# The True Colors of Money: Racial Diversity and Asset Management*

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**Abstract**

We study the role of race and ethnicity in the investment decisions of mutual fund managers and investors. Funds managed by white-dominant teams allocate smaller portfolio weights to firms led by minority CEOs compared to funds managed by minority-dominant teams. Minority-dominant fund management teams do not deliver superior performance on held firms led by minority CEOs, suggesting no race-related informational advantage. Considering flow-performance sensitivity, funds managed by minority-dominant teams are equally penalized for poor performance but are not rewarded as much for superior performance compared to white-dominant funds. Our results uncover differential treatment of minority-led funds and firms by investors.

**Keywords:** Racial/Ethnic Diversity, Mutual Funds, Social Identity Theory, In-group Bias, Flow-to-performance Sensitivity

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# 1 Introduction

Over the past few decades, the U.S. population has gone through seismic demographic shifts. The U.S. Census Bureau reports that in 2020, non-Hispanic whites accounted for 60.1% of the U.S. population, down from 69.1% in 2000 and 79.6% in 1980. The Bureau projects that this percentage will decline to 56% by 2030 and 44% by 2060.[1] Clearly, America is becoming more racially and ethnically diverse, and this trend is driving historical, cultural, political, and economic consequences. The focus on immigration and racial issues in the 2016 and 2020 elections, the recent resurgence in white supremacy, and the rise of the Black Lives Matter movement have all brought racial and ethnic issues to the forefront of U.S. politics and news cycles.[2] At the same time, diversity, equity, inclusion, and support for underrepresented minorities have become key pillars in the code of conduct of corporate America as well as in U.S. academic institutions.

The prominence of these demographic changes underscores the need for better understanding of the economic consequences, along with the potential biases and inequities, associated with ethnic and racial attributes. This study takes a step in that direction. We focus our attention on the role of race and ethnicity in the investment decisions of mutual fund managers and investors.

With over $20 trillion in assets under management, the mutual fund industry presents a natural environment for studying the economic consequences and potential inequities associated with racial diversity.[3] Indeed, the identities of both mutual fund managers and the executives of the firms in which they invest are publicly available and their racial affiliation can typically be identified. We

1. See Table 3 in "Demographic Turning Points for the United States: Population Projections for 2020 to 2060" by Jonathan Vespa, Lauren Medina, and David M. Armstrong, available at https://www.census.gov/content/dam/Census/library/publications/2020/demo/p25-1144.pdf. For the year 2020 numbers see https://www.census.gov/quickfacts/fact/table/US/POP010220.

2. Throughout the paper, we follow the conventional distinction between the terms "race" and "ethnicity," whereby racial affiliation focuses on physical attributes, while ethnicity refers to origin, culture, language, or religious affiliation. For our purposes, we adhere to the U.S. Census standard that considers White, Black, Asian, and American Indian as races, while Hispanic is considered an origin, and thereby associated with ethnic (rather than racial) affiliation. Moreover, we follow the convention of considering non-Hispanic Whites as the majority and all others as minorities, which includes Hispanics, Blacks, Asians, and American Indians. For expositional ease, we sometimes use the term "racial affiliation" to reflect both racial and ethnic affiliation.

3. See for example https://www.statista.com/statistics/255518/mutual-fund-assets-held-by-investment-companies-in-the-united-states/.

exploit this convenient feature to construct a comprehensive database of the racial affiliations of both mutual fund managers and the executives of the firms in which mutual funds invest.

We then study the investment choices and performance of white-dominant vs. minority-dominant mutual fund management teams and how they relate to the race of the executives of the firms in which they invest. We also study how investors respond to the success or failure of white-dominant vs. minority-dominant mutual fund management teams. These analyses allow us to assess whether white-dominant and minority-dominant fund management teams—and white and minority-led companies—are treated equally by investors.

We find that mutual funds that are managed by white-dominant teams allocate lower portfolio weight to firms led by minority CEOs when compared to minority-dominant management teams. However, fund managers do not exhibit superior performance on equity holdings for which the CEO's race coincides with their own, suggesting no race-related informational advantage. When considering flow-performance sensitivity, we find that, compared to white-dominant mutual funds, minority-dominant funds are equally penalized when they perform poorly but not equally rewarded when presenting superior performance. Taken together, our results are consistent with the view that both mutual funds and firms that are led by minorities receive unequal treatment from investors.

To facilitate our analysis, we first construct a comprehensive dataset identifying the racial/ethnic identities of 41,147 actively-managed U.S. mutual fund managers and C-suite executives of U.S.-listed firms during the period of 2007 to 2017. To achieve this, we manually search for these individuals over company websites, press releases, news articles, annual reports, social media sites such as LinkedIn, and other sources. We then use photos, videos or biographical information to deduce the individual's racial/ethnic identity. This search allows us to obtain the race/ethnicity in 78% of the cases (32,182 individuals). To deduce the race/ethnicity in the remaining cases, we develop a simple algorithm that estimates the probability that a given pair of first and last names belongs to a certain race/ethnicity. This algorithm relies on Bayesian inference in conjunction with baseline frequency tables for first and last names in the U.S. population obtained from Harvard

Dataverse and the U.S. Census Bureau.[4] The manual search and the algorithm jointly identify the race/ethnicity of 40,448 individuals (98.7% of executives and fund managers in the sample).

In our first set of analyses, we study how the decision of a mutual fund to include a given company in its portfolio is associated with the racial diversity of the fund's management team vis-à-vis the race of the firm's CEO. We find an in-group racial tilt in fund managers' portfolios – specifically, mutual fund management teams dominated by white individuals allocate a higher portfolio weight to firms led by white CEOs compared to minority-dominant fund management teams. The racial/ethnic affiliation of non-CEO executives does not appear to be influential on fund managers' investment decisions, reflecting the prominence of the CEO role. To check the robustness of these results, we conduct a placebo test in which we replace actively-managed funds with passive funds. Here we find no difference in the investment weight of white-dominant vs. minority-dominant fund management teams in firms led by minority CEOs. This reinforces the view that it is the investment choices of fund managers in actively-managed funds that contribute to the different investment patterns associated with the identity of the firm's CEO.

We consider two possible explanations for the in-group racial tilt. The first is social identity preference, according to which individuals favor others affiliated with groups to which they belong (Tajfel and Turner 1979; Akerlof and Kranton 2000). Alternatively, the different investment patterns may be the result of an informational advantage. For example, the investment decisions of minority-dominant funds may be driven by firm-relevant information about firms managed by minority CEOs. To differentiate between these two hypotheses, we consider the performance of firms held by mutual funds stratified by the racial/ethnic identity of their CEO. If the racial tilt is driven by social identity preference rather than informational advantage, we would expect minority-dominant funds' holdings in minority-led firms not to outperform their holdings in white-led firms. Alternatively, if the racial tilt is driven by information, minority-dominant funds may have superior performance on their holdings in minority-led firms compared to white-led firms.

4. The first dataset provides frequencies of first names by race/ethnicity based on information extracted from three distinct proprietary mortgage application datasets. The Census data provides frequencies of last names. For details on the data, please see Section 3.2.2.

To test which channel explains the fund managers' investment decisions, we form portfolios using the equity holdings of minority-dominant and white-dominant funds, and compare the performance of their equity holdings broken down by the firm CEO's race. We find that the performance of minority-led and white-led firm holdings are not statistically different across minority-dominant and white-dominant funds. These results suggest that informational advantage is less likely to explain the differential investment patterns of minority-dominant and white-dominant funds.

In our final analysis, we consider how the response of mutual fund investors to fund performance is associated with the racial diversity of the fund's management team. It is well documented that mutual fund returns and fund flows are related (Sirri and Tufano 1998; Brown, Harlow, and Starks 1996; Chevalier and Ellison 1997). That is, superior performance is rewarded by inflows and poor performance is penalized by outflows. In our setting, we find that investors withdraw capital from minority-dominant and white-dominant funds following poor performance in a similar manner. By contrast, the inflows following superior performance of white-dominant funds are significantly higher than the corresponding inflows for minority-dominant funds. That is, minority-dominant funds suffer similar penalties following poor performance but do not experience the full benefits of positive inflows following good performance.

Taken together, our results suggest that both minority-dominant funds and firms experience unequal treatment by investors. The vast majority of funds are led by white-dominant teams, who allocate lower weights to firms led by minority CEOs in their portfolios. This difference is not likely to be driven by informational advantage, as both white-dominant management teams and minority-dominant teams do not demonstrate better performance for firm holdings in which the CEO's race coincides with their own. Finally, investors respond differently to the performance of minority-dominant vs. white-dominant funds; the former are equally penalized for poor performance but not equally rewarded following superior performance as measured by fund flows.

The paper proceeds as follows. Section 2 reviews related literature. Section 3 describes the data, our process of identifying racial/ethnic identity, and summary statistics. Sections 4 and 5 provide empirical results. Section 6 concludes. An internet appendix provides details on the race identification procedures as well as auxiliary results.

## 2 Literature Review

Despite the growing attention to the role of racial diversity in organizations and society in general, formal evidence on the role of race in capital markets is relatively scarce. Our paper contributes to several strands of the literature. First, our work fits into the large literature on the role of culture in the determination of economic outcomes (Guiso, Sapienza, and Zingales 2006). Grinblatt and Keloharju (2001) document that cultural background could influence investors' tendency to trade certain stocks. Other aspects of culture, such as religion and heritage, also appear to affect corporate decision-making (Hilary and Hui 2009; Pan, Siegel, and Yue Wang 2020). Merkley, Michaely, and Pacelli (2020) find that cultural differences among agents produce higher quality consensus forecasts among sell-side analysts. Our paper documents how racial affiliation is related to capital flows in financial markets. Specifically, we relate racial affiliation to mutual fund portfolio choice and investors' flows to mutual funds. We focus our attention on the mutual fund industry as an important financial intermediary facilitating capital flows from investors to firms.

We also contribute to the literature on mutual fund managers' portfolio choices. On the one hand, fund managers could have an informational advantage facilitating their investment choices (e.g., through social networking (Cohen, Frazzini, and Malloy 2008)). On the other hand, fund managers could be systematically biased in their portfolio choices due to personal or other preferences (e.g., home bias (Pool, Stoffman, and Yonker 2012) and partisan affiliation (Wintoki and Xi 2019; Evans et al. 2020), among others). Our work explores the role of racial affiliation, a key individual characteristic, in managers' decision-making by considering the racial identities of both fund managers and the CEOs of firms in which they choose to invest.

