Knowing Me, Knowing You?

Similarity to the CEO and Fund Managers' Investment Decisions[✧]

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ABSTRACT

We study whether investors' demographic similarity to CEOs affects their investment decisions. Mutual fund managers are found to overweight firms led by CEOs who resemble them in terms of age, ethnicity and gender. This finding is robust to excluding educational and local ties and is supported by variation in similarity caused by CEO departures. Investing in firms run by similar CEOs, on average, is associated with superior performance and is more pronounced when uncertainty is higher. Results suggest that demographic similarity to CEOs facilitates informed trading. They further suggest that CEOs matter to investors.

JEL *classification:* G11, G23, J10

Keywords: CEO-investor similarity, familiarity bias, information advantages, investment decisions, mutual fund performance

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Chief executive officers (CEOs)' influence on firm performance (e.g., Bertrand and Schoar (2003), Bennedsen, Pérez-González, and Wolfenzon (2010)) suggests that information about a firm's top management should affect decisions to invest in a firm. However, little is known about whether and how investors take management into account when they make investment decisions. Our study addresses this issue.

While previous work has focused on effects of professional investors' job experience, networks and geography in portfolio decisions (e.g., Cici, et al. (2016), Cohen, Frazzini, and Malloy (2008), Coval and Moskowitz (2001), Pool, Stoffman, and Yonker (2012)), we propose a different factor: investors' demographic similarity to firms' CEOs.

Demographic similarity to CEOs may help investors overcome asymmetric information enabling them to screen investment opportunities more efficiently, consistent, e.g., with models of statistical discrimination (Arrow (1973), Cornell and Welch (1996)). Investors may be better able to assess the behavior and speeches of CEOs who resemble them and, thus, might form more exact expectations about firms' prospects and CEOs' decisions. As similarity attracts (McPherson, Smith-Lovin, and Cook (2001)), investors may further acquire more information about similar CEOs and find it easier to communicate with them, which may facilitate both screening and monitoring. On the contrary, similarity may have adverse effects on investment decisions if it leads to a familiarity bias. In that case, investors prefer investments in firms as their CEOs resemble them. This bias is consistent with models of taste-based discrimination, where agents have preferences for members of their own group while being prejudiced against others (e.g., Becker (1957)). Prejudices may also cause investors to erroneously believe they are better able to assess similar CEOs and to trust (monitor) these CEOs more (less).

Using a large panel of CEOs and mutual fund managers for the period 2001-2011, we find that the latter invest significantly more in firms led by CEOs who resemble them in terms of age, ethnicity and gender. Educational and local ties between fund managers and CEOs as well as CEO demographics themselves do not explain this similarity-based overweighting of CEOs.

Variation in CEO-fund manager similarity caused by CEO departures provides additional support for our result. We find that fund managers are more likely to sell a firm's stock after CEO departures that decrease demographic similarity to a firm's CEO. Plausibly exogenous variation in similarity caused by sudden CEO deaths further supports this result.

Because overweighting of stocks is consistent with both informed trading and a familiarity bias, we perform additional tests to infer whether similarity-based overweighting reflects information advantages or a bias. As a first test, we examine the relation between asymmetric information and overweighting. If demographic similarity to CEOs facilitates screening and monitoring investments as it mitigates asymmetric information, we would expect fund managers to overweight similar CEOs more (i.e., exploit informational advantages) when uncertainty is higher. However, in case of a familiarity bias, we would not expect such a systematic positive relation. We find that overweighting of similar CEOs is more pronounced when macroeconomic and firm-specific uncertainty are higher. These results provide a first indication that overweighting reflects information advantages rather than a familiarity bias.

As a second and more direct test, we consider the performance consequences of investing in firms run by CEOs who are similar to fund managers. While information advantages should be associated with superior performance, a familiarity bias should be associated with no or a negative performance. Our results suggest that similarity-based overweighting, on average, is associated with superior performance, consistent with information advantages. In particular, when we analyze the trades of funds, we find that the difference in next-quarter risk-adjusted returns between the stocks bought and the stocks sold is significantly higher for trades in similar CEOs. For example, compared to the fund's concurrent trades in firms of less similar CEOs, we find that the difference in Carhart alphas between stocks bought and stocks sold is up to 31.2 basis points higher if all managers in a fund manager team have a similar age, the same ethnicity and the same gender as the CEO. Robustness tests, including the performance of fund holdings and sub-portfolios of CEO characteristics, support the above results.

Interestingly, the superior average performance is found to be driven by similarity in age and gender. This finding suggests that fund managers have a better understanding of, and are ultimately more informed about, CEOs who are of a similar age and gender. In contrast, a buy-sell strategy in firms run by CEOs with the same ethnicity as the fund manager does not generate significant outperformance. We conclude that similarity in ethnicity does not facilitate informed trading but rather causes a familiarity bias, which induces fund managers to overweight similar CEOs without additional information. This heterogeneous effect is consistent with McPherson, Smith-Lovin, and Cook (2001). The authors point out that ethnical differences cause the strongest divide in society, whereas people of different age and gender are less prejudiced against each other as they interact more often (in households, neighborhoods, etc.). This reasoning provides an explanation for why the benefits of similarity can outweigh the costs in case of similar age and gender, but not in case of similar ethnicity.[1]

Taken together, this study suggests that professional investors can use easily observable information – i.e., their own demographic similarity to firm's CEOs – when they invest in firms. While this information might seem to be irrelevant for investment decisions, our evidence indicates that, on average, it helps mutual fund managers mitigate informational asymmetries and make superior investment decisions.[2] In additional tests, we find that overall performance at the fund level, on average, is positively affected by fund managers' overweighting of demographically similar CEOs. This result indicates that the superior investment decisions related to similarity-based investing also translate into better performance for fund investors.

[1] The results of Kumar, Niessen-Ruenzi, and Spalt (2015) as well as Gompers, Mukharlyamov, and Xuan (2016) support the above reasoning. The former find that investor flows are significantly lower for mutual funds managed by fund managers with foreign-sounding names, although these managers do not perform differently. The latter study the role of ethnicity and gender for collaborations of venture capitalists (VCs) and find a significantly negative investment success when VCs of the same ethnicity collaborate.

[2] Ex ante, it is not clear that a fund manager should invest in her own or a different group to generate superior performance. Empirical studies on the relation between CEO demographics and firm performance either suggest that CEO demographics do not matter for firm performance or yield ambiguous results. For example, Wolfers (2006) finds no significant difference in the stock returns of firms run by men or women, while Flabbi, et al. (2016) find that female executives either have positive or negative effects on performance. Further, studies that include CEO age or gender typically find no systematic impact on firm value (e.g., Custódio and Metzger (2014) or Li, Lu, and Phillips (2016)). Nevertheless, we control for CEO demographics in robustness tests.

The mutual fund industry constitutes an optimal test ground to study the role that similarity to CEOs plays for investment decisions. Mutual funds are not allowed to acquire control blocks of voting rights and – in contrast to banks, venture capitalists and some other investors – they are not approached by their investee firms and have no contracts with these firms to influence firm performance post investment. In addition, fund managers have no or only limited personal contact to firms' CEOs. These aspects facilitate drawing inferences from empirical results on investment decisions and their performance implications. Furthermore, fund managers' decisions have an immediate impact on fund investors' wealth, which can be measured easily. In this regard, the amount of $16.3 trillion held in U.S. mutual funds at the end of 2016 (Investment Company Institute (2017)) makes it particularly important to understand how fund managers make investment decisions and what the performance consequences are.

Our study contributes to the literature in several ways. First, we contribute to the literature which suggests that CEOs matter, e.g., Bertrand and Schoar (2003), Adams, Almeida, and Ferreira (2005), Bennedsen, Pérez-González, and Wolfenzon (2010), Custódio and Metzger (2013), Jenter, Matveyev, and Roth (2016). While these studies examine whether CEOs play a role for corporate outcomes, such as performance, our study takes on the investor's point of view. Specifically, we address the question whether CEOs matter by relating CEO attributes to investors' decisions. To the best of our knowledge, our study is among the first to take on this perspective.[3] Our evidence suggests that CEOs matter to investors.

Second, our study contributes to the emerging literature on the role of similarities between economic agents for financial decision making. The studies most closely related to our work are Fisman, Paravisini, and Vig (2017), Jannati, et al. (2016), and Wintoki and Xi (2017). Using data from an Indian bank, Fisman, Paravisini, and Vig (2017) find that cultural proximity between lenders and borrowers increases access to credit and loan size and reduces collateral

[3] Grinblatt and Keloharju (2001) provide evidence that investors are more likely to buy, hold, and sell the stocks of Finnish firms that have chief executives of the same cultural background.

requirements and default. This result suggests that cultural proximity serves to mitigate information frictions in lending. Our study corroborates their results as we also provide evidence that similarity between economic agents may improve investment decisions by mitigating information frictions. While the authors study agents' cultural similarity (i.e., shared codes, beliefs and ethnicity), we show that demographic similarity matters. In contrast to Fisman, Paravisini, and Vig (2017), we provide large-scale evidence for the U.S. mutual fund market, i.e., a different cultural, demographic and economic setting.

Both Jannati, et al. (2016) and Wintoki and Xi (2017) provide evidence for the existence of in-group biases caused by (dis)similarities. The former study sell-side equity analysts and find that earnings forecasts are lower when Republican analysts assess firms run by Democrat CEOs, when domestic analysts assess firms run by foreign CEOs, and when male analysts assess firms run by female CEOs. Wintoki and Xi (2017) provide evidence for a partisan bias in asset management. They show that fund managers overweight companies managed by executives and directors with whom they share a similar political partisan affiliation. They find that fund managers' overweighting of stocks does not reflect superior information. In contrast to the two aforementioned studies, our paper suggests that similarity between economic agents leads to information advantages rather than a bias. Further, while Wintoki and Xi (2017) study political attitudes, we study exogenous demographics (i.e., shared status, not values). This difference might explain why our results deviate, although we also consider investment decisions of U.S. mutual fund managers.

A potential limitation of our study is that we cannot rule out that the superior performance associated with investing in similar CEOs might reflect insider trading. Although it is illegal to provide material nonpublic information only to specific investors ("tipping") and although law prohibits "tipped" investors to trade on such information, CEOs might be more likely to provide inside information to demographically similar fund managers due to, e.g., higher levels of attraction and trust. Given that fund managers and CEOs only meet rarely, if they meet at all, it

appears unlikely that the above reasoning fully explains our findings. In this regard, Solomon and Soltes (2015) find that investors make more informed trading decisions when they meet privately with management. However, the improvement in trading is concentrated in hedge funds, but is not present for other investors (e.g., investment advisors, mutual or pension funds).

The remainder of this paper is organized as follows. Section 1 describes our data and variables. Section 2 presents empirical results on the decision of fund managers to invest in firms run by similar CEOs. In Section 3, we attempt to answer the question whether similarity-based investing reflects information advantages or rather a familiarity bias. Section 4 concludes.

