $PctMgrMatch^{Onolytics\_Ethnicity}$ is the fraction of fund managers with the same ethnicity based on the classification of first and last names using the Onolytics software. *Similarity Score (Age+Ethnicity), Similarity Score (Age+Gender), Similarity Score (Ethnicity+Gender)* are the pairwise *Similarity Score* variables based on all possible combinations of two demographics. The control variables are the same as in Table 2. All regressions include style and industry-time (i.e., year-quarter) fixed effects as well as CEO ethnicity fixed effects (as in Table 2). t-statistics are based on standard errors clustered at the fund-stock level.

Similarity measure	**Coeff.**	**t-statistic**	**Obs**
Avg. Age Gap	-0.001	-4.46	4,323,383
$PctMgrMatch^{Age\ gap\ 3yrs}$	0.009	2.20	4,323,383
$PctMgrMatch^{SameAgeCohort}$	0.011	3.27	4,323,383
$PctMgrMatch^{Census\_Ethnicity}$	0.102	13.03	2,575,696
$PctMgrMatch^{Onolytics\_Ethnicity}$	0.027	6.64	2,965,895
Similarity Score (Age+Ethnicity)	0.038	14.82	4,322,245
Similarity Score (Age+Gender)	0.070	27.24	4,323,383
Similarity Score (Ethnicity+Gender)	0.071	33.16	4,433,235

Table B.2 – Sub-samples of funds with limited access to firm management

This table reports results from re-estimating the baseline regressions shown in Panel A of Table 2 (see Panel A) and Panel A of Table 5 (see Panel B) for sub-samples of funds with limited access to firm management. Sub-samples comprise either funds with below-median fund size (*Small funds*), or funds with below-median fund family size (*Small fund families*), or funds with below-median manager tenure (*Low-tenure managers*), where manager tenure is measured as tenure in the fund industry. For brevity, only the coefficients on the main variables of interest, *Similarity Score* and its interactions, are reported. Control variables, including all fixed effects, are the same as in Table 2 and Table 5, respectively. t-statistics are based on standard errors clustered at the fund-stock level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Portfolio choice of low-access funds (sub-samples for Panel A of Table 2)

Dependent variable:	***Excess weight***					
Sub-sample:	Small funds		Small fund families		Low-tenure managers	
Similarity Score	**0.063**	*******	**0.035**	*******	**0.062**	*******
	(19.57)		**(9.40)**		**(17.34)**	
Controls as in Table 2	Yes		Yes		Yes	
Number of observations	1,588,954		1,584,604		2,317,108	
Adj. R-Squared	0.253		0.381		0.347	

Panel B: Trade performance of low-access funds (sub-samples for Panel A of Table 5)

Dependent variable:	***Carhart alpha***					
Sub-sample:	Small funds		Small fund families		Low-tenure managers	
Similarity Score × Buy	**0.151**	*******	**0.154**	*******	**0.090**	******
	(3.63)		**(3.51)**		**(2.48)**	
Similarity Score	-0.032		0.015		-0.045	
	(-0.73)		(0.33)		(-1.10)	
Buy	-0.163	***	-0.135	**	-0.182	***
	(-3.20)		(-2.57)		(-4.49)	
Controls as in Table 5	Yes		Yes		Yes	
Number of observations	1,839,405		1,594,923		2,594,488	
Adj. R-Squared	0.138		0.137		0.139	

Table B.3 – Testing for screening discrimination: The joint tenure of fund managers and CEOs