Furthermore, our results relate to the literature on in-group bias and favoritism and their effect on economic outcomes. Individuals tend to do business with people who share similar backgrounds to theirs (Tajfel and Turner 1979; Akerlof and Kranton 2000). Such in-group bias has been documented in various settings, including court decisions (Depew, Eren, and Mocan 2017), loan approvals (Pan, Siegel, and Yue Wang 2020) and resume screening by employers (Bertrand and Mullainathan 2004). More closely related to our paper, Kumar, Niessen-Ruenzi, and Spalt (2015) show that funds with managers who have foreign-sounding names experience lower annual fund flows.[5] Our paper differs by studying the racial affiliation of both mutual fund managers and the CEOs of the firms in which they invest and by identifying the actual racial/ethnic identities of fund managers and firm executives.

Lastly, our results on flow-performance sensitivity add to the literature studying the determinants of investors' choices among mutual funds. Prior literature mainly focuses on fund manager skills.[6] Recent evidence shows that investors may also take into account non-financial factors, such as a fund's corporate social responsibility (Hartzmark and Sussman 2019). Our results on the differential flow-performance sensitivity between minority-dominant and white-dominant fund management teams highlight racial affiliation as another factor in investors' choices.

# 3 Data and the Identification of Race/Ethnicity

## 3.1 Data

Our sample period is January 2007 to December 2017. We combine data from various sources. The primary mutual-fund data come from the survivorship-bias-free Morningstar Direct Database, which provides the full names of mutual fund managers and their start and end dates with the fund. We restrict attention to US domestic equity funds – funds that invest more than 90% of their holdings in domestic US equities in at least one year during our sample period. We obtain additional mutual fund information from the CRSP Mutual Fund Database, which provides fund class level information such as fund returns, share classes, total net assets (TNA), fund family,

5. Kumar, Niessen-Ruenzi, and Spalt (2015) identify foreign-sounding names using surveys asking participants whether certain names sound foreign. They do not directly consider racial affiliation as we do in this paper.

6. Researchers have considered skill measures based on a variety of return benchmarks, such as raw returns (Bergstresser and Poterba 2002; Ivković and Weisbenner 2009), market-adjusted returns (Chevalier and Ellison 1997; Barber, Huang, and Odean 2016), alpha estimates (Del Guercio and Tkac 2002; Sensoy 2009), etc.

and expense ratio, among other fund characteristics. To conduct our analysis, we aggregate fund class level information to fund portfolio level.[7] Fund size is calculated as the sum of total net asset values across share classes, whereas fund return, fund flows, and expense ratios are calculated as the size-weighted average. We exclude funds with less than $10 million in TNA.

Given that our research question considers the active investment decisions of mutual-fund managers, we restrict attention to actively-managed funds only.[8] Similar to Pool, Stoffman, and Yonker (2012), we only include in our sample funds in the nine Morningstar style categories,[9] to avoid balanced funds, target-date funds, and industry-specific funds. Our final mutual fund data consists of 1,843 funds with 3,881 portfolio managers.

We obtain quarterly mutual fund holdings data from Thomson Reuters. We merge these data with CRSP and Morningstar using the MFLinks dataset.[10] We match fund holdings data with the held firms' returns and characteristics obtained from CRSP and Compustat.

We obtain the full names (first, last, and middle initials) of C-suite executives of firms included in the portfolios of the mutual funds in our sample from ExecuComp and Capital IQ by filtering on job titles.[11] ExecuComp covers S&P 1500 firms starting from 1992, while Capital IQ covers a larger range of firms starting from 1996. Following the executive compensation literature, we rely first on ExecuComp as a source for executive data, and we rely on Capital IQ whenever C-suite executive information is not available from ExecuComp. Our final firm dataset consists of 6,179 firms and 37,266 C-suite executives of which 8,726 are Chief Executive Officers.

7. Mutual funds often feature several share classes targeting different types of investors. Nevertheless, the portfolio compositions across share classes are usually identical.

8. We do this by filtering out managed mutual funds for which the index fund flag from CRSP equals "D" or when the fund's name includes words like "Index," "Idx," or "index." We also exclude funds that consistently hold more than 500 different equity securities, as such funds are effectively functioning as index funds even though their name does not identify them as such.

9. Morningstar style categories are constructed as a 3-by-3 size/value grid (i.e., Large Blend, Large Growth, Large Value, Mid-Cap Blend, Mid-Cap Growth, Mid-Cap Value, Small Blend, Small Growth, or Small Value).

10. We restrict Thomson Reuters holdings data to observations where FDATE is equal to RDATE, following the data cleaning process in Pool et al. (2019).

11. In Capital IQ, we use the field "ProfunctionName" which contains C-suite keywords, including Chief Executive Officer, Chief Operating Officer, Chief Administrative Officer, Chief Compliance Officer, Chief Financial Officer, Chief Information Officer, Chief Investment Officer, Chief Legal Officer, Chief Technology Officer, and Chief Operations Officer. Similarly, we use the field "TITLE" to identify C-suite members from ExecuComp.

## 3.2 Identifying racial/ethnic affiliation

Overall, we need to identify the racial/ethnic identities of 41,147 (37,266+3,881) different fund managers and C-suite executives. Similar to the U.S. Census Bureau, we consider the following categories: white, black, American indian, Asian, and Hispanic. We are able to complete this identification through manual search for 32,182 individuals (78%). For the remaining 8,965 we apply an algorithm, which identifies the race of 8,430 of them, while 535 individuals remain unidentified (1.3%). We now describe the identification process in detail.

### 3.2.1 Manual search

Our primary method for identifying the race of fund managers, CEOs, and other C-suite executives is employing research assistants who manually search names in our sample over company websites, press releases, news articles, company annual reports, social media sites such as LinkedIn, and other web sources. Examples of these web sources are provided in Figure A1 in the Online Appendix. We identify the race of an individual by considering available photos, videos, and biographical information such as their birth location, educational institutions, past/current employers, and professional affiliations. Using this manual process, we are able to identify the race/ethnicity of 32,182 individuals, 78% of the fund managers and C-suite executives in our sample.[12]

### 3.2.2 Algorithm for identifying race

To identify the race of the remaining 22% of individuals in our database, we employ an algorithm relying on the first and last names of these individuals and their frequencies in populations of certain races and ethnicities obtained from two databases. First, we rely on the 2010 U.S. census

12. An alternative source of racial/ethnic affiliation for corporate executives is the Institutional Shareholders Services (ISS) database. This data source focuses on members of boards of directors and named executive officers and does not cover mutual fund managers at all. The ISS database identifies the race of 3,264 out of the 37,266 C-suite executives in our data (about 8.8%). Thus the ISS database is not sufficiently comprehensive for our purposes. Nevertheless, for the subset of C-suite executives covered by ISS, we compare our manual identification of race/ethnicity with theirs for the purpose of accuracy validation. We find that in 94.9% of these cases, our racial/ethnic identification is identical to that of ISS. Of the remaining 5.1% of the individuals (169 individuals), our manual search is able to identify the race of 77 individuals. We have double checked the race of each one of these individuals and in nearly all cases, we found that our manual identification was the correct one.

data, which provides the frequency of surnames in the U.S. population by racial/ethnic affiliation. The second dataset is obtained from Harvard Dataverse, which provides a list of first names by race based on information from three distinct proprietary mortgage datasets.[13].

For each first or last name, these two data sets provide a powerful statistical tool for estimating the probability that an individual is affiliated with a particular racial/ethnic group through Bayesian inference. The details of the identification algorithm are described in the Online Appendix, where we also discuss the algorithm's accuracy. Overall, the algorithm correctly identifies about 98.7% of individuals. We prefer the manual search to the algorithm as a primary identification method because the algorithm tends to under-identify minorities, especially black individuals. Thus, we use the algorithm only when the manual search fails. Out of the 8,965 individuals unidentified by manual search, the algorithm identifies the race/ethnicity of 8,430. Finally, 535 individuals remain unidentified even after applying the algorithm.

#### 3.2.3 Measuring racial diversity

Mutual funds are typically managed by teams of portfolio managers (Patel and Sarkissian 2017). We measure the fund's management team's racial diversity by considering the racial/ethnic affiliations of all managers in the team. We designate a fund manager as a "minority" if her racial affiliation is not "non-Hispanic White." We consider a fund to be minority-dominant if the ratio of managers with a minority affiliation exceeds 50%, and white-dominant otherwise. We also sometimes use the term all-white to designate funds for which all managers are white.

13. The three distinct mortgage datasets include: (1) mortgage applications from a lender in 2010; (2) a merged dataset between HMDA and DataQuick for 2010 that excludes any loans from the lender in the first dataset; and (3) mortgage applications from a subprime lender in 2007. The data is from Tzioumis (2018), which includes 4,250 unique first names and their classifications on six mutually exclusive racial and ethnic origins in US. The link to the data is here: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/TYJKEZ

### 3.3 Summary statistics

Table 1 reports summary statistics of fund and firm characteristics as well as the race and gender distributions of leadership in funds and firms.[14] Panel A depicts the racial distribution of fund management teams. It shows that 92% of individual portfolio managers are white. This is in stark contrast to the percentage of white individuals in the U.S. population, which ranges between 61% and 69% during our sample period. Jointly considering gender and race together, we document that 86% of portfolio managers in our sample are white males. On the management team level, about 79% of teams are all-white, 14% are white-dominant (but not all white), and about 7% of management teams are minority-dominant.

Panels B and C of Table 1 show the race distribution of firm CEOs and C-suite executive teams. We find that the proportion of white individuals is around 93% for CEOs and C-suite executives alike. Jointly considering race and gender, we document that about 90% of CEOs and 86% of C-suite executives are white males.

It is also interesting to consider the time trends of racial diversity among fund management teams and firm CEOs. Panel A of Figure 1 shows the total number of funds per year sorted by the racial diversity of their management team. Over the ten-year sample period, we observe a decline in the percentage of all-white management teams, suggesting that such teams have become more inclusive and started hiring minority managers. However, the increase in the percentage of funds managed by minority-dominant teams remains modest. On the firm side, Panel B shows there is also a modest increase in the number of firms with minority CEOs. As of 2017, about 6% of firms have minority CEOs as compared to 4.5% in 2007.

Panel D of Table 1 reports summary statistics for mutual fund characteristics in our sample. The average fund size is $1,368 million, the average expense ratio is 1.1%, the number of managers in a management team is 3.4 on average, and the average fund age is 12 years. About 13% of

14. Our focus in this paper is not on gender diversity, but we do include gender in our analysis as a control variable. We use GenderAPI to identify the gender of both mutual fund managers and firm leadership by their first name. We only keep the gender identification if the accuracy rate exceeds 90%. We consider a fund to be female-dominant if the ratio of female managers exceeds 50%.

funds are identified as socially conscious, and 31% are identified as direct-sold.[15] The panel also reports differences between the characteristics of white-dominant and minority-dominant funds. Minority-dominant funds tend to be smaller and younger, have higher turnover, and charge lower fees.