1 Data and variables

1.1 Data

We combine several data sources to obtain our sample of mutual fund managers and CEOs for the period 2001 to 2011. First, we obtain information on fund characteristics from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP MF). Fund characteristics include, e.g., fund returns, total net assets under management, fund fees, fund age, fund families, fund location, and investment objectives. 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)).[4] The CRSP MF data are matched with 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 from the CRSP/Compustat Merged Database.

[4] 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 objective.

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 (2015)), and eliminate cases for which MS Direct reports anonymous management teams. We merge MS Direct with the former databases using fund CUSIPs.

Information on CEOs' names, their age and gender are from ExecuComp and Board Analyst's The Corporate Library.[5] Using both databases allows us to cover a broader range of common stocks held by mutual funds and reduces the bias towards larger firms. We eliminate observations where a firm is run by a team of CEOs 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 and both 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. Following Niessen-Ruenzi and Ruenzi (2017), 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

[5] Board Analyst's The Corporate Library covers firms from 2001 onwards.

unavailable, we follow Chevalier and Ellison (1999) and assume that fund managers are 21 upon receiving their bachelor's degree.

Our final sample consists of 2,487 actively managed diversified U.S. domestic equity funds, 4,862 fund managers, 5,552 CEOs, and 3,716 common stocks.

1.2 Variables

We use different measures of demographic similarity between CEOs and fund managers based on 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*).[6] In terms of age, we use an interval of plus or minus five years around the CEO's age as our main similarity measure (but use different age measures for robustness in Section 2.2). *Avg. PctMgrMatch* measures the average fraction of fund managers with the same age, ethnicity and gender as the CEO. As alternative similarity measures we use 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 *SimilarityScore* 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 2, we use the variable *Excess weight* as the dependent variable to study the relation between fund managers' investment decisions and their similarity to CEOs. *Excess weight* is defined as the weight 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. In Section 3, we examine the performance of fund managers' investment decisions based on risk-adjusted returns. We use the stock characteristic-adjusted performance measure of Daniel, et al. (1997) (*DGTW*), compounded over the three months within a quarter. We also use quarterly stock performance based on Carhart (1997) 4-factor alphas (*Carhart alpha*). We determine these alphas by taking

[6] As in 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.

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.

In the analyses in Sections 2 and 3, we control for several stock and fund characteristics that could have an impact on 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 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).

1.3 Summary statistics

Table 1 reports summary statistics for our sample. In Panel A, we report 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 2.7% of all CEOs are females, fund managers are on average 45 years old and 11.3% are female. The above figures compare well to existing CEO and fund manager studies (e.g., Custódio and Metzger (2014), Bär, Kempf, and Ruenzi (2011), Niessen-Ruenzi and Ruenzi (2017)).

Panel B reports summary statistics for our measures of demographic CEO-fund manager similarity. The mean values for *PctMgrMatch* are 0.216 for similar age, 0.275 for same ethnicity and 0.885 for same gender. *Avg. PctMgrMatch* has a mean of 0.46. 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 similarity score has a mean of 0.98 and a median of 1. Its minimum (maximum) value is 0 (3).

Panels C and D 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 87%, an expense ratio of 1.28% per year and generates a Carhart (1997) 4-factor alpha of 10 basis points per quarter based on gross-of-fee returns. The fund characteristics in our sample compare well to related studies (e.g., Pástor, Stambaugh, and Taylor (2015) or Pool, Stoffman, and Yonker (2012)).

2 Demographic similarity to CEOs and fund manager's investment decisions

In this section, we examine whether and how demographic similarity between CEOs and fund managers is related to the investment decisions of the latter. Section 2.1. provides our baseline regression results. In Section 2.2, we investigate whether these results are robust to variations

in our empirical setup and address alternative explanations. Finally, in Section 2.3 we present results from regressions where we exploit variation in CEO-fund manager similarity around different CEO turnover events.

2.1 Stock selection when fund managers are similar to firms' CEOs

To capture a fund manager's preference for a stock, we use the variable *Excess weight* as our dependent variable. That means we examine the weights fund managers assign to the stocks in their portfolios relative to the average weight in the fund's investment style in a given quarter. The use of style-adjusted weights addresses the potential concern that funds overweight CEO characteristics because the firms run by CEOs with specific characteristics better match their investment style. To examine how fund managers' portfolio weights are influenced by their similarity to firms' CEOs, we relate the excess weight that the fund places on the stock to our measures for demographic similarity between CEOs and fund managers. In particular, as shown in equation (1) we regress *Excess weight* on the different similarity measures and several controls for stock and fund characteristics (all described in section 1.2):

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

$ExcessWeight_{i,j,t}$ 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. $Similarity_{i,j,t}$ represents the similarity measure, which is either the *SimilarityScore* or the three individual *AllMatch* dummies or the fraction of a fund's managers who are similar to a firm's CEO in terms of age, ethnicity or gender (*PctMgrMatch*) at the end of quarter t. $X_{i,j,t-1}$ is a vector of control variables at the stock and fund level, all defined as in Table 1. All control variables except for the *Team* dummy are lagged by one quarter. To control for unobservable style characteristics, the regressions include style fixed effects. We also include industry-time fixed effects to address the concern that funds simply differ in their preference for particular

industries in which specific CEO characteristics are more prevalent. Industries are based on the 48-industry classification proposed by Fama and French (1997). Standard errors are clustered at the fund-stock level.

We report the regression result in Table 2. Panel A reports the results of equation (1) when we use the *SimilarityScore* and the individual *AllMatch* dummies, i.e., the components of the score. Panel B reports the results when we instead use *Avg. PctMgrMatch* and the three *PctMgrMatch* variables. The results in both panels of Table 2 provide evidence that fund managers place significantly larger weights than peer funds on stocks of firms run by CEOs who resemble them. Irrespective of the similarity measure we use, the effect of CEO-fund manager similarity is always positive and statistically significant. Results are also economically significant. For example, the first column of Panel A suggests that, all else equal, an additional shared characteristic between fund managers and CEOs leads to an increase in the excess weight by almost 5.7 basis points. That is, compared to a fund manager without any match between her and a firm's CEO, a fund manager who is similar to the CEO in age, ethnicity and gender, overweights a stock by 17 basis points. The economic magnitude of this effect is strong, given that the average excess weight and the average portfolio weight in our sample amount to 0 and 94 basis points, respectively. [7]

Regarding the control variables, we find that the funds in our sample tend to place larger bets on smaller and less frequently traded firms with higher returns in the previous quarter. This finding is consistent with the evidence in, e.g., Chan, Chen, and Lakonishok (2002) and Jiang, Verbeek, and Wang (2014) that active funds expect to find more investment opportunities in

[7] In unreported tests, we further investigate whether a higher *SimilarityScore* also induces a fund manager to hold a stock. To test this, we run pooled regressions with the dependent variable *Hold* which equals one if the fund holds a stock, and zero otherwise. For each fund, we include all stocks that are currently held by at least one fund in their investment style. We control for the same fund and stock characteristics as before as well as the average weight of the stock in the investment style. We find a positive impact of the *SimilarityScore* on the decision to hold a stock. The coefficient of 0.0016 suggests that a fund manager who resembles the CEO in terms of age, ethnicity and gender has a 0.48 basis points higher probability to hold the stock. This effect is economically meaningful, given that the average likelihood to hold the stock, i.e., the average value of *Hold*, is 4.3 basis points.

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 on average have smaller excess weights. This finding is in line with, e.g., Bär, Kempf, and Ruenzi (2011) and Huang, et al. (2016) who document that teams and larger funds and families tend to hold more diversified portfolios. Lastly, as expected, stock concentration in the fund portfolio has a significant positive impact on the excess weight in a particular stock.

2.2 Robustness tests and alternative explanations

In the following, we present the results of various robustness tests for our main finding from Section 2.1. We present the results in Table 3. For brevity, we suppress all control variables. Panel A reports results for several alternative measures of demographic similarity between CEOs and fund managers. With respect to age similarity, we calculate *PctMgrMatch* based on a maximum gap of three or ten years between CEOs and fund managers instead of the five-year gap we use as our main age similarity measure. We also calculate the fraction of the fund's managers who are in the same age cohort (e.g., 40s, 50s) or were born in the same decade (e.g., 1950s, 1960s) as the CEO. As a last age similarity measure, we calculate the simple 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 *ExcessWeight*. Regarding ethnicity, we present results for two alternative classifications. First, we use the dominating ethnicity of surnames from the ethnicity classification of the Census 2000 (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, we now 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, e.g., Ellahie, Tahoun, and Tuna (2016) and Giannetti and Zhao (2016). This algorithm bases the origin of a name on both

the first and last name instead of just the surname.[8] As last step, we construct alternative versions of the *SimilarityScore*, which limit the score to two demographic dimensions each.

In Panel B, we address the concern that the documented overweighting of similar CEOs stems from connections between fund managers and CEOs. In this regard, Cohen, Frazzini, and Malloy (2008) document that fund managers overweight firms led by CEOs with whom they have educational ties. Coval and Moskowitz (1999), Coval and Moskowitz (2001) and Pool, Stoffman, and Yonker (2012), among others, show that fund managers have a preference for local investments. Hence, it might be the case that fund managers invest in similar CEOs only because they know or have met each other. For example, both might belong to the same alumni network or local club. To address this concern, we rerun our regressions after removing local stocks, stocks with educational ties between CEOs and fund managers, or both.[9] Unless mentioned otherwise, we report results only for the *SimilarityScore* from Panel A of Table 2. However, the results are qualitatively similar for each individual demographic dimension.

In Panel C, we report results on alternative estimations of equation (1). First, we estimate the regression without control variables and fixed effects. Second, we replace the dependent variable *ExcessWeight* with either the normal portfolio weight, with *ExcessWeight* divided by the average weight in the investment style, or with an indicator variable equal to one if *ExcessWeight* is positive (zero otherwise). Third, we add different sets of fixed effects to the regression model. Specifically, we add fund fixed effects to control for unobservable fund characteristics and family-time fixed effects to rule out that the overweighting decision is due

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8 From Onolytics, we also obtain information on the likely religion for a given first and last name. In unreported tests, we calculate the similarity between CEOs and fund managers based on whether they have the same religion. We again find a significant positive impact of similarity on *Excess weight*. In all tests where we use Onolytics, we eliminate cases where the ethnicity is identified as “International”.