This table reports results from re-estimating the regressions shown in Panel A of Table 2 (see column 1) and Panel A of Table 5 (see columns 2 and 3) when interacting our main variables of interest, *Similarity Score* and *Similarity Score x Buy*, with the variable *Joint Tenure*, which is the average number of quarters that a funds' managers have an investment connection with the firm's CEO. For each fund manager-CEO pair, we identify the first report date in the sample (i.e., since 2001) at which the fund manager has invested into a firm of the given CEO (irrespective of the fund or firm). We then calculate the time distance between the current quarter and this first report date and average this distance across all fund managers of a given fund in a given period. In column 1, the main variable of interest is the interaction term *Similarity Score × Joint Tenure*, while in columns 2 and 3, the main variable of interest is the triple interaction term *Similarity Score × Buy × Joint Tenure*. Control variables, including all fixed effects, are the same as in Table 2 and Table 5, respectively, and are suppressed for brevity. The reported t-statistics are based on standard errors clustered at the fund-stock level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Dependent variable:	***Excess Weight***		***DGTW***		***Carhart Alpha***	
Buy × Similarity Score × Joint Tenure			**-0.010**	*******	**-0.008**	******
			(-3.47)		**(-2.44)**	
Buy × Similarity Score			0.183	***	0.170	***
			(5.78)		(4.69)	
Buy × Joint Tenure			0.011	***	0.000	
			(2.84)		(0.07)	
Buy			-0.212	***	-0.125	***
			(-5.58)		(-2.85)	
Similarity Score × Joint Tenure	**-0.002**	*******	0.002		0.002	
	(-8.36)		(0.81)		(0.92)	
Similarity Score	0.073	***	-0.054	*	-0.064	*
	(30.69)		(-1.79)		(-1.83)	
Joint Tenure	0.006	***	0.018	***	0.025	***
	(20.67)		(6.03)		(7.28)	
Stock controls	Yes		Yes		Yes	
Fund controls	Yes		No		No	
Fund-time fixed effects	No		Yes		Yes	
Industry-time fixed effects	Yes		Yes		Yes	
Style fixed effects	Yes		No		No	
Number of observations	4,322,245		4,731,250		4,671,220	
Adj. R-Squared	0.259		0.133		0.1380	

Table B.4 – Trade performance per demographic dimension

This table presents results from regressions of measures of fund manager trade performance in the next quarter on the interaction term *Similarity x Buy* and its baseline effects, along with controls for CEO demographics and lagged stock characteristics (similar to those used in Table 2). The dependent variables capturing next-quarter stock performance are the compounded stock characteristic-adjusted stock return within the quarter, as per Daniel et al. (1997) (*DGTW*), or the Carhart (1997) four-factor alpha of the stock (*Carhart Alpha*). *Buy* is an indicator variable equal to one if the fund has increased the number of shares in a stock during the quarter, and zero if the fund has decreased the number of shares. *Similarity* is a placeholder, which stands either for the variable *PctMgrMatch* (in the age, ethnicity or gender dimension), or for the *AllMatch* indicator variables, which are all defined as in Table 2. Panels A, B, and C, respectively, report results for similarity based on age, ethnicity, and gender. Control variables for stock characteristics and CEO demographics are the same as in Table 5, valid in the quarter preceding the stock performance calculation. All regressions include fund-time and industry-time fixed effects (with time fixed effects corresponding to year-quarter fixed effects). t-statistics (reported in parentheses) are based on standard errors clustered at the fund-stock level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Similarity in age

Dependent variable:	***DGTW***		***Carhart Alpha***	
	PctMgrMatch	*AllMatch*	*PctMgrMatch*	*AllMatch*
Similarity × Buy	**0.156 *****	**0.169 *****	**0.098 ***	**0.135 ****
	(3.41)	**(3.39)**	**(1.85)**	**(2.34)**
Interaction baseline terms	Yes	Yes	Yes	Yes
Stock and CEO controls	Yes	Yes	Yes	Yes
Fund-time fixed effects	Yes	Yes	Yes	Yes
Industry-time fixed effects	Yes	Yes	Yes	Yes
Observations	4,732,213	4,732,213	4,672,185	4,672,185
Adj. R-Squared	0.133	0.133	0.138	0.138

Panel B: Similarity in ethnicity

Dependent variable:	***DGTW***		***Carhart Alpha***	
	PctMgrMatch	*AllMatch*	*PctMgrMatch*	*AllMatch*
Similarity × Buy	**-0.059**	**-0.072 ***	**-0.039**	**-0.063**
	(-1.47)	**(-1.65)**	**(-0.84)**	**(-1.27)**
Controls as in Panel A	Yes	Yes	Yes	Yes
Observations	4,850,244	4,850,244	4,788,980	4,788,980
Adj. R-Squared	0.133	0.133	0.138	0.138

Panel C: Similarity in gender

Dependent variable:	***DGTW***		***Carhart Alpha***	
	PctMgrMatch	*AllMatch*	*PctMgrMatch*	*AllMatch*
Similarity × Buy	**0.302 *****	**0.237 *****	**0.156 ****	**0.219 *****
	(4.93)	**(6.92)**	**(2.21)**	**(5.54)**
Controls as in Panel A	Yes	Yes	Yes	Yes
Observations	4,850,244	4,851,370	4,790,106	4,790,106
Adj. R-Squared	0.133	0.133	0.138	0.138

cfr working paper series

centre for financial research
cologne

cfr working papers are available for download from www.cfr-cologne.de.