Panel E of Table 1 reports summary statistics for firm characteristics. The average firm size (total assets) in our sample is $9.82 billion, and the average firm age is 21. The number of C-suite executives is on average 3.2 per firm. About 93% of firms in the sample are headquartered in the U.S. The panel also reports differences between the characteristics of firms with white vs. minority CEOs. We find that firms with a minority CEO are smaller and younger and have lower investments, debt, and cash flows.

Panel A of Table 2 provides summary statistics for fund management teams' race/ethnicity, broken down into the nine Morningstar style categories. Overall, there is not much variation across styles, with the all-white category accounting for at least 73%-85% of funds and the minority-dominant category accounting for 3%-11% of funds across all styles. Panel B provides summary statistics for firm CEOs' race/ethnicity broken down into the Fama-French 12 industries. We find that minority CEOs are more prevalent in the Business Equipment – Computers, Software, and Electronic Equipment and the Healthcare, Medical Equipment, and Drugs industries. By contrast, some traditional industries such as Oil, Gas, and Coal Extraction and Production as well as Utilities have a much lower prevalence of minority CEOs.

# 4 Fund Management Racial Diversity and Portfolio Choice

In the classic portfolio choice problem, an investor's holdings in any assets are determined by their risk preference and beliefs. Recent literature has shown that investors' preferences on certain stocks could also be driven by other factors such as geographic preference (Sialm, Sun, and Zheng 2013; Pool, Stoffman, and Yonker 2012), corporate social responsibility (Starks 2009), and social

15. Following Sun (2014), we identify a fund as direct-sold if the fund does not have a share class that charges a front load, rear load, or 12b-1 fee greater than 25bps.

connectedness (Kuchler et al. 2020), among others. This section examines the role of the mutual fund management team's racial diversity in their portfolio choices. Specifically, we study whether the racial diversity of a mutual fund's management team is associated with the racial identity of the CEOs of the firms in which the fund invests.

According to the social identity theory developed by Tajfel and Turner (1979) and introduced into economic analysis by Akerlof and Kranton (2000), individuals have a tendency to assign others into categories ("categorization"), associate themselves with certain groups ("identification"), compare their own group with other groups ("comparison"), and create a favorable bias toward the group to which they belong. Such in-group favoritism has been demonstrated experimentally (Chen and Li 2009) and found in venture capitalists' co-investment decisions (Gompers, Mukharlyamov, and Xuan 2016).

Given that race and ethnicity serve as primary forms of social identity, we hypothesize that minority-dominant fund management teams are more likely to favor and hence invest in firms with minority CEOs. We focus primarily on the race/ethnicity of CEOs because they are the key decision-makers and the most high profile executives of the firm. CEO characteristics are also well documented to be associated with firm investment, profitability, and other key corporate decisions and outcomes. For example, CEOs' absences from headquarters are associated with critical corporate news disclosures (Yermack 2014). CEOs' over-optimism is associated with higher managerial effort that leads to higher profitability and market value (Hilary et al. 2016). CEOs' socioeconomic backgrounds affect their capital allocation decisions and firm investment efficiency (Duchin, Simutin, and Sosyura 2021). In Section 4.3, we also consider the role of the racial/ethnic identity of other C-suite executives.

We start with a univariate analysis of how a fund's holdings in firms are associated with the racial/ethnic diversity of the fund's management team vis-à-vis the race/ethnicity of the firms' CEOs. Table 3 presents the average percentage of mutual fund investment in firms with minority/white CEOs broken down by the racial diversity of the fund's management team. Overall, 94.2% of all funds under management are invested in firms led by white CEOs, as compared to

5.8% in firms led by minority CEOs. The relatively low weight assigned to firms with minority CEOs is expected given their low frequency as reported in the previous section. Minority-dominant funds, however, are significantly more inclined than white-dominant funds to invest in firms led by minority CEOs. The differences are both statistically and economically significant. Minority-dominant funds invest 0.61% more of their portfolio weight in minority-led firms than white-dominant funds do, which accounts for 10.6 percent ($= 0.61\%/5.78\%$) relative to the baseline portfolio weight invested in minority-led firms.

We next turn to formalizing these results through a regression analysis. In doing so, we need to control for both fund-level and firm-level characteristics. To facilitate this, we consider two versions of our analysis, one at the fund level and the other at the firm level. Together, these two analyses draw a complete picture of the racial tilt in fund managers' decisions.

## 4.1 Fund level analysis

To control for fund characteristics, we consider the following specification at the fund level for each fund $i$ and year $t$:

$$y_{it} = \beta_0 + \beta_1 MinorityFund_{it} + \gamma' X_{it} + \lambda_c + \mu_t + \varepsilon_{it}, \tag{1}$$

where $y_{it}$ is a measure of the excess weight assigned by fund $i$ in year $t$ to firms led by minority vs. white CEOs. Formally, it is the difference between the average of fund $i$'s portfolio weights invested in minority-led firms and those invested in white-led firms at the end of year $t$, that is:

$$y_{it} = \frac{\sum_{j \in \{MinorityCEOs_t\}} w_{ijt}}{\#\{MinorityCEOs_t\}} - \frac{\sum_{j \in \{WhiteCEOs_t\}} w_{ijt}}{\#\{WhiteCEOs_t\}}, \tag{2}$$

where $w_{ijt}$ is the share of fund $i$'s holding in firm $j$ at the end of year $t$, and $\{MinorityCEOs_t\}$ ($\{WhiteCEOs_t\}$) is the set of firms with minority (white) CEOs in year $t$.

The main variable of interest in eq. (1) is $MinorityFund_{it}$, which is a dummy variable equal to one when fund $i$'s portfolio management team is minority-dominant in year $t$. A positive coefficient on $MinorityFund_{it}$ indicates that minority-dominant fund teams assign higher weights to minority-led vs. white-led firms relative to white-dominant fund teams. A useful benchmark case to consider is if all funds followed a passive strategy of mimicking the market portfolio. In this case, $y_{it}$ would be constant across funds at any point in time, and the coefficient of $MinorityFund_{it}$ would be zero (controlling for year fixed effects). Thus, the sign of $MinorityFund_{it}$ is driven by fund managers' active deviations from a passive strategy. $X_{it}$ is a vector of control variables, consisting of the gender diversity of the fund management team, fund size, fund family size, fund age, turnover ratio, expense ratio, the fund's main distribution channel, and whether the fund is socially conscious. $\lambda_c$ are Morningstar style category ($c$) fixed effects and $\mu_t$ are year fixed effects.

The results are presented in Table 4. Controlling for year fixed effects, Column (1) shows that the coefficient of $MinorityFund_{it}$ is positive and statistically significant, indicating that relative to white-dominant funds, minority-dominant funds' portfolios assign higher investment weights to firms led by minority CEOs. When we further include the nine Morningstar style category fixed effects in Column (2), the coefficient on $MinorityFund_{it}$ remains positive and statistically significant with a slight drop in magnitude, suggesting that the results are not driven by fund style. Finally, in Columns (3) and (4), we split our sample into two subperiods, and find that the results are stronger in earlier years in the sample and slightly wane in more recent years. However, the difference between the two subperiods is statistically insignificant, suggesting the racial tilt we document is not driven by a specific subperiod of our sample.

## 4.2 Firm level analysis

To control for firm characteristics, we now look at the fund-firm relationship from the firm's point of view by considering the following model for each firm $j$ and year $t$:

$$y_{jt} = \beta_0 + \beta_1 MinorityCEO_{jt} + \gamma' X_{jt} + \lambda_d + \mu_t + \varepsilon_{jt}, \tag{3}$$

where $y_{jt}$ is a measure of the excess weight assigned to firm $j$ in year $t$ by funds led by minority-dominant teams vs. white-dominant teams. Formally, it is the difference between the average portfolio weight of firm $j$ across minority-dominant and white-dominant funds at the end of year $t$, that is,

$$y_{jt} = \frac{\sum_{i \in \{MinorityFunds_t\}} w_{ijt}}{\#\{MinorityFunds_t\}} - \frac{\sum_{i \in \{WhiteFunds_t\}} w_{ijt}}{\#\{WhiteFunds_t\}}, \tag{4}$$

where $w_{ijt}$ is fund $i$'s portfolio weight on firm $j$ at the end of year $t$, and $\{MinorityFunds_t\}$ ($\{WhiteFunds_t\}$) is the set of funds exceeding (not exceeding) 50% minority managers.

The main variable of interest in eq. (3) is $MinorityCEO_{jt}$, which is a dummy variable equal to one when firm $j$'s CEO is a minority in year $t$. A positive coefficient on $MinorityCEO_{jt}$ indicates that firms with minority CEOs tend to have a higher weight in fund portfolios managed by minority-dominant teams. As before, a useful benchmark case is if all funds followed a passive strategy of mimicking the market portfolio. In this case, $y_{jt}$ would be identically zero, and the coefficient of $MinorityCEO_{jt}$ would be zero as well. Thus, the sign of $MinorityCEO_{jt}$ reflects fund managers' deviations from a passive strategy. $X_{jt}$ is a vector of control variables consisting of firm size, investment, cash flow, firm age, debt ratio, CEO gender, number of C-suite members, and an indicator for whether the firm is headquartered in the U.S. $\lambda_d$ are industry ($d$) fixed effects and $\mu_t$ are year fixed effects.

The results are presented in Table 5. Column (1) shows that the coefficient on $MinorityCEO_{jt}$ is positive and statistically significant when controlling for year fixed effects, indicating that the difference in average investment proportion by minority-dominant vs. white-dominant funds is higher for minority-led firms as compared to white-led firms. Column (2) adds industry fixed effects with no major change to the results. Columns (3) and (4) distinguish between U.S. and non-U.S. firms. The racial tilt appears to be more pronounced for the group of foreign firms (accounting for about 7% of all firms) (Column (4)) but remains statistically significant when we only include firms headquartered in the US (Column (3)). Finally, in Columns (5) and (6), we split our sample period into two subperiods, and find that the results are significant in both.

## 4.3 Race and gender of the CEO and the rest of the C-suite

Our focus thus far has been on the race/ethnicity of the firm's CEO. However, it is possible that our documented racial tilt is not just associated with the CEO but also with other members of the firm's senior leadership team. To explore this, in column (7), we add a dummy variable equal to one if there is at least one minority C-suite executive, not including the CEO. We also control for whether at least one of the non-CEO C-suite members is female. We find that the minority CEO dummy coefficient remains statistically significant and similar in magnitude to that reported in the other columns. The coefficient on the dummies for CEO gender, the presence of non-CEO minority C-suite members, and the presence of non-CEO female C-suite members are all statistically insignificant. We conclude that the CEO's race is most relevant for the race preferences of portfolio managers.