9 We obtain the location of the fund’s management company from the CRSP MF database. Information on firm headquarters is obtained from Compustat. Consistent with the literature (e.g., Coval and Moskowitz (2001)), we define all stocks within a distance of 100 kilometers from fund headquarters as local stocks. The results are qualitatively the same if we alternatively eliminate all stocks from the same state as the fund company. We further define an educational connection between a fund and a CEO if at least one fund manager attended the same school as the CEO, which corresponds to the *CONNECTED1* measure in Cohen, Frazzini, and Malloy (2008). We eliminate observations for which local and educational information is missing.

to centralized research within the family. We also add fund-stock fixed effects to address the concern of an endogenous matching between funds and firms. In the case of fund-stock fixed effects, we compare the same fund's weight of the same stock when the similarity between CEO and fund manager changes. Finally, we replace the industry-time fixed effects with stock-time fixed effects. This allows us to compare concurrent investors of the same firm and to analyze whether investors with a higher similarity to the CEO have higher excess weights in the respective stock. In addition to the varying sets of fixed effects, we use different estimation techniques for equation (1). First, we use Fama and MacBeth (1973) regressions with Newey and West (1987) corrected standard errors using a lag length parameter of four. Second, we run the regression on a weighted sample where weights are based on a propensity score matching. For this exercise, we define the treatment group as either fund manager-CEO combinations with a positive *SimilarityScore*, i.e., with at least one shared characteristic or as fund manager-CEO combinations with a maximum *SimilarityScore*. This approach takes into account that observations with positive or maximum *SimilarityScores* could differ on observable characteristics and, therefore, aligns treatment and control group. For example, a British male CEO in his 50s is more likely to be similar to investors. If these CEOs run different firms than other CEOs, the propensity score matching takes this into account. To obtain propensity scores, we run logistic regressions of the respective treatment on all control variables from Table 2 as well as on industry- and style fixed effects.[10]

All robustness tests presented in Table 3 support our main finding from Section 2.1 that fund managers overweight firms led by CEOs who resemble them in terms of different demographic characteristics.

[10] We also address the concern that the relation between CEO-fund manager similarity and the excess weight is spurious by employing a bootstrap procedure where we randomly assign the similarity score to fund-stock observations and rerun regression (1), keeping all control variables unchanged. We repeat this random assignment 250 times. The results (not reported) show that none of the 250 coefficients on *SimilarityScore* is as large as the one we have obtained in the original regression.

To further address the concern that CEO demographics themselves, instead of demographic similarities to CEOs, play a role for fund managers' decisions to invest in firms, we repeat the regressions shown in Panel A of Table 2 and additionally control for CEO demographics, i.e., CEO age, CEO gender, and CEO ethnicity fixed effects. The results are shown in Appendix A. Including additional controls for CEO demographics does not change our results.

Finally, in Appendix A.2, we present results from regressions where 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. Again, the results corroborate our findings.

2.3 Evidence from CEO turnovers

In this section, we provide more direct support for the idea that demographic similarity between CEOs and fund managers influences investment decisions of the latter. In particular, we exploit variation in CEO-fund manager similarity caused by CEO departures. To do so, we examine trades in quarters of CEO departures and analyze whether a change in a fund manager's similarity to a CEO – as caused by the change of the CEO – has an impact on the fund managers' likelihood to sell the stock of the affected firm. By focusing on fund trades in the CEO turnover quarter only, we mitigate concerns that firm fundamentals change materially, which might cause fund managers to trade. Consistent with our reasoning and our findings from Section 2.1 and 2.2, we should expect to find that fund managers become 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 2001 to 2011. To analyze how these departures affect fund managers' 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. This way we ensure that variation in CEO-fund manager similarity can be attributed only to differences between old and new CEOs. Our dependent variable is

Sell, which is an indicator variable equal to one if the fund sells shares of the stock of a firm that experiences a CEO departure (zero otherwise). We relate the sell decision to several independent variables that measure changes in demographic similarity around CEO departures. These variables are $SimilarityIncrease^{Score}$, $SimilarityIncrease^{Age}$, $SimilarityIncrease^{Ethnicity}$ and $SimilarityIncrease^{Gender}$. All four variables are dummy variables, which are equal to one if the *SimilarityScore* or the respective *AllMatch* dummies (defined in Section 1.2) increase (zero otherwise). That is, the variables capture instances in which fund managers become more similar to the new CEO relative to the former CEO of the same company. Our regressions include stock-time fixed effects, which further mitigate concerns that fund managers simply trade in reaction to CEO departures because they probably coincide with changes in firm characteristics. However, our results also hold when we compare the trading behavior within the same stock in the same investment style. Table 4 reports our results. While Panel A reports our baseline regression results, Panel B reports results of regressions where we only consider funds with a positive weight in the stock before the CEO departure, i.e., we eliminate initiating buys in the turnover quarter.

One might argue that CEO departures are plausibly exogenous to fund managers, given that mutual funds are not allowed to possess control blocks of firms' voting rights and given that single fund managers are unlikely to significantly influence CEO turnover. However, one might also argue that mutual funds' trading behavior in a firm's stock (or the threat of voting with their feet) has an impact on the likelihood of a CEO being replaced (see, e.g. Parrino, Sias, and Starks (2003)). To address this concern, we perform an additional analysis where we focus on sudden, unexpected CEO deaths. We exclude cases of CEOs who were murdered or committed suicide. Because sudden deaths occur randomly and are likely to be exogenous to current firm and market conditions (see, e.g., Nguyen and Nielsen (2014) or Jenter, Matveyev, and Roth (2016)), they offer plausibly exogenous variation in CEO-fund manager similarity.

We use the sudden death data from Limbach, Schmid, and Scholz-Daneshgari (2016) who collect cases of sudden CEO deaths following the methodology of Nguyen and Nielsen (2014).

Different from most CEO departures used before (in particular retirements and forced turnovers), sudden CEO deaths are random events, which are unexpected to both firms and investors. Usually it is not immediately clear who will succeed the deceased CEO and firms typically need a considerable amount of time to find a successor. Moreover, fund managers first have to learn about the death, its consequences, and who will be the successor. Hence, we do not expect funds to react instantaneously. As a consequence, we focus on a longer period of time after the event. In particular, we compare the weight that a fund held in the stock at the beginning of the death quarter with the average portfolio weight in the stock in the year after the death. We define the indicator variable *Sell* as being equal to one if the average portfolio weight in the stock in the year after the death is lower than before the death (zero otherwise). We only include events where the successor is known six months after the death at the latest. We have 35 cases of sudden deaths between 2000 and 2011, which still leaves us with a sample size of more than 1,300 observations because several funds are affected by each death event. As before, the independent variables of interest are the *SimilarityIncrease* dummies described before. In our regressions, we add stock-time fixed effects to compare the behavior of investors for the same death event. Panel C of Table 4 reports our results.

The results presented in Table 4 support our expectation that an increase in similarity due to a CEO change makes a fund manager less likely to sell the stock of the affected firm. For example, the first column in Panel A suggests that, all else equal, an increase in total similarity between a fund manager and a CEO decreases the probability that the firm's stock will be sold by 2.8 percentage points. This difference accounts for almost 8% of the average likelihood to sell a stock (which is 35.8%). Corroborating the findings from Panel A and Panel B of Table 4, in Panel C we provide evidence that fund managers are also less likely to sell stocks of firms when CEO-fund manager similarity increases after sudden CEO deaths.

Taken together, the results from this section provide evidence that changes in the similarity to the CEO bring about changes in the portfolios of fund managers. This similarity-based investing is economically meaningful. We conclude that CEO-fund manager demographic similarity matters and that investors indeed react to who is leading a firm instead of just trading on basic firm characteristics.

3 Does overweighting of similar CEOs reflect an information advantage?

Because overweighting stocks is consistent with both a familiarity bias and informed trading by investors, in this section we perform additional tests to infer whether similarity-based overweighting reflects a bias or information advantages. Therefore, we examine the relation between similarity-based overweighting and asymmetric information in Section 3.1. In Section 3.2, we analyze the performance of trades in demographically similar and dissimilar CEOs, while we examine performance consequences at the fund level in Section 3.3.

3.1 Similarity-based investing and uncertainty

As a first test, we study the relation between asymmetric information and similarity-based investing. If similarity to CEOs helps fund managers overcome asymmetric information, we would expect them to invest more into firms run by demographically similar CEOs when uncertainty is higher. Put differently, if similarity to the CEO reduces information asymmetries, then fund managers can be expected to exploit their better understanding of similar CEOs more when uncertainty is higher. However, in case of a familiarity bias, we would not expect to find a systematic positive relation to the level of uncertainty. To test this prediction, we run regressions similar to those shown in Table 2 and interact our measures of CEO-fund manager similarity with measures of macroeconomic and firm-specific uncertainty. The results of these regressions are presented in Table 5. Stock and fund level control variables are the same as in Table 2 but suppressed for brevity. We include style and industry-time fixed effects and cluster standard errors at the fund-stock level as before.

We first test whether fund managers' investments in similar CEOs are more pronounced when macroeconomic uncertainty is higher. We use two measures of macroeconomic uncertainty, a recession indicator based on the Chicago Fed National Activity Index (*CFNAI recession*) and the economic policy uncertainty index proposed by Baker, Bloom, and Davis (2016). Regarding the latter, we create an indicator variable, *Economic policy uncertainty*, that equals one if the average uncertainty index in a quarter is above the median value for our sample period (zero otherwise). We interact the two aforementioned measures with the *SimilarityScore*. Panel A of Table 5 presents the regression results. We find that both interaction terms are significantly positive, indicating that similarity-based overweighting is more pronounced when macroeconomic uncertainty is higher.

Panel B of Table 5 presents results of regressions where we interact the *SimilarityScore* with three measures of firm-specific uncertainty. Our first measure of firm-specific uncertainty is *Conglomerate*, which is an indicator variable equal to one if a firm operates in more than one industry segment according to Compustat (zero otherwise). Cohen and Lou (2012) suggest that firms with more business segments are more difficult to value. Our second measure, *Analyst coverage*, is defined as the number of analysts covering the firm according the IBES database. A larger number of analysts covering a firm can be expected to reduce firm-specific uncertainty. The third measure is *CEO Duality*, which is an indicator variable that equals one if a firm's CEO is also the chairman of the company (zero otherwise). CEO duality measures a CEO's power in the firm and has been shown to be associated with significantly higher volatility of stock returns (Adams, Almeida, and Ferreira (2005)). Using the three measures, we find that similarity-based investing is more pronounced when firm-specific uncertainty is higher.

The results from Table 5 provide evidence for time-series and cross-sectional variation in fund managers' tendency to overweight similar CEOs. The decision to overweight is more pronounced in times of higher uncertainty, which suggests that investors exploit information advantages by investing in firms led by similar CEOs when uncertainty rises. In general, the

positive coefficient for *SimilarityScore* remains significant irrespective of the interaction tested. Hence, uncertainty only intensifies the impact of similarity on the decision to overweight, but does not completely explain the documented effect. Overall, the evidence provides a first indication that similarity-based overweighting is associated with information advantages rather than with a familiarity bias.