2020

No.	Author(s)	Title
20-10	J. Fink, Stefan Palan, E. Theissen	Earnings Autocorrelation and the Post-Earnings-Announcement Drift – Experimental Evidence
20-09	E. Theissen, C. Yilanci	Momentum? What Momentum?
20-08	V. Agarwal, L. Jiang, Q. Wen	Why Do Mutual Funds Hold Lottery Stocks?
20-07	V. Agarwal, S. Ruenzi, F. Weigert	Unobserved Performance of Hedge Funds
20-06	M. Ammann, S. Fischer, F. Weigert	Factor Exposure Variation and Mutual Fund Performance
20-05	P. Limbach, P. R. Rau, H. Schürmann	The Death of Trust Across the Finance Industry
20-04	A. Y. Chen, T. Zimmermann	Open Source Cross-Sectional Asset Pricing
20-03	L. Ahnert, P. Vogt, V. Vonhoff, F. Weigert	Regulatory Stress Testing and Bank Performance
20-02	P. Schuster, E. Theissen, M. Uhrig-Homburg	Finanzwirtschaftliche Anwendungen der Blockchain-Technologie
20-01	S. Ruenzi, M. Ungeheuer, F. Weigert	Joint Extreme Events in Equity Returns and Liquidity and their Cross-Sectional Pricing Implications

2019

No.	Author(s)	Title
19-06	S. Greppmair, E. Theissen	Small Is Beautiful? How the Introduction of Mini Futures Contracts Affects the Regular Contract
19-05	G. Cici, M. Hendriock, A. Kempf	Finding your calling: Skill matching in the mutual fund industry
19-04	O. Korn, P. M. Möller, Ch. Schwehm	Drawdown Measures: Are They All the Same?

19-03	G. Cici, M. Hendriock, S. Jaspersen, A. Kempf	#MeToo Meets the Mutual Fund Industry: Productivity Effects of Sexual Harassment
19-02	T. Johann, S. Scharnowski, E. Theissen, C. Westheide, L. Zimmermann	Liquidity in the German Stock Market
19-01	A. Betzer, P. Limbach, P. Raghavendra Rau, Henrik Schürmann	Till death (or divorce) do us part: Early-life family disruption and investment behavior

2018

No.	Author(s)	Title
18-06	M. Goergen, P. Limbach, M. Scholz-Daneshgari	On the Choice of CEO Duality: Evidence from a Mandatory Disclosure Rule
18-05	F. Brochet, P. Limbach, D. Bazhutov, A. Betzer, M. Doumet	Where Does Investor Relations Matter the Most?
18-04	G. Cici, A. Kempf, C. Peitzmeier	Knowledge Spillovers in the Mutual Fund Industry through Labor Mobility
18-03	T. Rischen, E. Theissen	Underpricing in the Euro Area Corporate Bond Market: New Evidence from Post-Crisis Regulation and Quantitative Easing
18-02	S. Lesmeister, P. Limbach, M. Goergen	Trust and Shareholder Voting
18-01	G. Cici, M. Hendriock, A. Kempf	The Impact of Labor Mobility Restrictions on Managerial Actions: Evidence from the Mutual Fund Industry

2017

No.	Author(s)	Title
17-04	G. Cici, P.B. Shane, Y. S. Yang	Do Connections with Buy-Side Analysts Inform Sell-Side Analyst Research?
17-03	G. Cici, S. Gibson, R. Moussawi	Explaining and Benchmarking Corporate Bond Returns
17-02	S. Jaspersen, P. Limbach	Screening Discrimination in Financial Markets: Evidence from CEO-Fund Manager Dyads
17-01	J. Grammig, E.-M. Küchlin	A two-step indirect inference approach to estimate the long-run risk asset pricing model

This document only covers the most recent cfr working papers. A full list can be found at www.cfr-cologne.de.

centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de