## 4.4 Placebo Tests

To further validate our results, we now consider a setup in which a racial tilt is not expected. Specifically, we conduct the same racial tilt analysis at both fund and firm levels for passive funds. Unlike the managers of actively-managed funds, the focus of our analysis, portfolio managers of passively-managed funds normally replicate the weights of indexes. In such cases, the coefficients of the minority fund and minority CEO dummies in models (1) and (3) are expected to be zero. Thus, finding a racial tilt with index funds would be a way to falsify our main results.

To identify passively-managed mutual funds, we include those where the index fund flag from CRSP equals "D" or when the fund's name includes words like "Index," "Idx," or "index." We include passively-managed mutual funds in the nine Morningstar style categories. There are 156 such funds and their total net assets are about 1.0 trillion dollars across all years.[16] For this analysis, we need to identify the race of 155 additional individuals (151 fund managers and 4 firm

16. In comparison, for the 1,843 actively-managed funds used in the main analysis, the total net assets are about \$1.8 trillion dollars across all years. We do not include passively managed exchange-traded funds (ETFs), which have collectively attracted significant inflows in the past decade (ICI 2021).

executives). We are able to complete this identification through manual search for 133 individuals (86%); we use the algorithm to identify the race of the remaining 22.

Results for this analysis are presented in Table 6. Panel A considers the fund-level analysis and should be compared to Table 4. The coefficient of the minority fund dummy is not statistically significant. Thus, we do not find a racial tilt in the portfolios of passive funds. Panel B repeats the analysis at the firm level and should be compared to Table 5. The coefficient of the minority CEO dummy is not statistically different from zero, again demonstrating the absence of a racial tilt. These results reinforce our baseline results, showing that when fund managers choose their portfolios actively, race and ethnicity do play a role in their decisions.

## 4.5 Channel: Social identity vs. informational advantage

Taken together, our results suggest that a mutual fund management team's racial composition is associated with the race of the CEOs of the firms in their portfolios. In this section, we attempt to differentiate between two possible explanations for this result. The first is social identity theory, according to which minority-dominant fund managers tend to overweight firms with minority CEOs due to in-group favoritism (Tajfel and Turner 1979; Akerlof and Kranton 2000). An alternative explanation is that fund managers have an information advantage for firms led by CEOs with the same racial/ethnic identity. Indeed, the literature has documented that cultural proximity plays a role in information transmission (Du, Yu, and Yu 2017; Huang 2015). Under this hypothesis, minority mutual fund managers would also assign a higher weight to firms led by minority CEOs.

To differentiate between these two hypotheses, we consider a difference-in-differences setting to compare the return spread of minority-led holdings over white-led holdings between minority-dominant funds and white-dominant funds. The information advantage channel implies that this difference-in-differences in performance would be positive, reflecting that the minority-led holdings of minority-dominant firms outperform. By contrast, the social identity theory would not predict superior performance associated with same-race holdings, and could even imply a negative difference-in-differences in performance, reflecting that minority-dominant funds may sacrifice performance to accommodate their in-group preference.

To conduct the performance comparison, we first obtain the quarterly equity holdings of the mutual funds in our sample from the Thomson Reuters Mutual Fund Holdings dataset.[17] Using the quarterly holdings data, we decompose the portfolio of each fund into minority-led and white-led sub-portfolios based on the racial identity of the CEO of each held firm.[18] We rebalance these portfolios quarterly. Following Coval and Moskowitz (2001), we update the fund's portfolio holdings at the beginning of every quarter, on the basis of the reported holdings from the previous quarter, and hold them constant over the subsequent three months.

Next, we compute the average monthly returns of these two sub-portfolios among minority-dominant and white-dominant funds. Let $\bar{R}^{M}_{M,t}$ ($\bar{R}^{W}_{M,t}$) denote the average monthly return of the minority-led sub-portfolio among the minority-dominant (white-dominant) funds during month $t$. Similarly, $\bar{R}^{M}_{W,t}$ ($\bar{R}^{W}_{W,t}$) denotes the average monthly return of the white-led sub-portfolio among the minority-dominant (white-dominant) funds during month $t$.

We start with the difference in performance of the two sub-portfolios within minority-dominant (white-dominant) funds:

$$S^{M}_{t} = \bar{R}^{M}_{M,t} - \bar{R}^{M}_{W,t},$$

$$S^{W}_{t} = \bar{R}^{W}_{M,t} - \bar{R}^{W}_{W,t},$$

where $S^{M}_{t}$ ($S^{W}_{t}$) is the return spread of minority-led over white-led holdings for minority-dominant (white-dominant) funds. Assuming there are no systematic return differences between minority-led and white-led firms, the information advantage hypothesis would predict the average of $S^{M}_{t}$ is positive and the average of $S^{W}_{t}$ is negative over time, reflecting that minority-led holdings outperform for minority-dominant funds while white-led holdings outperform for white-dominant funds.

To address the concern that there might be systematic return differences between minority-led

17. In some cases where funds report their holdings on a semi-annual basis, we impute quarterly holdings from the most recent prior semi-annual holdings (up to two quarters).

18. Within each sub-portfolio, the weights applied to minority-led (white-led) holdings are rescaled to sum to one.

and white-led firms, we further consider a difference-in-differences performance measure:

$$D_t = S_t^M – S_t^W.$$

The information advantage hypothesis would predict this measure is positive. To calculate this measure, we use both raw returns and abnormal returns (alphas) using the CAPM and a 4-factor model (Fama and French 1993; Carhart 1997).

Table 7 reports the average monthly returns and alphas of the minority-led and white-led sub-portfolios over time for minority-dominant funds (Columns (1) to (3)) and white-dominant funds (Columns (4) to (6)). The last row presents the return spreads for minority-dominant funds ($S^M$) in Columns (1) to (3), white-dominant funds ($S^W$) in Columns (4) to (6), and the difference-in-differences measure ($D$) in Columns (7) to (9).

As Columns (1) to (3) show, minority-dominant funds earn similar returns in their minority-led and white-led holdings, and the return spread ($S_M$) is positive but statistically insignificant for all three return measures. The evidence does not support the hypothesis that informational advantage is the main driver for minority-dominant funds' racial tilt. For white-dominant funds, the evidence from Columns (4) to (6) shows they also earn similar returns in their two sub-portfolios, which again is inconsistent with the informational advantage hypothesis. Moreover, the difference-in-differences performance measures ($D$) in Columns (7) to (9), which adjust for potential systematic patterns associated with the race of CEOs, are also statistically insignificant. We have also conducted this analysis over sub-samples of funds based on their characteristics such as fund size, fund age, and the tendency of funds to hold minority-led firms. In all cases, we did not find a statistically significant difference associated with either the return spreads ($S^M$, $S^W$) or the difference-in-differences measure ($D$) (see Appendix Table A3). Taken together, we do not find any evidence supporting that minority-dominant funds outperform on their minority-led holdings. These results suggest that the racial tilt in a mutual fund's portfolio is likely driven by a favorable preference based on social identity rather than superior information.

# 5 Fund Management Racial Diversity and Flow-Performance Sensitivity

We have so far considered the role of race and ethnicity in mutual fund managers' portfolio choices. Our results show that there is a racial tilt in a mutual fund manager's portfolio, which is likely to be driven by a race-related social identity preference. Therefore, firms likely receive differential treatment in their financing process, given the racial tilt in mutual fund portfolios and the lack of racial diversity in mutual fund management teams. This naturally raises the question of why the level of racial diversity is and remains low in the mutual fund industry.

One hypothesis is that mutual fund investors may exhibit differential treatment on the dimensions of race and ethnicity when they make investment decisions or evaluate fund performance. [19] In this section, we examine mutual fund investors' flow-performance sensitivity and how it varies across minority-dominant and white-dominant funds.

## 5.1 Graphical evidence

Prior literature has long documented the phenomenon of investors chasing past returns and the convex relationship between flow and fund performance (Sirri and Tufano 1998; Brown, Harlow, and Starks 1996; Chevalier and Ellison 1997). Figure 2 displays the flow-performance relationship for minority-dominant and white-dominant funds using a non-parametric approach. The horizontal axis is the rank of the fund's past performance in month $t-1$ measured by the percentile rank of its average monthly return from month $t-12$ to $t-1$. The vertical axis is the monthly flow measured by the percentage growth of new assets, assuming that all flows take place at the end of the month:

$$Flow_{it} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t})}{TNA_{i,t-1}}, \tag{5}$$

19. Other hypotheses include lack of racial diversity in the talent pipeline which restricts the labor market supply, or entrenched managers who prefer homogeneous teams (Evans et al. 2020).

where $TNA_{i,t}$ is fund $i$'s total net assets at the end of month $t$, and $R_{i,t}$ is the fund's return over month $t$.

As previously demonstrated in the literature, the figure shows a general positive relationship between flows and past performance for both minority-dominant and white-dominant funds. The differences in investors' flow responses between minority-dominant funds and white-dominant funds mainly appear for top performers (i.e., above the 90th percentile). While flows increase dramatically when white-dominant funds present superior performance, this convex pattern in the flow-performance relationship does not replicate for minority-dominant funds. In contrast, the difference in investors' flow responses between these two groups of funds is only marginal for bottom performers (i.e., below the 10th percentile); the flow-performance sensitivity for these two groups of funds is quite similar among medium performers. The figure suggests that minority-dominant funds earning superior returns do not garner disproportionate inflows as dramatically as white-dominant funds, but are similarly penalized when they perform poorly.

## 5.2 Piece-wise linear regression

To formally examine whether the flow-performance sensitivity varies across minority-dominant and white-dominant funds, we estimate the following piece-wise linear regression of flow on past performance, allowing for convexity:

$$
\begin{aligned}
Flow_{it} = \beta_0 &+ \beta_1 Perf^{Bottom}_{i,t-1} + \beta_2 Perf^{Medium}_{i,t-1} + \beta_3 Perf^{Top}_{i,t-1} + \theta_0 I_{MinorityFund,it-1} \\
&+ \theta_1 Perf^{Bottom}_{i,t-1} \times I_{MinorityFund,it-1} + \theta_2 Perf^{Medium}_{i,t-1} \times I_{MinorityFund,it-1} \\
&+ \theta_3 Perf^{Top}_{i,t-1} \times I_{MinorityFund,it-1} + \gamma' X_{it-1} + \lambda_c + \mu_t + \varepsilon_{it},
\end{aligned} \tag{6}
$$

where $Flow_{it}$ is the monthly flow defined in eq.(5), $I_{MinorityFund,it-1}$ is a dummy variable equal to one when fund $i$'s portfolio management team is minority-dominant in month $t-1$, $X_{it-1}$ is a vector of control variables, and $\lambda_c$ and $\mu_t$ are Morningstar style category ($c$) fixed effects and month fixed effects.