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

We now consider the performance of fund managers' investments as a more direct test of whether similarity-based overweighting reflects information advantages or a familiarity bias. In case of the former, we would expect to find a significantly positive effect of similarity-based overweighting on performance, reflecting informed trading. On the contrary, in case of a familiarity bias, we would expect to find either a negative performance effect or no effect. Therefore, we analyze whether the next-quarter performance of trades is related to the similarity between fund managers and CEOs. Several studies argue that trades may be more appropriate to identify information advantages and biases of fund managers than the holdings of a stock because they better capture active investment decisions (see, e.g., Chen, Jegadeesh, and Wermers (2000), Pool, Stoffman, and Yonker (2015)). Accordingly, we test whether trading returns, i.e., the performance of buys over sells, depend on CEO-fund manager similarity.

To study trading-based 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 where the number of shares does not change. We then run the following pooled regression at the fund-stock level (see equation (2)):

$$\begin{aligned} Perf_{i,j,t+1} = {} & \alpha + \beta_1 Similarity_{i,j,t} + \beta_2 Buy_{i,j,t} + \beta_3 Similarity_{i,j,t} \times Buy_{i,j,t} \\ & + \gamma' X_{j,t} + \varepsilon_{i,j,t+1} \end{aligned} \tag{2}$$

$Perf_{i,j,t+1}$ denotes the stock performance in the quarter following the trade and $Buy_{i,j,t}$ is an indicator variable equal to one for buys, and zero for sells. $Similarity_{i,j,t}$ represents the similarity measure between the managers of fund *i* and the CEO of stock *j*. To capture similarity, we use the fraction of fund managers who resemble a CEO in terms of age or ethnicity or gender, i.e., *PctMgrMatch*, as well as the corresponding *AllMatch* dummies and the *SimilarityScore*. In regression equation (2), β_2 captures the performance differences of buys and sells for funds without similarity to the CEO, while the sum of β_2 and β_3 measures the same difference, but now for funds with a positive similarity to the CEO. Thus, β_3 represents a difference-in-difference estimator for the comparison of buy-sell differences between trades of fund managers in similar and dissimilar CEOs. We present results based on risk-adjusted returns, using both holdings-based and factor-based performance measures. Specifically, we use the stock characteristic-adjusted performance measure of Daniel, et al. (1997) (*DGTW*) and the quarterly stock performance based on Carhart (1997) 4-factor alphas (*Carhart alpha*). Both are described in Section 1.2. $X_{j,t-1}$ is a vector of the same stock-level control variables as in equation (1) referring to the quarter preceding the stock performance calculation. For brevity, control variables are suppressed. As before, we add industry-time fixed effects and cluster standard errors at the fund-stock level. To better identify whether demographic similarity results in information advantages, we include fund-time fixed effects in the regressions. This way we can examine the relation between similarity and performance of trades within the same fund irrespective of the fund manager's baseline skill. Nevertheless, the results are qualitatively similar if we instead control for the same fund-level variables as before.

Table 6 presents our results. Panel A reports the results for the *SimilarityScore*, while Panels B, C and D report the results for the individual demographic dimensions age, ethnicity and gender (using both *PctMgrMatch* and the *AllMatch* dummies).[11] The results indicate that,

[11] We perform additional robustness tests on the results shown in Table 6. First, in Appendix A.3 we show results from regressions of equation (2) with additional controls for CEO demographics. The results are qualitatively

on average, demographic similarity to the CEO has a positive impact on the performance of fund manager's trades. The coefficient of the interaction term *Similarity* × *Buy* is positive and statistically significant in Panel A, B and D, independent of the performance measure we use. That means, average CEO-fund manager similarity, indicated by the similarity score, as well as similarity based on age and gender are associated with superior performance. The positive performance effect is economically meaningful. For example, the second column of Panel A suggests that the buy-sell difference based on Carhart alphas for trades is -13.8 basis points per quarter if a fund's managers do not resemble a CEO, neither in age, nor in ethnicity or gender. On the contrary, a buy-sell strategy of the same fund in the same quarter delivers a 31.2 (= 3 × 10.4) basis points higher performance per quarter for trades in firms led by CEOs who resemble a fund's managers in terms of age, ethnicity and gender. This difference is economically significant given that the average difference in quarterly Carhart alphas of stocks bought and stocks sold in the sample is -22 basis points. This general underperformance of stocks bought by funds relative to stocks sold is in line with evidence by Dyakov, Jiang, and Verbeek (2017) that mutual fund sells have outperformed their buys since the beginning of the millennium. When we look at the individual dimensions of the similarity score, we find that the positive impact of similarity is driven by age and gender similarity, which show difference-in-difference estimates for Carhart alphas of 13.6 and 22.4 basis points, respectively.

In addition to the aforementioned results, we document an interesting heterogeneity. Particularly, we find that fund managers do not perform better when they invest in firms led by CEOs with whom they share the same ethnicity. Panel C of Table 6 suggests that the difference between stocks bought and stocks sold in firms managed by CEOs with the same ethnicity as the fund manager is either insignificant or even slightly lower than the same difference for

similar to those in Table 6. Second, in Appendix A.4, we show that the results for the similarity score are qualitatively similar when we use net buys and net sells as in Kempf, Manconi, and Spalt (2017). In additional unreported regressions, we find that the results for the three demographic dimensions are also qualitatively similar when we use net buys and net sells.

trades in dissimilar CEOs. Hence, ethnicity-based investing is more consistent with a familiarity bias, comparable to the home-state bias of Pool, Stoffman, and Yonker (2012). The heterogeneous effect of demographic similarity we document is in line with McPherson, Smith-Lovin, and Cook (2001). The authors point out that differences in ethnicities 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 ethnical groups because the former interact much more often (in households, neighborhoods, etc.). This reasoning provides an explanation for why the benefits of similarity can outweigh the costs in case of similar age and gender, but not in case of similar ethnicity.

Despite the fact that trades are arguably more appropriate to identify fund managers' investment decisions, we test the robustness of the aforementioned performance results by providing holdings-based (instead of trade-based) results in Appendix A.5. In the analyses, we use Carhart (1997) 4-factor alphas as our performance measure and run a similar regression as regression equation (2), but without differentiating between buys and sells. The holdings-based results are consistent with the results from Table 6 and corroborate that similarity in age and gender as well as average similarity (measured by the similarity score) lead to superior performance. They further suggest that similarity based on ethnicity causes a familiarity bias. In particular, we find a significant negative impact of higher ethnic similarity on the performance of holdings.

Taken together, the performance results shown in this section suggest that, on average, similarity-based overweighting reflects informed trading. Fund managers are found to have an information advantage when they invest in demographically similar CEOs, especially when CEO-fund manager similarity is based on age and gender. On the contrary, compared to investments in dissimilar CEOs, fund managers perform worse or at least not better in firms run by CEOs with the same ethnicity. This latter finding indicates that performance differences between demographic dimensions exist.

3.3 Fund-level performance

In our final analysis, we test whether the previously documented performance impact of similarity-based investing translates into overall fund performance. This is particularly interesting for fund investors because they may directly benefit from, or bear the costs of, the similarity-based decisions of fund managers. However, as argued by Cici, et al. (2016), even if fund managers obtain information advantages or suffer from a familiarity bias with respect to their similarity to firms' CEOs, they run diversified funds and their own characteristics might not be sufficiently covered by CEOs of their own investment universe. As a consequence, even though fund managers overweight their own characteristics relative to peer funds, their portfolio will also consist of a large fraction of less similar CEOs. Thus, ex ante it is not clear that performance in the similar sub-portfolios also shows up at the fund level.

We measure a fund's probability to invest in similar CEOs (denoted *SimilarityOverweighting*) 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 characteristic in the fund's investment style. To take into account that portfolio weights in some manager characteristics (e.g., female) are smaller due to the small number of CEOs with a matching characteristic, we divide the deviation by the average weight of the manager's characteristic in the fund's style.[12] For funds with multiple managers, we take the average of the relative deviation across all managers. In order to capture a fund's overall tendency to invest in similar CEOs, we take the simple average of the three *SimilarityOverweighting* measures for age cohort, ethnicity and gender (i.e., *AverageOverweighting*). We run a pooled regression in which we relate fund performance in a quarter to the lagged *SimilarityOverweighting* and the same lagged fund-level control variables as in our previous analyses. Fund performance is measured

[12] In this regard, the measure is conceptually similar to the $bias_{state}$ measure in Giannetti and Laeven (2016). Also note that using the five-year age difference as before is not feasible at the sub-portfolio level as we cannot compare the weights across different funds with different manager ages. This is why we focus on portfolio weights in age cohorts.

analogously to stock performance based on Carhart alphas. In Panel A of Table 7, we use gross-of-fee returns, i.e., the net-of-fee return plus one twelfth of the annual total expense ratio, to measure performance. We do so because gross-of-fee returns are more suitable to capture differences in fund managers' investment decisions and skills. Yet, in Panel B of Table 7, we repeat the analysis using net-of-fee returns to identify costs and benefits for fund investors. The regressions include style and time fixed effects. Standard errors are clustered at the fund level.

The results from Table 7 suggest that the likelihood of fund managers to invest into demographically similar CEOs has performance consequences also at the fund level. This result does not depend on whether we measure fund performance via gross-of-fee returns or net-of-fee returns. Across dimensions, we find a similar impact as in Table 6, although the effect is not significant anymore in the gender dimension. However, the combination of the three *SimilarityOverweighting* variables in the *AverageOverweighting* measure, as presented in the first column, shows a significantly positive impact on fund performance. Hence, similarity-based investing, on average, is positive for fund performance and likely to be indicative of information advantages. In terms of economic significance, the first column in Panel A suggests that an increase in *AverageOverweighting* by one standard deviation is associated with an increase in quarterly Carhart alphas of 3.4 (1.42×0.024) basis points. This effect is economically meaningful as the average (median) Carhart alpha for funds in our sample is only 10 (6) basis points. Overall, we can conclude that similarity-based investing has a direct impact on the wealth of fund investors.

4 Conclusion

In this paper, we study whether and how professional investors' demographic similarity to CEOs affects their investment decisions. On the one hand similarity to the CEO may help fund managers screen and monitor firms more efficiently as it facilitates assessing and communicating with CEOs. On the other hand, similarity may lead to a familiarity bias.

We first provide evidence that mutual fund managers overweight firms led by CEOs who resemble them in terms of age, ethnicity and gender. Variation in similarity caused by CEO departures supports this finding. Subsequently, we provide results that indicate that similarity-based overweighting, on average, reflects information advantages, not a familiarity bias. Specifically, investing in similar CEOs is more pronounced when uncertainty is higher and, on average, is associated with superior performance of fund managers' trades and holdings.

Results suggest that investors are able to use their own similarity to firms' CEOs to mitigate informational asymmetries and make better investment decisions. Further, our results support studies from corporate finance, which conclude that CEOs matter. In contrast to these studies, our approach is to relate CEO attributes to fund managers' investment decisions instead of corporate outcomes. We find that CEOs matter to investors.

Finally, our evidence implies that both mutual fund investors and families should take fund manager demographics into account. Investors should do so when they select funds that tend to invest in firms associated with specific CEO demographics. Fund families should do so when they allocate fund managers to funds or teams.

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Table 1 – Summary statistics

This table reports sample characteristics. In Panel A, we report 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 A report the distribution of the 13 distinct CEO and fund manager ethnicities, for which we use the surname-based name classification algorithm of Ambekar, et al. (2009). In Panel B, we report summary statistics for measures of demographic CEO-fund manager similarity. The variables *AllMatch* are indicator variables equal to one if all of the fund's managers have the same age, ethnicity or gender as the CEO, respectively (zero otherwise). *SimilarityScore* is the sum of the three *AllMatch* dummies. The variables *PctMgrMatch* are defined as the fractions of fund managers in the fund with the same age (i.e., with a maximum age difference of 5 years), ethnicity or gender as the CEO, respectively. *Avg. PctMgrMatch* represents the average fraction of fund managers with the same age, ethnicity and gender as the CEO. In Panel C, we report quarterly summary statistics at the stock level. *Firm size* is the market capitalization of the firm at the end of the quarter in millions of dollars. *Firm age* is the difference in years between the current year and the first CRSP listing date. *Book-to-market ratio* represents the ratio of book value of shareholder equity and market capitalization of equity. *Quarterly stock return* is the the compounded monthly return within the quarter. Monthly returns are winsorized at the 1^{st} and 99^{th} percentile. *Quarterly stock turnover* is the average daily turnover ratio of a stock in a quarter, where turnover is defined as the daily number of shares traded divided by total shares outstanding. *Quarterly stock turnover* is the annualized the standard deviation of daily stock returns within a given quarter. *Amihud illiquidity* represents the mean-adjusted quarterly stock illiquidity based on a daily Amihud (2002) illiquidity measure. *Annual return* is the annual stock return. *Carhart stock performance* represents the quarterly Carhart (1997) 4-factor alpha of the stock, measured as the difference between realized and expected excess return within the quarter. 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. Panel D presents quarterly summary statistics for key variables at the fund level. *Portfolio weight* is the percentage of total portfolio value that the fund holds in the stock. *Excess weight* is the 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. *Team* is an indicator variable equal to one if the fund is managed by a team, and zero otherwise. *Fund size* is the total net assets under management in millions of dollars and *Fund age* is shown in years. *Turnover ratio* is fund turnover, defined as the minimum of security purchases and sales divided by the average total net assets under management during the calendar year. *Expense ratio* represents funds' fees charged for total services. *Fund flows* are estimated as the fund's percentage growth rate over a quarter adjusted for the internal growth of the fund as in Sirri and Tufano (1998). *Stock concentration* represents the Herfindahl index of portfolio weights for a fund in a quarter. *Family size* is the total net assets under management of the fund family in millions of dollars. *Size score, Value score, and Momentum score* are the value-weighted average quintile scores of the stocks in the fund portfolio along the respective dimension following Daniel et al. (1997). *Carhart alpha* represents the quarterly Carhart (1997) 4-factor alpha based on gross-of-fee returns.

Panel A: CEO and fund managers characteristics

	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
Eastasian (%)	2.61	3.46
Easteuropean (%)	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

Table 1 – Summary statistics (continued)

Panel B: Measures of demographic CEO-fund manager similarity

	Mean	**Median**	**SD**
$PctMgrMatch^{Age}$	0.22	0.00	0.33
$PctMgrMatch^{Ethnicity}$	0.28	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 C: 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
Carhart alpha (%)	0.94	-0.35	22.53

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

	Mean	**Median**	**SD**
Portfolio weight (%)	0.94	0.58	1.15
Excess weight (%)	0.00	-0.15	0.98
Team	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
Carhart alpha (%), gross-of-fees	0.10	0.06	3.11

Table 2 – CEO-fund manager similarity and portfolio choice

This table presents results from pooled regressions on the relation of a fund's excess portfolio weight in a stock and the similarity of the CEO with the fund's managers. The dependent variable is *ExcessWeight*, defined as the portfolio weight of the stock in the fund portfolio (in percent) minus the average weight of the stock in portfolios of the fund's investment style. In the first column of Panel A, the main independent variable is *SimilarityScore*, representing the sum of the three *AllMatch* dummies. In the last three columns of Panel A, the main independent variable is *AllMatch*, an indicator variable equal to one if all of the fund's managers have the same age, ethnicity, or gender as the CEO, and zero otherwise. In Panel B, the main independent variable is *PctMgrMatch*, defined as the fraction of fund managers in the fund with the same age (i.e., with a maximum age difference of 5 years) or ethnicity or gender as the CEO, respectively. *Avg. PctMgrMatch* represents the average fraction of fund managers with the same age, ethnicity and gender as the CEO. *PctMgrMatch, Avg. PctMgrMatch, AllMatch* and *SimilarityScore* are valid at the end of the quarter for which we calculate excess weights. Additional independent controls at the stock level are the natural logarithm of *Firm Size,* the natural logarithm of *Firm Age*, the *Book-to-market ratio*, *Quarterly return, Quarterly stock turnover*, *Quarterly volatility*, and *Amihud illiquidity*, all defined as in Table 1, and suppressed in Panel B of the table. At the fund level, we control for the *Team* dummy, the natural logarithm of *Fund size*, the natural logarithm of *Fund age*, the *Turnover ratio*, the *Expense ratio*, *Quarterly fund flows, Stock concentration*, *Size score, Value score, Momentum Score*, and the natural logarithm of *Family size*, all defined as in Table 1. All control variables except for the *Team* dummy (which is valid concurrently to *PctMgrMatch*) are valid as of the end of the quarter preceding the calculation of the dependent variable. A constant is included in all regressions but not reported for brevity. Regressions are run with industry-time and style 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.

Table 2 – CEO-fund manager similarity and portfolio choice (continued)

Panel A: Complete matches between CEOs and fund managers

Dependent variable:			*ExcessWeight*		
SimilarityScore	**0.057 *****				
	(30.44)				
AllMatch^{Age}		**0.025 *****			**0.023 *****
		(7.13)			**(6.54)**
AllMatch^{Ethnicity}			**0.042 *****		**0.037 *****
			(13.37)		**(11.22)**
AllMatch^{Gender}				**0.084 *****	**0.085 *****
				(28.35)	**(27.99)**
Firm size	-0.054 ***	-0.054 ***	-0.054 ***	-0.054 ***	-0.054 ***
	(-29.93)	(-29.97)	(-30.48)	(-30.79)	(-30.13)
Firm age	0.012 ***	0.012 ***	0.011 ***	0.011 ***	0.011 ***
	(9.04)	(8.98)	(8.93)	(8.77)	(8.73)
Book-to-market ratio	0.006 ***	0.006 ***	0.005 ***	0.006 ***	0.006 ***
	(4.16)	(3.68)	(3.63)	(3.89)	(4.11)
Quarterly return	0.040 ***	0.041 ***	0.042 ***	0.042 ***	0.040 ***
	(17.03)	(17.27)	(18.20)	(18.04)	(17.01)
Quarterly stock turnover	-0.469 ***	-0.496 ***	-0.431 ***	-0.441 ***	-0.465 ***
	(-4.00)	(-4.24)	(-3.78)	(-3.86)	(-3.98)
Quarterly volatility	-0.003	-0.001	-0.006	-0.008	-0.003
	(-0.35)	(-0.10)	(-0.80)	(-1.06)	(-0.44)
Amihud illiquidity	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.52)	(-0.37)	(-0.39)	(-0.50)	(-0.56)
Team	-0.007 ***	-0.041 ***	-0.030 ***	-0.019 ***	-0.010 ***
	(-2.61)	(-15.04)	(-11.18)	(-7.74)	(-3.76)
Fund size	-0.041 ***	-0.042 ***	-0.041 ***	-0.041 ***	-0.041 ***
	(-31.74)	(-32.06)	(-32.03)	(-32.00)	(-31.75)
Fund age	0.040 ***	0.041 ***	0.039 ***	0.038 ***	0.040 ***
	(14.11)	(14.39)	(14.11)	(13.71)	(14.18)
Turnover ratio	-0.051 ***	-0.053 ***	-0.054 ***	-0.054 ***	-0.052 ***
	(-18.82)	(-19.57)	(-20.15)	(-20.48)	(-18.90)
Expense ratio	13.064 ***	12.571 ***	12.646 ***	13.080 ***	13.272 ***
	(18.45)	(17.97)	(18.40)	(18.64)	(18.67)
Quarterly fund flows	0.022 ***	0.022 ***	0.020 ***	0.020 ***	0.022 ***
	(6.67)	(6.64)	(6.39)	(6.27)	(6.77)
Stock concentration	33.009 ***	33.129 ***	33.642 ***	33.441 ***	32.946 ***
	(24.91)	(25.05)	(25.85)	(25.59)	(24.80)
Size score	-0.155 ***	-0.158 ***	-0.164 ***	-0.160 ***	-0.154 ***
	(-32.71)	(-33.50)	(-36.25)	(-34.95)	(-32.18)
Value score	-0.051 ***	-0.053 ***	-0.051 ***	-0.050 ***	-0.052 ***
	(-10.22)	(-10.58)	(-10.30)	(-10.16)	(-10.26)
Momentum score	-0.084 ***	-0.082 ***	-0.075 ***	-0.074 ***	-0.084 ***
	(-19.76)	(-19.44)	(-18.30)	(-18.17)	(-19.69)
Family size	-0.033 ***	-0.034 ***	-0.031 ***	-0.031 ***	-0.033 ***
	(-36.59)	(-36.93)	(-36.16)	(-36.31)	(-36.57)
Industry-time fixed effects	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	4,322,245	4,323,736	4,443,135	4,444,260	4,322,245
Adj. R-Squared	0.258	0.257	0.257	0.257	0.258

Table 2 – CEO-fund manager similarity and portfolio choice (continued)

Panel B: Fraction of fund managers similar to the CEO

Dependent variable:			*ExcessWeight*		
Avg. PctMgrMatch	0.051 ***				
	(8.75)				
$PctMgrMatch^{Age}$		0.006 *			0.006 *
		(1.71)			(1.72)
$PctMgrMatch^{Ethnicity}$			0.023 ***		0.023 ***
			(8.10)		(7.74)
$PctMgrMatch^{Gender}$				0.026 ***	0.026 ***
				(6.62)	(6.44)
Stock controls	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes
Industry-time fixed effects	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	4,322,245	4,323,736	4,443,135	4,444,260	4,322,245
Adj. R-Squared	0.257	0.257	0.257	0.257	0.257