The specification follows a standard piece-wise linear setup, in which we estimate the flow-performance sensitivity separately for the bottom 10%, the middle 80%, and the top 10% performance. Specifically, we define:

$$
\begin{aligned}
Perf_{i,t-1}^{Bottom} &= min(Perf_{i,t-1}, c_{10}), \\
Perf_{i,t-1}^{Medium} &= max(min(Perf_{i,t-1} - c_{10}, c_{90} - c_{10}), 0), \\
Perf_{i,t-1}^{Top} &= max(Perf_{i,t-1} - c_{90}, 0),
\end{aligned}
$$

where $Perf_{i,t-1}$ is fund $i$'s performance at time $t-1$ measured by the percentile rank of its average monthly return from month $t-12$ to $t-1$, and $c_p$ is the $p$-th percentile of fund $i$'s performance at time $t-1$.

We then augment this piece-wise linear regression with the interaction term between the three performance variables with the minority-dominant fund indicator ($I_{MinorityFund,it-1}$). The coefficients on the three performance variables capture the flow-performance sensitivity of the three (i.e., bottom, middle, and top) regions for the white-dominant funds, and the coefficients on the interaction terms capture the difference in flow-performance sensitivity between minority-dominant and white-dominant funds. Control variables include fund characteristics (i.e., fund size, fund family size, social conscious dummy), month fixed effect, and Morningstar style category fixed effects. The standard errors are double clustered at the fund and month level.

The results are presented in Table 8. Notice that the coefficients on $I_{MinorityFirm,jt-1}$ are not statistically significant, indicating that on average there is no significant difference in the flows into minority-dominant funds vs. white-dominant funds, controlling for fund characteristics. In other words, we do not find that minority-dominant funds on average attract fewer flows than non-minority funds. However, the evidence does show that the racial composition of fund management teams affects how investors' flows respond to past fund performance. The coefficient on the interaction term between fund performance and the minority-dominant fund indicator in the top performance region is negative and statistically significant, suggesting that investors respond less to the superior performance of minority-dominant funds than they do that of white-dominant funds.

In contrast, the coefficients on the interaction terms for the middle and bottom performance regions are statistically insignificant. Consistent with the graphical evidence, our regression results suggest that minority-dominant fund management teams are not rewarded as much as white-dominant teams for their superior performance but are equally penalized for their poor performance.

These results are consistent and nicely complement recent evidence documented in an experimental setting in the venture capital investing literature. Lyons-Padilla et al. (2019) find that asset allocators favored the white-led, racially homogeneous venture capital fund team when credentials were stronger. However, our results do not support their finding that asset allocators favored the black-led, racially diverse team when credentials were weaker.[20] Similar effects have been documented in the labor market as well. Through a field experiment, Bertrand and Mullainathan (2004) find that race affects the benefits of a better resume – a higher quality resume elicits 30% more callbacks for white names but a far smaller increase for African-American-sounding names.

## 5.3 Heterogeneity analysis

The key result from the previous analysis is the existence of differential flow-performance response related to the racial diversity of a fund's management team. Such differential responses may be driven by investors' different levels of coarse thinking (Mullainathan, Schwartzstein, and Shleifer 2008) – stereotype or categorization – related to race and ethnicity. When mutual fund investors are subject to coarser stereotypes or categorization, they respond less to informational content (e.g., a fund manager's past performance). Therefore, our findings suggest that mutual fund investors have coarser stereotypes or categorization towards funds managed by minority-dominant teams as compared to funds managed by white-dominant teams, consistent with the interpretation proposed by Bertrand and Mullainathan (2004). We next explore heterogeneity in these differential responses across characteristics of both investors and funds to provide further evidence for this explanation.

20. Lyons-Padilla et al. (2019) conducted an online experiment with actual asset allocators and asked them to rate venture capital funds based on a one-page summary of the fund's performance history, in which they manipulated the race of the managing partner (white or black) and the strength of the fund's credentials (stronger or weaker).

**Heterogeneity by investor characteristics.** Our interpretation requires investors to pay attention to the racial composition of fund management teams; however, mutual funds are often owned by retail investors who are documented as unsophisticated and paying limited attention to less salient information.[21] Therefore, given the low salience of fund management profile information, one concern with our interpretation is that the differential flow responses may be driven by other confounding fund characteristics rather than race.

To address this concern, we split mutual fund investors by their level of sophistication, assuming that more sophisticated investors are more likely to pay attention to the profiles of fund managers. We measure investor sophistication by a fund's distribution channel (Barber, Huang, and Odean 2016; Guercio and Reuter 2014, and classify a fund as direct-sold (more sophisticated) or broker-sold (less sophisticated) following Sun (2014). We conduct the same piece-wise linear regression of eq.(6) for direct-sold and broker-sold funds. The results are reported in Columns (1) and (2) of Table 9. Consistent with our hypothesis, the differential responses related to the racial diversity of fund management teams are only manifested with sophisticated investors (direct-sold funds), and are statistically insignificant for less sophisticated investors (broker-sold funds).

**Heterogeneity by fund characteristics.** Next, we explore the heterogeneity of racial differential flow responses across fund size and age. We hypothesize that small and young funds do not have a sufficient track record, and thereby investors in such funds are more prone to resorting to coarse thinking, stereotypes, or categorization. For small and young funds, factors affecting investors' level of coarse thinking and stereotyping – the racial diversity of fund management teams being one such factor – may materially affect how investors respond to incremental information. To this end, we expect the wedge in flow-performance sensitivity between minority-dominant and white-dominant funds to be more pronounced among small and young funds.

To test this hypothesis, we split funds into two groups based on whether their fund size falls

21. For example, Barber, Odean, and Zheng (2005) find that investors pay less attention to fund expenses relative to fund loads. Investors use resources learning about a fund when they make their initial investments but cease learning afterwards (Bergstresser and Poterba 2002). Also, investors' disagreement across fund managers' skills does not increase after a change of fund managers (Schwarz and Sun 2021).

below or above the median in each year, and whether their total net assets falls below or above the median in each year. We run the same piece-wise linear regression of eq.(6) for different groups separately. The results are reported in Columns (3) to (6) of Table 9. As Columns (3) and (4) show, the main effects on a fund's past performance in the top region captures the flow response to top performance for white-dominant funds. This evidence that, among white-dominant funds, younger funds have a higher flow response to superior performance than older funds is consistent with the previous literature (Chevalier and Ellison 1997; Spiegel and Zhang 2013). More importantly, as predicted in the discussion above, the coefficients on the interaction term for the top performance measure show that the differential responses to superior performances between white-dominant and minority-dominant funds are more pronounced for young funds than old funds. Similarly, when considering large vs. small funds (Columns (5) and (6)), we observe a pattern in line with our hypothesis, although the difference between the interaction terms for top performances are not statistically significant.

Taken together, we find differential flow-performance sensitivity related to the race/ethnicity of the fund management teams. For poor performance, minority-dominant and white-dominant funds are equally penalized; however, for superior performance, investors reward white-dominant teams more and minority-dominant teams less. These results only appear for direct-sold funds whose investors are more sophisticated and likely to perform more due diligence on information about a fund's management. We also find more pronounced results for younger and smaller funds, whose investors are more prone to coarse thinking (i.e., stereotypes or categorization), supporting the explanation that mutual fund investors have coarser stereotypes or categorization for minority-dominant funds as compared to white-dominant funds.

# 6 Conclusion

We study the role of race and ethnicity in the investment decisions of mutual fund managers and mutual fund investors. We identify the race/ethnicity of mutual fund managers and firms' leadership using their full names and applying a manual search supplemented by a Bayesian algorithm. We document that the proportion of minority fund managers and C-suite executives is small in comparison to the growing proportion of minorities in the U.S. population. Minorities comprise only 7.8% of fund managers and 6.5% of firm CEOs. We examine the role played by racial diversity in capital flows within the mutual fund industry by focusing on mutual fund managers' portfolio choices and on funds' flow-performance sensitivity.

Our results show that white-dominant, actively-managed fund teams invest a smaller proportion of their portfolio in firms led by a minority CEO than funds managed by a minority-dominant team do. Our placebo test reinforces this result, as we do not observe a similar racial tilt within passive funds. We find that fund managers do not deliver superior performance on equity holdings for which the CEO's race coincides with their own, suggesting that the portfolio tilt is not driven by an informational advantage. Though we propose that the racial tilt is likely driven by social identity theory (social categorization), such non-pecuniary preference may also be driven by social connections or geographic proximity; the racial tilt can also be affected by awareness or familiarity. Providing further evidence for these various mechanisms could be an avenue for future research.

Considering flow-performance sensitivity, we document a race-related asymmetry in the way fund managers are compensated based on their performance. Specifically, we find that funds managed by a minority-dominant team are equally penalized when they perform poorly but are not rewarded as much for superior performance when compared to white-dominant funds. Though without observing the race/ethnicity of mutual fund investors, we cannot directly examine a similar racial tilt in their portfolios, future research could explore this direction in an experimental setting or in another context.[22]

Our research is closely related to the increase in public discussion of racial/ethnic diversity in U.S. corporations. Along with leading institutional investors' recent engagement in promoting board ethnic diversity[23], and state legislatures enacting laws to mandate ethnic minority quotas on

22. For example, a recent paper by D'Acunto et al. (2021) that studies a P2P lending platform in India finds pervasive and sizable in-group vs. out-group discrimination in individual lenders' decisions.

23. See 2021 proxy voting guidelines for BlackRock (https://www.blackrock.com/corporate/literature/fact-sheet/blk-responsible-investment-guidelines-us.pdf) and State Street (https://www.ssga.com/library-content/pdfs/asset-stew

corporate boards,[24] our study highlights an additional important channel embedded in investment decisions that may affect racial/ethnic diversity in U.S. corporations. Given our evidence that actively managed funds exhibit race-related differential treatment in their investment decisions and receive race-related differential flow incentives from their investors, the racial composition of fund management teams may shape the allocation of capital to firms and contribute to the racial diversity in U.S. corporations. Our comprehensive dataset of the racial and ethnic identities of major players in the financial market may facilitate future research on race-related topics on the corporation side. For example, our data can help explore how the recent engagement of institutional investors and state legislatures affects the racial diversity of leadership teams of U.S. corporations, how these two forces will interact with the channel of differential treatment from actively managed funds, and how the economic activities and valuation of the firms will be affected.

ardship/racial-diversity-guidance-article.pdf)

24. Recently, California (2020 AB 979) became the first state to pass legislation mandating ethnic minority quotas on corporate boards.