Table 3 – Robustness and alternative explanations

This table presents robustness checks for the baseline regression of Table 2. For brevity, we only report coefficients of interest and suppress control variables. If not indicated otherwise, the dependent variable is *ExcessWeight*, defined as in Table 2. In Panel A, we use alternative measures for the similarity between CEO and the fund's managers. $PctMgrMatch^{AgeGap3}$ and $PctMgrMatch^{AgeGap10}$ are the fraction of the fund's managers with an age distance to the CEO of less than 3 and 10 years, respectively. $PctMgrMatch^{SameAgeCohort}$ is the fraction of the fund's managers in the same age cohort as the CEO. $PctMgrMatch^{SameDecade}$ is the fraction of the fund's managers born in the same decade as the CEO. *Avg. age gap* is the average age distance between the fund managers and the CEO in years. $PctMgrMatch^{CensusEthnicity}$ is the fraction of fund managers with the same ethnicity (White, Black, Asian, or Hispanic), based on the Census 2000 ethnicity classification of surnames. $PctMgrMatch^{OnolyticsEthnicity}$ is the fraction of fund managers with the same ethnicity, based on the classification of first and last names using the Onolytics software. *SimilarityScore (Age+Ethnicity), SimilarityScore (Age+Gender), SimilarityScore (Ethnicity+Gender)* are the pairwise *SimilarityScores* based on the respective two dimensions. In Panel B, we rerun the baseline regression of Table 2 after eliminating either local stocks, stocks with educational ties, or both. Local stocks are defined as stocks of companies in a distance of less than 100 kilometres from the fund's management company. Educational ties exist if at least one fund manager attended the same university as the CEO. In Panel C, we modify the empirical approach. Results are presented for the *SimilarityScore*. We modify the specification either by estimating the regression without controls and fixed effects or by replacing the dependent variable *ExcessWeight* with the normal portfolio weight of the stock, with the relation between *ExcessWeight* and the average weight of the stock in the segment, or with an indicator variable equal to one if *ExcessWeight* is positive, and zero otherwise. We also modify the regression specification by adding either, fund fixed effects, family-time fixed effects, fund-stock fixed effects, or stock-time fixed effects. In addition, we report results of a Fama and MacBeth (1973) regression with Newey and West (1987) adjusted standard errors using a lag length parameter of four and of a weighted matched sample, where weights are based on a propensity score matching. The treatment group is either defined as observations with a positive *SimilarityScore* or with the maximum *SimilarityScore*. Propensity scores are calculated by running a logistic regression of a treatment indicator on the same control variables as in Table 2. If not indicated otherwise, the regressions include style and industry-time fixed effects. t-statistics are based on standard errors clustered at the fund-stock level.

Panel A: Alternative similarity measures

	Coeff.	t-statistic	Number of observations
$PctMgrMatch^{AgeGap10}$	0.007	2.96	4,323,736
$PctMgrMatch^{AgeGap3}$	0.008	2.10	4,323,736
$PctMgrMatch^{SameDecade}$	0.014	4.25	4,323,736
$PctMgrMatch^{SameAgeCohort}$	0.009	3.09	4,323,736
Avg. age gap	-0.001	-3.68	4,323,736
$PctMgrMatch^{CensusEthnicity}$	0.057	10.19	2,580,211
$PctMgrMatch^{OnolyticsEthnicity}$	0.024	7.19	2,972,184
SimilarityScore (only age+ethnicity)	0.034	14.35	4,322,598
SimilarityScore (only age+gender)	0.066	26.83	4,323,383
SimilarityScore (only ethnicity+gender)	0.065	31.93	4,442,772

Table 3 – Robustness and alternative explanations (continued)

Panel B: Exclude local stocks and educational networks

	Coeff. *SimilarityScore*	t-statistic	Number of observations
Exclude local stocks	0.057	32.04	3,753,822
Exclude educational networks	0.050	25.46	3,623,975
Exclude local stocks + educational networks	0.052	27.00	3,142,293

Panel C: Alternative estimation methods

	Coeff. *SimilarityScore*	t-statistic	Number of observations
Without controls or fixed effects	0.083	48.96	5,728,174
Normal portfolio weight	0.067	34.37	4,322,245
ExcessWeight/Weight in style	0.059	32.20	4,322,245
I (ExcessWeight>0)	0.030	37.40	4,322,245
Fund fixed effects	0.010	5.59	4,322,245
Fund-stock fixed effects	0.012	5.70	4,176,391
Stock-time fixed effects	0.063	31.53	4,322,643
Family-time fixed effects	0.025	13.42	4,322,155
Fama and MacBeth (1973)	0.032	6.66	4,322,643
Weighted sample: SimilarityScore>0	0.012	2.90	6,615,785
Weighted sample: Max. SimilarityScore	0.019	2.43	193,391

Table 4 – Changes in similarity around CEO turnovers

This table presents results from pooled regressions on the relation of the decision to sell a stock in the quarter of a CEO turnover event and the change in similarity to the CEO around the event. The dependent variable in Panel A and B is *Sell*, an indicator variable equal to one if the fund has decreased its number of shares in the stock in the quarter of the turnover event, i.e., switch quarter, and zero otherwise. We limit the analysis to funds whose managers do not switch in the quarter of the CEO turnover. The main independent variables are the *SimilarityIncrease* dummies, which are, respectively, equal to one if the *SimilarityScore* or the individual *AllMatch* dummy (for age, ethnicity, or gender) increases, and zero otherwise. In Panel B, we eliminate initiating buys, i.e., observations with a zero pre-switch weight, where pre-switch weight represents the portfolio weight of the fund in the stock (in percent) at the end of the quarter before the turnover event. Panel C presents results from pooled regressions on the relation of the decision to decrease the portfolio weight in a stock a stock in the year after the CEO's sudden death and the change in similarity to the CEO around the death event. We limit the analysis to sudden deaths where the successor is announced in the six months after the death at the latest. We only focus on funds whose managers do not change after the event. In Panel C, the dependent variable *Sell* is an indicator variable equal to 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 are run with stock-time fixed effects. A constant is included in all regressions but not reported for brevity. 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: Baseline result

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

Panel B: Drop initiating buys

Dependent variable:	Sell			
	Score	*Age*	*Ethnicity*	*Gender*
SimilarityIncrease	**-0.033 *****	**-0.024 *****	**-0.065 *****	**-0.051 ***
	(-7.19)	**(-4.71)**	**(-10.08)**	**(-1.84)**
Stock-time fixed effects	Yes	Yes	Yes	Yes
Number of observations	89,786	89,848	95,334	95,356
Adj. R-Squared	0.039	0.039	0.040	0.039

Panel C: Sudden CEO deaths only

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

Table 5 – Similarity-based investing and uncertainty

This table presents results from pooled regressions on the relation between the excess weight in a stock and the similarity between fund manager and CEO when adding several time, firm and CEO characteristics and their interaction with the *SimilarityScore*. The dependent variable is *ExcessWeight*, defined as in Table 2. The main independent variable is *SimilarityScore*, defined as in Table 2, as well as its interaction with several interaction variables (*Int*). The regressions include the same fund- and stock-level control variables as in Table 2. In Panel A, we interact SimilarityScore with time period variables and, hence, do not include the base effect of the respective time variable as it is already subsumed in the industry-time fixed effects. In the first column, the time variable is *CFNAI recession*, an indicator variable equal to one if at least one month of the quarter is a recession month according to the three months moving average of the Chicago Fed National Activity Index, and zero otherwise. In the second column, we interact *SimilarityScore* with *Economic policy uncertainty*, an indicator variable set to one if the average quarterly baseline economic policy uncertainty index by Baker, Bloom, and Davis (2016) is above the median over the sample period, and zero otherwise. In Panel B, we interact *SimilarityScore* with several variables at the firm level. The interaction variables in the first two columns are *Conglomerate* and *Analyst coverage*, respectively. *Conglomerate* is an indicator variable equal to one if the firm operates in more than one industry segment, and zero otherwise. *Analyst coverage* is the number of analysts following the stock in the respective year. The interaction variable in the third column is *CEO Duality*, which is an indicator variable equal to one if the CEO is also chairman of the board, and zero otherwise. Regressions are run with industry-time and style fixed effects. A constant is included in all regressions but not reported for brevity. 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: General economic uncertainty

Dependent variable:	Excess weight	
Interaction variable (Int):	CFNAI recession	Economic policy uncertainty
SimilarityScore × Int	**0.020 *****	**0.014 *****
	(10.09)	**(7.16)**
SimilarityScore	0.052 ***	0.0490 ***
	(27.44)	(22.19)
Stock controls	Yes	Yes
Fund controls	Yes	Yes
Industry-time fixed effects	Yes	Yes
Style fixed effects	Yes	Yes
Number of observations	4,322,245	4,322,245
Adj. R-Squared	0.258	0.258

Panel B: Firm-specific uncertainty

Dependent variable:	Excess weight		
Interaction variable (Int):	Conglomerate	Analyst coverage	CEO Duality
SimilarityScore × Int	**0.019 *****	**-0.000 ***	**0.008 *****
	(6.44)	**(-1.73)**	**(2.98)**
SimilarityScore	0.047 ***	0.0610 ***	0.053 ***
	(21.60)	(24.82)	(23.23)
Int	-0.016 ***	-0.000	-0.001
	(-4.36)	(-0.77)	(-0.22)
Stock controls	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes
Industry-time fixed effects	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes
Number of observations	4,035,450	4,298,753	4,162,198
Adj. R-Squared	0.261	0.258	0.260

Table 6 – Performance of buys and sells

This table presents results from pooled OLS regressions that analyze the impact of similarity on the performance of trades in the next quarter. The dependent variable is the next-quarter stock performance. Stock performance is either the compounded stock-characteristic adjusted stock return within the quarter of Daniel, et al. (1997) (*DGTW*) or the Carhart (1997) 4-factor alpha of the stock (*Carhart alpha*). To obtain the Carhart alpha, we take the difference of realized and expected return. We calculate the expected excess return of the stock as the sum of the products of estimated factor loadings and current factor values, where 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 otherwise. *Similarity* represents either the *PctMgrMatch* variable in the age, ethnicity or gender dimension, the corresponding *AllMatch* dummy variable, or the *SimilarityScore*, all defined as in Table 2. Panel A reports results for the *SimilarityScore*, while in Panel B, C, and D, similarity is measured for the age, ethnicity, or gender dimension, respectively. Stock-level control variables are the same as in Table 2, valid in the quarter preceding the stock performance calculation, and suppressed for brevity. Regressions are run with fund-time and industry-time 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 score

	Stock performance	
Dependent variable:	DGTW	Carhart alpha
	SimilarityScore	*SimilarityScore*
Similarity × Buy	**0.111 *****	**0.104 *****
	(5.04)	**(4.11)**
Buy	-0.105 ***	-0.138 ***
	(-4.72)	(-4.59)
Similarity	0.098 ***	0.035
	(5.33)	(1.33)
Stock controls	Yes	Yes
Fund-time fixed effects	Yes	Yes
Industry-time fixed effects	Yes	Yes
Number of observations	4,731,427	4,671,402
Adj. R-Squared	0.133	0.138

Table 6 – Performance of buys and sells (continued)