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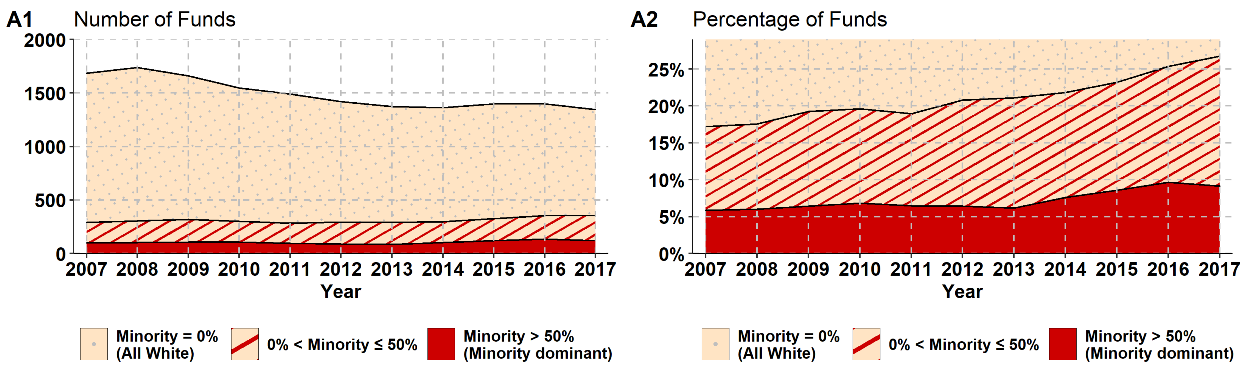
Panel A: Fund Manager Race Distribution




Panel B: Firm CEO Race Distribution

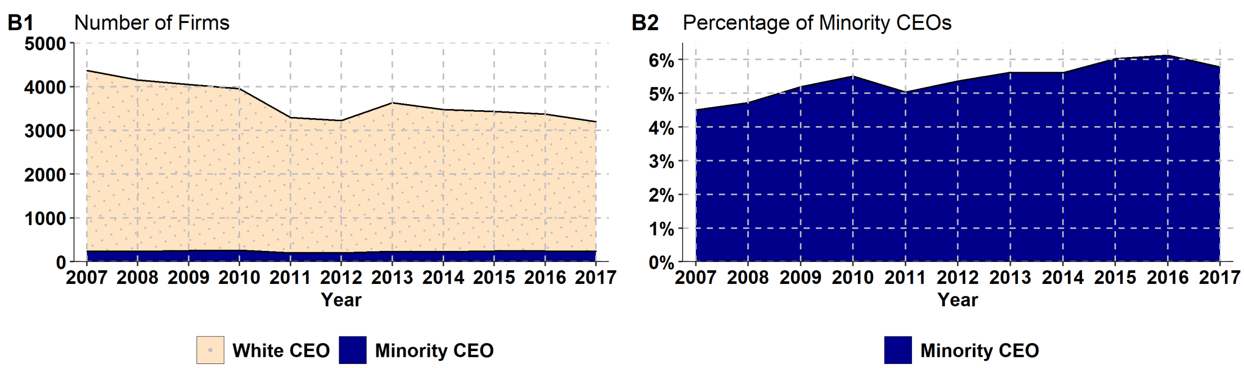



Figure 1: Fund Manager and Firm CEO Race Distribution Through Time

These figures show the time series for the number of actively-managed US equity funds in our sample by portfolio management teams of different race compositions, and the number of firms held by those funds by the race of the firm's CEO. Panel A shows the number of mutual funds managed by all-white, white-dominant, and minority-dominant portfolio management teams. The all-white group includes funds managed by portfolio management teams in which all managers are white. Funds belong to the white-dominant group if at least 50% of their portfolio managers are white but there is also at least one non-white portfolio manager in the team. Funds belong to the minority-dominant group if at least 50% of their portfolio managers are not non-Hispanic white. Panel B shows the number of firms managed by white and minority CEOs. A CEO is considered minority if he/she is not non-Hispanic white.

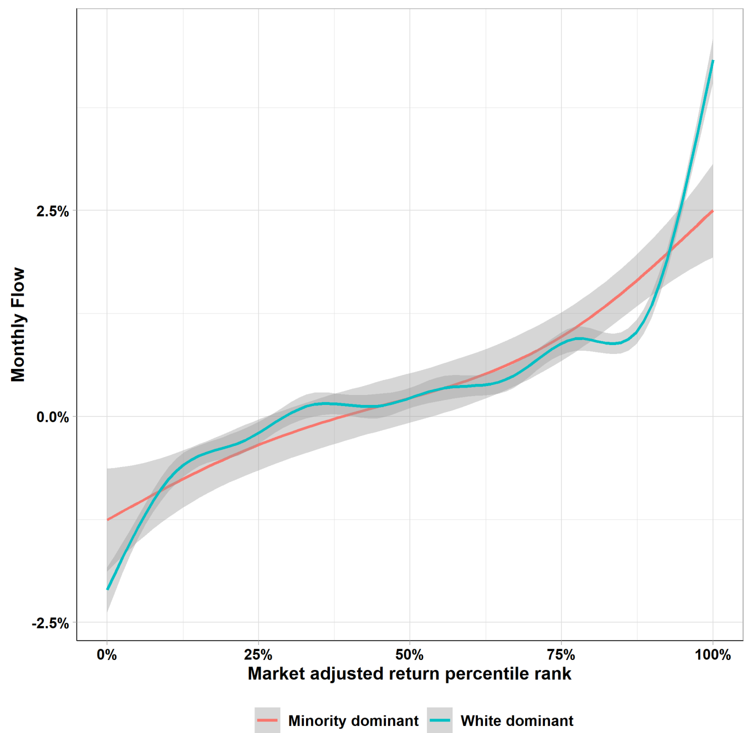



Figure 2: Flow-performance Sensitivity: Minority-dominant vs. White-dominant Funds

This figure shows flow-performance sensitivities separately for minority-dominant and white-dominant funds. The horizontal axis is the funds' past performance at time $t-1$ measured by the percentile rank of its average monthly return from month $t-12$ to $t-1$. The vertical axis is the percentage of monthly fund net flow in month $t$. The solid red and green lines represent the non-parametric fitting on the relationship between flow and performance. The shaded areas in grey represent the corresponding 95% confidence intervals.

Table 1: Summary Statistics

This table reports summary statistics for the sample of actively-managed US equity funds in the nine Morningstar style categories we use in our main analysis. The sample includes 14,649 observations at the fund and year level and 41,193 observations at the firm and year level from 2007 to 2017. We show race and gender distribution in fund management teams (Panel A), firms' C-suites (Panel B) and firms' CEOs (Panel C). Panel D shows the summary statics for fund side variables. *Number of fund managers* is the number of managers co-managing the same fund at the same time. *Fund Size* is calculated as the fund's total net assets (TNA). *Fund Family Size* is calculated as the aggregation of the total net assets across funds within the same fund family. *Fund Age* is calculated as the difference in years between the current date and the fund's inception date. *Turnover Ratio* is the percentage of portfolio holdings replaced in a given year. *Direct-sold fund*, as opposed to a broker-sold fund, is a dummy variable equal to one if the fund does not have a share class that charges a front load, rear load, or 12b-1 fee greater than 25bs, following Sun (2014). *Socially Conscious Fund* is a dummy variable equal to one if the fund is identified as a socially conscious fund by Morningstar Direct. In Panel E, we collect summary statistics for firm level variables. *C-suite Size* is the number of managers at a firm's C-suite level. *Firm Size* is calculated as the firm's total assets. *Cash Flow* is calculated as the sum of earnings before extraordinary items and equipment depreciation at the beginning of the fiscal year. *Firm age* is calculated as the number of years since the year of the company's IPO. *Debt ratio* is calculated as the ratio of total liabilities to total assets. *Investment* is calculated as capital expenditure over net property, plant, and equipment. *Headquarters in US* is a dummy variable equal to one if the firm's headquarters location is in the US.

Panel A: Race Distribution in Fund Teams

| Individual level | |
|---|---|
| White | 92.2% |
| Minority | 7.8% |
| Asian | 6.1% |
| Hispanic | 0.7% |
| Black | 1.0% |
| Male | 91.2% |
| White Male | 85.4% |
| Minority Male | 5.8% |
| Female | 8.8% |
| **Team level** | |
| All-White | 78.9% |
| White-dominant (Excluding All-White) | 14.0% |
| Minority-dominant | 7.1% |

Panel B: Race Distribution in Firm C-suite

| Individual level | |
|---|---|
| White | 92.9% |
| Minority | 7.1% |
| Asian | 4.8% |
| Hispanic | 1.6% |
| Black | 0.7% |
| Male | 92.0% |
| White Male | 85.8% |
| Minority Male | 6.2% |
| Female | 8.0% |
| **Team level** | |
| All-White | 83.7% |
| White-dominant (Excluding All-White) | 10.3% |
| Minority-dominant | 6.0% |

Panel C: Race Distribution of Firm CEOs

| | |
|---|---|
| White | 93.5% |
| Minority | 6.5% |
| Asian | 4.7% |
| Hispanic | 1.3% |
| Black | 0.5% |
| Male | 95.8% |
| White Male | 89.6% |
| Minority Male | 6.2% |
| Female | 4.2% |

(Table 1 Continued)

Panel D: Fund characteristics (fund-year level, 2007-2017, #Obs=14,649)

| | Full sample | | | | | | Minority-dominant vs. White-dominant funds | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) | Minority (M) | White (W) | Diff (M-W) | t-statistic |
| Number of fund managers | 14,649 | 3.38 | 3.43 | 2.00 | 2.00 | 4.00 | 2.52 | 3.45 | -0.93 | 19.42 |
| Fund Size (in millions) | 14,649 | 1,368 | 3,109 | 90 | 324 | 1,207 | 1,204 | 1,381 | -177 | 1.89 |
| Fund Family Size (in millions) | 14,649 | 67,802 | 193,482 | 1,245 | 10,671 | 37,562 | 51,764 | 69,040 | -17,276 | 3.81 |
| Fund Age | 14,649 | 11.96 | 10.28 | 4.45 | 10.13 | 16.33 | 10.92 | 12.10 | -1.18 | 4.22 |
| Turnover Ratio (%) | 14,649 | 66.57 | 59.31 | 27.00 | 52.00 | 88.00 | 77.48 | 65.74 | 11.75 | 5.53 |
| Expense Ratio (%) | 14,649 | 1.07 | 0.40 | 0.88 | 1.09 | 1.29 | 0.99 | 1.07 | -0.08 | 5.90 |
| Front Load Fee (%) | 14,649 | 2.66 | 2.76 | 0.00 | 0.00 | 5.75 | 2.50 | 2.67 | -0.17 | 1.94 |
| Rear Load Fee (%) | 14,649 | 1.45 | 1.82 | 0.00 | 1.00 | 2.00 | 1.21 | 1.47 | -0.25 | 4.65 |
| 12b-1 Fee (%) | 14,649 | 0.50 | 0.44 | 0.00 | 0.30 | 1.00 | 0.49 | 0.50 | 0.00 | 0.31 |
| Direct-sold (%) | 14,649 | 30.72 | 46.13 | 0.00 | 0.00 | 100.00 | 32.79 | 30.56 | 2.23 | 1.48 |
| Socially Conscious Fund (%) | 14,649 | 12.91 | 33.53 | 0.00 | 0.00 | 0.00 | 16.16 | 12.65 | 3.50 | 2.99 |

Panel E: Firm characteristics (firm-year level, 2007-2017, #Obs=41,193)

| | Full sample | | | | | | Minority-led vs. White-led firms | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | St. Dev. | Pctl(25) | Median | Pctl(75) | Minority (M) | White (W) | Diff (M-W) | t-statistic |
| C-Suite Size | 41,193 | 3.17 | 1.18 | 2.00 | 3.00 | 4.00 | 3.17 | 3.20 | -0.02 | 1.00 |
| Firm Size (in billions) | 40,893 | 9.82 | 44.09 | 0.24 | 1.02 | 3.90 | 8.28 | 10.02 | -1.74 | 2.23 |
| Investment (in billions) | 39,274 | 1.81 | 6.32 | 0.02 | 0.10 | 0.65 | 1.39 | 1.85 | -0.47 | 3.82 |
| Cash Flow (in billions) | 38,628 | 2.04 | 6.82 | 0.02 | 0.14 | 0.85 | 1.64 | 2.09 | -0.45 | 3.33 |
| Firm Age | 40,873 | 21.34 | 15.97 | 9.00 | 17.00 | 28.00 | 17.62 | 21.76 | -4.14 | 13.17 |
| Debt Ratio (%) | 40,797 | 58.26 | 47.92 | 35.77 | 55.91 | 77.12 | 51.28 | 58.78 | -7.50 | 5.79 |
| Headquarters in US (%) | 40,893 | 93.19 | 25.20 | 100.00 | 100.00 | 100.00 | 81.18 | 94.20 | -13.02 | 16.67 |

## Table 2: Fund Category and Firm Industry Distribution

This table reports the race distribution of mutual funds' management teams by style categories and the race distribution of firms' CEOs by the Fama-French 12 industries in actively-managed US Domestic Equity Mutual Funds in our sample. Panel A reports the race distribution of portfolio manager teams across fund categories. All-white percentage is calculated as the percentage of funds managed by all-white portfolio management teams relative to total number of funds in the specific fund category. White dominant (excluding all-white) percentage is calculated as the percentage of funds with a management team that is more than 50% and less than 100% white relative to the total number of funds. Minority dominant percentage is the percentage of funds managed by portfolio manager teams that are over 50% minority relative to the total number of funds. Panel B reports the CEO race distribution of firms in the Fama-French 12 industries from 2007 to 2017.

Panel A: Fund Manager Race Distribution by Fund Categories

| Fund Category | #funds | %All-White | %White dominant (excluding All-White) | %Minority dominant |
|---|---|---|---|---|
| Large Growth | 1608 | 80.9% | 11.5% | 7.6% |
| Large Value | 1332 | 80.7% | 14.7% | 4.6% |
| Large Blend | 1226 | 75.0% | 14.5% | 10.5% |
| Small Growth | 828 | 75.9% | 15.6% | 8.5% |
| Mid-Cap Growth | 757 | 85.0% | 10.3% | 4.7% |
| Small Blend | 672 | 76.6% | 15.2% | 8.2% |
| Small Value | 484 | 73.5% | 20.9% | 5.6% |
| Mid-Cap Value | 422 | 75.0% | 21.7% | 3.4% |
| Mid-Cap Blend | 393 | 82.1% | 13.9% | 4.0% |

Panel B: Firm CEO Race Distribution by Fama-French 12 Industries

| Industry description | #firms | %White CEO | %Minority CEO |
|---|---|---|---|
| Finance | 1441 | 94.2% | 5.8% |
| Business Equipment – Computers, Software, and Electronic Equipment | 1224 | 85.1% | 14.9% |
| Healthcare, Medical Equipment, and Drugs | 1012 | 90.4% | 9.6% |
| Other | 815 | 93.8% | 6.2% |
| Wholesale, Retail, and Some Services (Laundries, Repair Shops) | 511 | 93.9% | 6.1% |
| Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing | 488 | 93.9% | 6.1% |
| Oil, Gas, and Coal Extraction and Products | 331 | 96.8% | 3.2% |
| Consumer Nondurables – Food, Tobacco, Textiles, Apparel, Leather, Toys | 253 | 92.4% | 7.6% |
| Telephone and Television Transmission | 162 | 91.2% | 8.8% |
| Utilities | 153 | 96.5% | 3.5% |
| Chemicals and Allied Products | 144 | 92.5% | 7.5% |
| Consumer Durables – Cars, TVs, Furniture, Household Appliances | 128 | 91.5% | 8.5% |

Table 3: Fund Manager Race and Portfolio Choice: Univariate Analysis

This table explores how fund managers' race affects their portfolio choice. This table presents a univariate analysis on an equal-weighted average share of a fund's public equity holdings invested in firms led by minority or white CEOs across all funds (Column (1)), minority-dominant funds (Column (2)), white-dominant funds (Column (3)), and the difference between minority-dominant and white-dominant funds (Column (4)).

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | All Funds | Minority-dominant Funds (M) | White-dominant Funds (W) | Diff (M-W) |
| Minority CEO | 5.78 | 6.34 | 5.73 | 0.61 |
| | (0.03) | (0.11) | (0.03) | (0.12) |
| White CEO | 94.22 | 93.66 | 94.27 | -0.61 |
| | (0.03) | (0.11) | (0.03) | (0.12) |

Table 4: Fund Manager Race and Portfolio Choice: Fund Level Regression

This table examines how the racial diversity of a fund's management team affects the average portfolio weight the fund invests in firms led by minority vs. white CEOs. The dependent variable is the difference between the average of the portfolio weight invested by fund $i$ across minority-led and white-led firms in year $t$, that is:

$$y_{it} = \frac{\sum_{j \in \{MinorityCEOs_t\}} w_{ijt}}{\#\{MinorityCEOs_t\}} - \frac{\sum_{j \in \{WhiteCEOs_t\}} w_{ijt}}{\#\{WhiteCEOs_t\}},$$

where $w_{ijt}$ is the share of fund $i$'s public equity holdings invested in firm $j$ in year $t$. $\{MinorityCEOs_t\}$ ($\{WhiteCEOs_t\}$) is the set of firms with minority (white) CEOs invested in by all the funds in the sample at year $t$. *Minority Fund* is a dummy variable equal to one if the fund manager team has over 50% minority managers and zero otherwise. We control for fund characteristics. *Fund Size* is defined as the logarithm of the fund's total net assets. *Fund Family Size* is defined as the logarithm of the fund family's total net assets (i.e., the aggregated total net assets across funds within the same fund family). *Fund Age* is defined as the number of years since the fund's inception date. *Turnover Ratio* is the percentage of portfolio holdings replaced in a given year. *Direct-sold fund*, as opposed to a broker-sold fund, is a dummy variable equal to one if the fund does not have a share class that charges a front load, rear load, or 12b-1 fee greater than 25bs, following Sun (2014). *Socially Conscious Fund* is a dummy variable equal to one if the fund is identified as a socially conscious fund by Morningstar Direct. Fund Morningstar category is included as a control. Standard errors (shown in parentheses) are clustered at the fund and year level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Full Sample | Full Sample | 2007-2012 | 2012-2017 |
| Minority Fund | 0.18 | 0.14 | 0.15 | 0.12 |
| | (0.07) | (0.07) | (0.08) | (0.10) |
| Female Fund | -0.05 | -0.06 | -0.21 | 0.18 |
| | (0.12) | (0.14) | (0.12) | (0.23) |
| Fund Size | 0.002 | 0.003 | -0.02 | 0.02 |
| | (0.02) | (0.02) | (0.02) | (0.03) |
| Fund Family Size | 0.01 | 0.01 | 0.02 | -0.004 |
| | (0.01) | (0.01) | (0.01) | (0.02) |
| Fund Age | 0.01 | 0.01 | 0.01 | 0.01 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Turnover Ratio | 0.08 | 0.01 | 0.07 | -0.08 |
| | (0.03) | (0.03) | (0.03) | (0.05) |
| Expense Ratio | 3.06 | 4.45 | 11.51 | -9.65 |
| | (7.38) | (7.12) | (7.00) | (10.36) |
| Direct Sold | 0.04 | 0.02 | 0.05 | -0.03 |
| | (0.06) | (0.05) | (0.05) | (0.08) |
| Socially Conscious | 0.03 | -0.04 | -0.1 | -0.01 |
| | (0.09) | (0.08) | (0.08) | (0.11) |
| Year FE | Yes | Yes | Yes | Yes |
| Morningstar Style Category FE | No | Yes | Yes | Yes |
| Observations | 13,815 | 13,815 | 7,963 | 5,852 |
| Adjusted $R^2$ | 0.07 | 0.14 | 0.11 | 0.13 |