Panel B: Similarity in age

	Stock performance			
Dependent variable:	DGTW		Carhart alpha	
	PctMgrMatch	*AllMatch*	*PctMgrMatch*	*AllMatch*
Similarity × Buy	**0.156 *****	**0.168 *****	**0.099 ***	**0.136 ****
	(3.43)	**(3.38)**	**(1.87)**	**(2.36)**
Buy	-0.089 ***	-0.073 ***	-0.061 ***	-0.054 ***
	(-4.89)	(-4.42)	(-2.92)	(-2.84)
Similarity	-0.097 ***	-0.079 **	0.069 *	0.038
	(-2.76)	(-2.01)	(1.66)	(0.83)
Stock controls	Yes	Yes	Yes	Yes
Fund-time fixed effects	Yes	Yes	Yes	Yes
Industry-time fixed effects	Yes	Yes	Yes	Yes
Number of observations	4,732,698	4,732,698	4,672,675	4,672,675
Adj. R-Squared	0.133	0.133	0.138	0.138

Panel C: Similarity in ethnicity

	Stock performance			
Dependent variable:	DGTW		Carhart alpha	
	PctMgrMatch	*AllMatch*	*PctMgrMatch*	*AllMatch*
Similarity × Buy	**-0.069 ***	**-0.077 ***	**-0.046**	**-0.074**
	(-1.70)	**(-1.78)**	**(-0.99)**	**(-1.48)**
Buy	-0.043 **	-0.051 ***	-0.031	-0.033 *
	(-2.24)	(-3.07)	(-1.41)	(-1.76)
Similarity	0.072 **	0.067 *	-0.170 ***	-0.111 ***
	(2.27)	(1.87)	(-4.63)	(-2.67)
Stock controls	Yes	Yes	Yes	Yes
Fund-time fixed effects	Yes	Yes	Yes	Yes
Industry-time fixed effects	Yes	Yes	Yes	Yes
Number of observations	4,862,812	4,862,812	4,800,981	4,800,981
Adj. R-Squared	0.133	0.133	0.138	0.138

Table 6 – Performance of buys and sells (continued)

Panel D: Similarity in gender

	Stock performance			
Dependent variable:	DGTW		Carhart alpha	
	PctMgrMatch	*AllMatch*	*PctMgrMatch*	*AllMatch*
Similarity × Buy	**0.306 *****	**0.242 *****	**0.161 ****	**0.224 *****
	(5.00)	**(7.06)**	**(2.28)**	**(5.65)**
Buy	-0.330 ***	-0.234 ***	-0.185 ***	-0.203 ***
	(-5.90)	(-8.06)	(-2.87)	(-6.06)
Similarity	0.879 ***	0.848 ***	1.097 ***	0.986 ***
	(13.24)	(13.46)	(13.88)	(13.08)
Stock controls	Yes	Yes	Yes	Yes
Fund-time fixed effects	Yes	Yes	Yes	Yes
Industry-time fixed effects	Yes	Yes	Yes	Yes
Number of observations	4,863,621	4,863,621	4,801,790	4,801,790
Adj. R-Squared	0.133	0.133	0.138	0.138

Table 7 – Fund performance

This table presents results from pooled OLS regressions on the relation of quarterly mutual fund performance and the lagged propensity to invest in similar CEOs *(SimilarityOverweighting)* using Carhart (1997) 4-factor alphas, based on gross-of-fee returns (Panel A) and net-of-fee returns (Panel B). The performance measures are presented in percent. The main independent variable is the respective *SimilarityOverweighting*, measured as the deviation of the fund's weight in its manager's age cohort, ethnicity, and gender from the average weight of the characteristic in the investment style, divided by the average weight of the characteristic in the investment style. The first column presents results for *AverageOverweighting*, which is the average of the three distinct *SimilarityOverweighting* variables. Additional independent controls at the fund level are the same as in Table 2. All independent variables are valid as of the end of the quarter preceding the fund performance calculation. Regressions are run with time and style fixed effects. t-statistics reported in parentheses are based on standard errors clustered at the fund level. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Gross-of-fee returns

Dependent variable:	Carhart alpha			
	Average Overweighting	*Age cohort*	*Ethnicity*	*Gender*
SimilarityOverweighting	**0.024 ****	**0.022 ****	**0.024**	**0.088**
	(2.38)	**(2.09)**	**(0.69)**	**(1.49)**
Team	-0.064 **	-0.063 **	-0.057 *	-0.056 *
	(-2.10)	(-2.08)	(-1.91)	(-1.87)
Fund size	-0.045 ***	-0.046 ***	-0.043 ***	-0.043 ***
	(-4.40)	(-4.42)	(-4.22)	(-4.24)
Fund age	0.097 ***	0.098 ***	0.092 ***	0.093 ***
	(4.05)	(4.08)	(3.84)	(3.89)
Turnover ratio	-0.088 ***	-0.087 ***	-0.084 ***	-0.083 ***
	(-2.99)	(-2.96)	(-2.87)	(-2.87)
Expense ratio	-6.544	-6.564	-6.678	-6.657
	(-1.31)	(-1.31)	(-1.35)	(-1.34)
Quarterly fund flows	-0.077	-0.076	-0.064	-0.064
	(-0.82)	(-0.81)	(-0.68)	(-0.67)
Stock concentration	-0.310	-0.321	-0.273	-0.283
	(-0.31)	(-0.32)	(-0.28)	(-0.29)
Size score	-0.021	-0.020	-0.029	-0.026
	(-0.53)	(-0.53)	(-0.78)	(-0.68)
Value score	-0.129 ***	-0.128 ***	-0.123 ***	-0.126 ***
	(-2.83)	(-2.82)	(-2.75)	(-2.82)
Momentum score	-0.052	-0.050	-0.058	-0.054
	(-1.20)	(-1.14)	(-1.34)	(-1.25)
Family size	0.008	0.008	0.008	0.008
	(1.53)	(1.54)	(1.48)	(1.50)
Style fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Number of observations	51,935	51,973	53,580	53,618
Adj. R-Squared	0.079	0.079	0.079	0.079

Panel B: Net-of-fee returns

Dependent variable:	Carhart alpha			
	Average Overweighting	*Age cohort*	*Ethnicity*	*Gender*
SimilarityOverweighting	**0.024 ****	**0.022 ****	**0.023**	**0.089**
	(2.36)	**(2.07)**	**(0.67)**	**(1.50)**
Controls as in Panel A	Yes	Yes	Yes	Yes
Number of observations	51,935	51,973	53,580	53,618
Adj. R-Squared	0.083	0.082	0.082	0.082

Knowing Me, Knowing You?
Similarity to the CEO and Fund Managers' Investment Decisions

September 2017

Appendix

This Appendix presents additional results to accompany the paper "Knowing Me, Knowing You? Similarity to the CEO and Fund Managers' Investment Decisions".

Table A1 – CEO-fund manager similarity and portfolio choice: Controlling for CEO demographics

This table presents results from pooled regressions on the relation of a fund's excess portfolio weight in a stock and the similarity of the CEO with the fund's managers. The dependent variable is *ExcessWeight*, defined as the portfolio weight of the stock in the fund portfolio (in percent) minus the average weight of the stock in portfolios of the fund's investment style. The regressions are similar to those in Panel A of Table 2 except for additional controls for CEO demographics. These controls are *CEO age*, defined as the natural logarithm of the CEO's age in years, *CEO gender*, which is an indicator variable equal to one if the CEO is female, and CEO ethnicity fixed effects. *SimilarityScore* is the sum of the three *AllMatch* dummies. *AllMatch* is an indicator variable equal to one if all of the fund's managers have the same age, ethnicity, or gender as the CEO, and zero otherwise. Additional independent controls at the stock level are the natural logarithm of *Firm Size*, the natural logarithm of *Firm Age*, the *Book-to-market ratio*, *Quarterly return*, *Quarterly stock turnover*, *Quarterly volatility*, and *Amihud illiquidity*, all defined as in Table 1. At the fund level, we control for the *Team* dummy, the natural logarithm of *Fund size*, the natural logarithm of *Fund age*, the *Turnover ratio*, the *Expense ratio*, *Quarterly fund flows*, *Stock concentration*, *Size score*, *Value score*, *Momentum Score*, and the natural logarithm of *Family size*, all defined as in Table 1. All control variables except for the *Team* dummy are valid as of the end of the quarter preceding the calculation of the dependent variable. A constant is included in all regressions but not reported for brevity. Regressions are run with industry-time and style 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.

Dependent variable:	*ExcessWeight*			
SimilarityScore	**0.061 *** **			
	(31.47)			
AllMatch^{Age}		**0.027 *** **		
		(7.26)		
AllMatch^{Ethnicity}			**0.048 *** **	
			(13.73)	
AllMatch^{Gender}				**0.090 *** **
				(28.94)
CEO age	0.034 ***	0.015 *	0.002	0.003
	(3.95)	(1.75)	(0.22)	(0.36)
CEO gender	0.052 ***	0.008	0.006	0.072 ***
	(8.26)	(1.34)	(1.00)	(11.12)
CEO ethnicity fixed effects	Yes	Yes	Yes	Yes
Stock controls	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes
Industry-time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Number of observations	4,322,245	4,323,383	4,433,235	4,434,723
Adj. R-Squared	0.258	0.257	0.257	0.259

Table A.2 – Sub-portfolio weights of CEO characteristics

This table presents results from regressions on the impact of similarity between a fund's managers and the CEO on the aggregate weights of CEO characteristics. We present separate results for similarity based on age cohort, on ethnicity, or on gender. The dependent variable is the fund's excess weight of an age cohort, ethnicity, or of female CEOs, measured as the fund's portfolio weight in the respective group relative to the average weight of the group in the fund's investment style. If a particular group is not held by a fund, we assign a sub-portfolio weight of zero. In Panel A, we report results of pooled OLS regressions with the excess sub-portfolio weight as dependent variable. The main independent variables are the respective *PctMgrMatch* or the *AllMatch* dummy, defined as in Table 2, and valid at the end of the quarter, for which we calculate portfolio weights. Additional control variables at the fund level are as in Table 2. All control variables except for *Team* are valid at the beginning of the quarter, for which we calculate portfolio weights. Regressions are run with time and style fixed effects. t-statistics reported in parentheses are based on standard errors clustered by fund. In Panel B, we run a Fama and MacBeth (1973) regression. t-statistics reported in parentheses are based on Newey and West (1987) adjusted standard errors using a lag length parameter of four. The regressions include the same independent variables as in Panel A as well as style fixed effects. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table A.2 – Sub-portfolio weights of CEO characteristics (continued)

Panel A: Pooled OLS regressions

Dependent variable:	Excess sub-portfolio weight					
	Age cohort		Ethnicity		Female	
PctMgrMatch	**0.264 ****		**0.380 *****		**0.132**	
	(2.41)		**(3.18)**		**(1.31)**	
AllMatch		**0.319 *****		**0.410 *****		**0.212 ***
		(2.61)		**(2.73)**		**(1.67)**
Team	0.038 **	0.067 ***	0.028 ***	0.052 ***	0.037	0.056
	(2.22)	(3.29)	(2.73)	(3.95)	(0.82)	(1.20)
Fund size	-0.017 ***	-0.016 ***	-0.010 ***	-0.010 ***	-0.034 **	-0.034 **
	(-2.90)	(-2.78)	(-2.88)	(-2.77)	(-2.03)	(-2.02)
Fund age	0.011	0.010	0.007	0.006	0.049	0.049
	(0.81)	(0.74)	(0.84)	(0.72)	(1.38)	(1.37)
Turnover ratio	-0.035 ***	-0.035 ***	-0.019 **	-0.018 **	-0.019	-0.020
	(-2.58)	(-2.60)	(-2.40)	(-2.32)	(-0.72)	(-0.75)
Expense ratio	-9.588 ***	-9.562 ***	-5.385 ***	-5.389 ***	-4.384	-4.410
	(-3.30)	(-3.29)	(-3.21)	(-3.21)	(-0.89)	(-0.90)
Quarterly fund flows	-0.011	-0.011	-0.010	-0.010	-0.025	-0.025
	(-0.90)	(-0.85)	(-1.32)	(-1.32)	(-0.61)	(-0.61)
Stock concentration	-1.517	-1.519	-0.960	-0.972	-0.857	-0.868
	(-1.11)	(-1.10)	(-1.14)	(-1.15)	(-0.68)	(-0.69)
Size score	0.462 ***	0.462 ***	0.281 ***	0.281 ***	-0.120 **	-0.120 **
	(18.93)	(18.89)	(19.44)	(19.31)	(-2.53)	(-2.53)
Value score	-0.286 ***	-0.284 ***	-0.175 ***	-0.174 ***	0.345 ***	0.346 ***
	(-11.62)	(-11.49)	(-11.75)	(-11.65)	(4.50)	(4.51)
Momentum score	0.062 ***	0.063 ***	0.036 ***	0.036 ***	-0.100 **	-0.101 **
	(3.64)	(3.64)	(3.47)	(3.49)	(-2.26)	(-2.27)
Family size	-0.002	-0.002	-0.001	-0.001	-0.012	-0.011
	(-0.47)	(-0.52)	(-0.61)	(-0.60)	(-1.17)	(-1.16)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	366,120	366,120	618,215	618,215	46,989	46,989
Adj. R-Squared	0.005	0.005	0.003	0.003	0.010	0.011

Table A.2 – Sub-portfolio weights of CEO characteristics (continued)

Panel B: Fama and MacBeth (1973) regressions

Dependent variable:	Excess sub-portfolio weight					
	Age cohort		Ethnicity		Female	
PctMgrMatch	**0.230 *****		**0.424 *****		**0.134 *****	
	(3.50)		**(4.95)**		**(3.34)**	
AllMatch		**0.302 *****		**0.452 *****		**0.233 *****
		(3.99)		**(4.38)**		**(4.03)**
Team	0.027 *	0.054 ***	0.022 ***	0.049 ***	0.041	0.061 **
	(1.90)	(2.77)	(2.88)	(8.06)	(1.62)	(2.35)
Fund size	-0.013 ***	-0.013 **	-0.008 **	-0.008 **	-0.027 *	-0.027 *
	(-2.71)	(-2.55)	(-2.45)	(-2.37)	(-1.75)	(-1.72)
Fund age	0.005	0.005	0.004	0.004	0.041	0.041
	(0.75)	(0.64)	(0.85)	(0.70)	(1.13)	(1.11)
Turnover ratio	-0.047 ***	-0.047 ***	-0.026 ***	-0.025 ***	-0.019	-0.020
	(-2.94)	(-2.97)	(-3.01)	(-2.97)	(-0.99)	(-1.02)
Expense ratio	-9.613 ***	-9.612 ***	-5.344 ***	-5.342 ***	-6.064 *	-6.136 *
	(-7.34)	(-7.30)	(-6.88)	(-6.85)	(-1.82)	(-1.85)
Quarterly fund flows	-0.010	-0.009	-0.008	-0.008	-0.004	-0.005
	(-0.61)	(-0.58)	(-0.89)	(-0.86)	(-0.14)	(-0.15)
Stock concentration	-3.762 ***	-3.767 ***	-2.290 ***	-2.314 ***	0.793	0.792
	(-4.09)	(-4.08)	(-4.01)	(-4.02)	(0.70)	(0.70)
Size score	0.526 ***	0.527 ***	0.318 ***	0.319 ***	-0.161 **	-0.161 **
	(6.23)	(6.24)	(6.21)	(6.20)	(-2.33)	(-2.32)
Value score	-0.315 ***	-0.313 ***	-0.193 ***	-0.191 ***	0.304 ***	0.306 ***
	(-8.28)	(-8.19)	(-8.32)	(-8.35)	(3.13)	(3.14)
Momentum score	0.059 *	0.059 *	0.032	0.032	-0.104	-0.104
	(1.84)	(1.82)	(1.59)	(1.61)	(-1.11)	(-1.12)
Family size	-0.006 ***	-0.006 ***	-0.004 ***	-0.004 ***	-0.009	-0.009
	(-3.46)	(-3.65)	(-3.87)	(-3.97)	(-1.46)	(-1.46)
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	366,120	366,120	618,215	618,215	46,989	46,989
Avg. R-Squared	0.007	0.007	0.006	0.006	0.049	0.050

Table A.3 – Performance of buys and sells: Controlling for CEO demographics

This table presents results from pooled OLS regressions that analyze the impact of similarity on the performance of trades in the next quarter. The regressions are similar to those in Table 6, except for additional controls for CEO demographics. These controls are *CEO age*, defined as the natural logarithm of the CEO's age in years, *CEO gender*, which is an indicator variable equal to one if the CEO is female, and CEO ethnicity fixed effects. The dependent variable is the next-quarter stock performance. Stock performance is either the compounded stock-characteristic adjusted stock return within the quarter of Daniel, et al. (1997) (*DGTW*) or the Carhart (1997) 4-factor alpha of the stock (*Carhart alpha*). Stock-level control variables are the same as in Table 2, valid in the quarter preceding the stock performance calculation, and suppressed for brevity. Regressions are run with fund-time and industry-time 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.

Dependent variable:	DGTW				Carhart alpha			
	SimilarityScore	*AllMatch*^{Age}	*AllMatch*^{Ethnicity}	*AllMatch*^{Gender}	*SimilarityScore*	*AllMatch*^{Age}	*AllMatch*^{Ethnicity}	*AllMatch*^{Gender}
Similarity × Buy	**0.114 *****	**0.169 *****	**-0.072 ***	**0.237 *****	**0.110 *****	**0.135 ****	**-0.063**	**0.219 *****
	(5.16)	**(3.39)**	**(-1.65)**	**(6.92)**	**(4.34)**	**(2.34)**	**(-1.27)**	**(5.54)**
Buy	-0.163 ***	-0.074 ***	-0.052 ***	-0.231 ***	-0.144 ***	-0.055 ***	-0.036 *	-0.201 ***
	(-6.29)	(-4.48)	(-3.15)	(-7.95)	(-4.81)	(-2.89)	(-1.90)	(-5.99)
Similarity	-0.041 *	-0.075 *	0.058	-0.086	-0.045	-0.054	0.043	-0.088
	(-1.70)	(-1.89)	(1.56)	(-0.87)	(-1.61)	(-1.16)	(1.00)	(-0.74)
CEO age	-0.039	-0.043	-0.059	-0.059	-0.847 ***	-0.846 ***	-0.872 ***	-0.873 ***
	(-0.62)	(-0.67)	(-0.97)	(-0.97)	(-11.32)	(-11.12)	(-11.99)	(-12.00)
CEO gender	-1.058 ***	-1.070 ***	-1.065 ***	-1.040 ***	-1.245 ***	-1.253 ***	-1.243 ***	-1.226 ***
	(18.93)	(19.80)	(19.91)	(12.10)	(18.48)	(19.20)	(19.28)	(11.80)
CEO ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4,731,250	4,732,213	4,850,244	4,851,370	4,671,220	4,672,185	4,788,980	4,790,106
Adj. R-Squared	0.133	0.133	0.133	0.133	0.138	0.138	0.138	0.138

Table A.4 – Performance of net buys and net sells

This table presents results from pooled OLS regressions similar to those in Table 6. We replace the *Buy* indicator with a net buy indicator (*NB*) as in Kempf, Manconi, and Spalt (2017). *NB* is an indicator variable equal to one if the portfolio weight of the stock in the fund portfolio is higher than the portfolio weight that the stock would have if the fund had not changed its stock holdings from the previous quarter. 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.

Dependent variable:	DGTW	Carhart alpha
Similarity Score × NB	**0.042 ****	**0.063 *****
	(2.28)	**(2.96)**
NB	-0.105 ***	-0.113 ***
	(-4.72)	(-4.43)
Similarity Score	0.098 ***	0.056 ***
	(5.33)	(2.59)
Stock controls	Yes	Yes
Fund-time fixed effects	Yes	Yes
Industry-time fixed effects	Yes	Yes
Number of observations	6,224,503	6,154,285
Adj. R-Squared	0.128	0.257

Table A.5 – Holdings performance

This table presents results from pooled OLS regressions that analyze the impact of similarity on the performance of stock holdings in the next quarter. The dependent variable is the next-quarter risk-adjusted stock performance, measured as a Carhart (1997) 4-factor alpha and defined as in Table 7. The main independent variables are either the *PctMgrMatch* variable in in the age, ethnicity, or gender dimension, the corresponding *AllMatch* dummy variable, or the *SimilarityScore*, all defined as in Table 2. Stock-level control variables are the same as in Table 2, valid in the quarter preceding the stock performance calculation, and suppressed for brevity. Regressions are run with fund-time and industry-time fixed effects. t-statistics (reported in parentheses) are based on standard errors clustered at the fund-stock level. Regressions are run with fund-time fixed effects and t-statistics (reported 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						
SimilarityScore	**0.076 *****						
	(3.85)						
$PctMgrMatch^{Age}$		0.132 ***					
		(4.93)					
$AllMatch^{Age}$			0.096 ***				
			(3.23)				
$PctMgrMatch^{Ethnicity}$				-0.194 ***			
				(-8.18)			
$AllMatch^{Ethnicity}$					-0.149 ***		
					(-5.43)		
$PctMgrMatch^{Gender}$						1.152 ***	
						(18.08)	
$AllMatch^{Gender}$							1.097 ***
							(16.74)
Stock controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-time f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	5,516,503	5,518,881	5,518,881	5,665,820	5,665,820	5,667,510	5,667,510
Adj. R-Squared	0.131	0.131	0.131	0.131	0.131	0.131	0.131