Table 5: Fund Manager Race and Portfolio Choice: Firm Level Regression

This table examines how the racial diversity of a fund's management team affects the average portfolio weight the fund invests in firms led by minority vs white CEOs. The dependent variable is the difference between the average of the portfolio weight invested by fund $i$ across minority-led and white-led firms at time $t$, that is:

$$y_{jt} = \frac{\sum_{i \in \{MinorityFunds_t\}} w_{ijt}}{\#\{MinorityFunds_t\}} - \frac{\sum_{i \in \{WhiteFunds_t\}} w_{ijt}}{\#\{WhiteFunds_t\}},$$

where $w_{ijt}$ is fund $i$'s portfolio weight on firm $j$ at the end of year $t$. $MinorityFunds_t$ is the set of funds exceeding 50% minority managers, and $WhiteFunds_t$ is the set of funds not exceeding 50% minority managers. We control for firm characteristics. *Minority CEO* is a dummy variable equal to one if the firm's CEO's race is a minority. *Female CEO* is a dummy variable equal to one if the firm's CEO's gender is female. *Minority other C-suite present* is a dummy variable equal to one if there are other minority C-suite members. *Female other C-suite present* is a dummy variable equal to one if there are other female C-suite members. *Firm Size* is defined as the logarithm of the firm's total assets. *Investment* is defined as capital expenditure over net property, plant, and equipment. *Cash Flow* is defined as the sum of earnings before extraordinary items and equipment depreciation at the beginning of the fiscal year. *Firm Age* is defined as the number of years since the year of the company's IPO. *Debt Ratio* is defined as the ratio of total debt to total assets. *C-suite Size* is the number of executives within the firm's C-suite. *Headquarters in the US* is a dummy variable equal to one if the firm's headquarters location is in the US. Firm industry (based on the Fama-French 12 industry classification) is included as a control. Standard errors (shown in parentheses) are clustered at the firm and year level.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Full Sample | Full Sample | US Firms | Non US Firms | 2007-2012 | 2013-2017 | Full Sample |
| Minority CEO | 0.18 | 0.19 | 0.16 | 0.31 | 0.17 | 0.22 | 0.20 |
| | (0.08) | (0.08) | (0.09) | (0.12) | (0.10) | (0.11) | (0.09) |
| Female CEO | 0.09 | 0.08 | 0.12 | -0.44 | -0.06 | 0.24 | 0.08 |
| | (0.09) | (0.09) | (0.09) | (0.27) | (0.11) | (0.13) | (0.10) |
| Minority other C-suite present | | | | | | | -0.02 |
| | | | | | | | (0.07) |
| Female other C-suite present | | | | | | | 0.02 |
| | | | | | | | (0.05) |
| Firm Size | -0.15 | -0.16 | -0.18 | -0.03 | -0.12 | -0.21 | -0.16 |
| | (0.02) | (0.02) | (0.02) | (0.04) | (0.02) | (0.02) | (0.02) |
| Investment | -0.13 | -0.14 | -0.15 | 0.03 | -0.15 | -0.13 | -0.14 |
| | (0.05) | (0.05) | (0.06) | (0.03) | (0.05) | (0.06) | (0.05) |
| Cash Flow | 0.14 | 0.15 | 0.18 | -0.05 | 0.16 | 0.14 | 0.15 |
| | (0.05) | (0.05) | (0.05) | (0.03) | (0.05) | (0.06) | (0.05) |
| Firm Age | -0.003 | -0.003 | -0.004 | -0.02 | -0.003 | -0.003 | -0.003 |
| | (0.002) | (0.002) | (0.002) | (0.01) | (0.002) | (0.002) | (0.002) |
| Debt Ratio | 0.26 | 0.23 | 0.24 | 0.27 | 0.22 | 0.25 | 0.23 |
| | (0.06) | (0.06) | (0.07) | (0.14) | (0.07) | (0.08) | (0.06) |
| Number of C-Suite | 0.02 | 0.02 | 0.02 | 0.03 | 0.02 | 0.02 | 0.02 |
| | (0.02) | (0.02) | (0.02) | (0.04) | (0.02) | (0.02) | (0.02) |
| Headquarter in US | 0.24 | 0.22 | | | 0.24 | 0.20 | 0.22 |
| | (0.09) | (0.09) | | | (0.11) | (0.10) | (0.09) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 35,631 | 35,628 | 33,082 | 2,546 | 20,050 | 15,578 | 35,628 |
| Adjusted $R^2$ | 0.02 | 0.02 | 0.03 | 0.07 | 0.01 | 0.03 | 0.02 |

## Table 6: Placebo Tests: Fund Level and Firm Level Regressions with Passive Funds

This table examines whether our findings of racial tilt in the fund level and firm level regressions replicate for passively-managed US Domestic Equity Mutual Funds in the nine Morningstar style categories. Panel A corresponds to Table 4, which finds racial tilt in portfolio holdings due to a fund manager's race. Panel B corresponds to Table 5, which finds racial tilt in firm shareholding by funds due to a firm's CEO's race.

Panel A: Fund Level Regression

| | (1) | (2) |
|---|---|---|
| Minority Fund | -0.08 | -0.07 |
| | (0.12) | (0.08) |
| Female Fund | -0.02 | 0.08 |
| | (0.22) | (0.18) |
| Fund Size | 0.03 | 0.01 |
| | (0.04) | (0.03) |
| Fund Family Size | 0.02 | 0.04 |
| | (0.04) | (0.02) |
| Fund Age | 0.01 | 0.002 |
| | (0.01) | (0.01) |
| Turnover Ratio | -0.08 | -0.02 |
| | (0.04) | (0.03) |
| Expense Ratio | 27.37 | 3.92 |
| | (22.96) | (13.45) |
| Direct Sold | 0.01 | 0.05 |
| | (0.10) | (0.05) |
| Socially Conscious | 0.87 | 0.74 |
| | (0.32) | (0.20) |
| Year FE | Yes | Yes |
| Morningstar Style Category FE | No | Yes |
| Observations | 1,210 | 1,210 |
| Adjusted $R^2$ | 0.29 | 0.5 |

Panel B: Firm Level Regression

| | (1) | (2) |
|---|---|---|
| Minority CEO | -0.01 | -0.01 |
| | (0.07) | (0.07) |
| Female CEO | 0.08 | 0.13 |
| | (0.09) | (0.09) |
| Firm Size | -0.09 | -0.10 |
| | (0.02) | (0.02) |
| Investment | -0.33 | -0.30 |
| | (0.09) | (0.09) |
| Cash Flow | 0.45 | 0.43 |
| | (0.09) | (0.09) |
| Firm Age | 0.005 | 0.01 |
| | (0.002) | (0.00) |
| Debt Ratio | 0.05 | 0.03 |
| | (0.02) | (0.02) |
| Number of C-Suite | -0.04 | -0.03 |
| | (0.02) | (0.02) |
| Headquarter in US | 0.07 | 0.04 |
| | (0.08) | (0.08) |
| Year FE | Yes | Yes |
| Industry FE | No | Yes |
| Observations | 35,829 | 35,829 |
| Adjusted $R^2$ | 0.23 | 0.24 |

Table 7: Performance of Minority-dominant (White-dominant) Funds and Holdings

This table reports the average monthly returns of funds' minority-CEO holdings and white-CEO holdings and the return spread between these two. We report the raw returns, CAPM, and 4-factor alpha for minority-dominant funds (Columns (1)-(3)), white-dominant funds (Columns (4)-(6)), and the return difference between these two groups (Columns (7)-(9)). Standard errors are summarized in parentheses.

| | Minority Funds (M) | | | White Funds (W) | | | Diff (M-W) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Raw | CAPM | 4-factor | Raw | CAPM | 4-factor | Raw | CAPM | 4-factor |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Minority-CEO Holdings Return (M, %) | 0.959 | 0.053 | 0.045 | 0.897 | 0.047 | 0.042 | 0.062 | 0.006 | 0.001 |
| | (0.456) | (0.118) | (0.113) | (0.424) | (0.103) | (0.097) | (0.059) | (0.052) | (0.053) |
| White-CEO Holdings Return (W, %) | 0.885 | 0.056 | 0.040 | 0.838 | 0.014 | 0.015 | 0.047 | 0.042 | 0.027 |
| | (0.406) | (0.062) | (0.040) | (0.403) | (0.058) | (0.032) | (0.024) | (0.024) | (0.022) |
| | | $S^M$ | | | $S^W$ | | | $D = S^M - S^W$ | |
| L/S (M-W, %) | 0.075 | -0.002 | 0.004 | 0.059 | 0.034 | 0.027 | 0.015 | -0.036 | -0.026 |
| | (0.124) | (0.119) | (0.117) | (0.101) | (0.102) | (0.101) | (0.059) | (0.053) | (0.053) |

# Table 8: Fund Manager Race and Flow to Performance Sensitivity

This table reports how flow to performance differs by the racial diversity of funds' management teams. The dependent variable is the funds' monthly flow at time $t$. The independent variables used in the regressions include measures of fund performance in the preceding years, the *Minority Fund* indicator, and other fund characteristics variables. *Bottom performance* is the lowest 10% of performance, defined as $min(Performance_{t-1}, c_1)$. *Medium performance* is the middle 80% $max(min(Performance_{t-1} - c_1, c_2 - c_1), 0)$. *Top performance* is highest 10% of performance, defined as $max(Performance_{t-1} - c_2, 0)$. $c_1$ is the 10th percentile of performance at time $t-1$. $c_2$ is the 90th percentile of performance at time $t-1$. Fund performance is measured by the average of the past 12 months of fund returns. *Minority Fund* is a dummy variable indicating whether the fund management team is minority-dominant. *Female Fund* is a dummy variable indicating whether the fund management team is female-dominant. *Fund Size* is defined as the logarithm of the fund's total net assets at the end of the previous year. *Fund Family Size* is defined as the logarithm of the fund family's total net assets (i.e., the aggregated total net assets across funds within the same fund family) at the end of the previous year. *Fund Age* is defined as the number of years since the fund's inception date. *Turnover Ratio* is the percentage of portfolio holdings replaced in the previous year. *Direct-sold fund*, as opposed to a broker-sold fund, is a dummy variable equal to one if the fund does not have a share class that charges a front load, rear load, or 12b-1 fee greater than 25bs, following Sun (2014), based on fee information from the previous year. *Category flow* is the total net flows received by all the funds in the corresponding Morningstar style category in the past month. *Return STD* is the standard deviation of monthly fund returns over the past 36 months. The coefficients on the piece-wise decomposition in each performance group represent the flow to performance sensitivities. Standard errors (shown in parentheses) are clustered at the fund and month level.

| | (1) | (2) |
|---|---|---|
| Dependent variable: | Fund monthly flow | |
| Bottom Performance | 0.140 | 0.121 |
| | (0.017) | (0.016) |
| Medium Performance | 0.019 | 0.020 |
| | (0.002) | (0.001) |
| Top Performance | 0.304 | 0.323 |
| | (0.030) | (0.029) |
| Bottom Performance × Minority Fund | -0.091 | -0.101 |
| | (0.068) | (0.069) |
| Medium Performance × Minority Fund | 0.004 | 0.004 |
| | (0.005) | (0.005) |
| Top Performance × Minority Fund | -0.157 | -0.152 |
| | (0.067) | (0.066) |
| Minority Fund | 0.006 | 0.008 |
| | (0.006) | (0.006) |
| Female Fund | 0.001 | 0.002 |
| | (0.003) | (0.003) |
| Fund Size | -0.002 | -0.002 |
| | (0.000) | (0.000) |
| Fund Family Size | 0.002 | 0.002 |
| | (0.000) | (0.000) |
| Fund age | -0.0001 | -0.0002 |
| | (0.0000) | (0.0000) |
| Turnover Ratio | 0.001 | 0.002 |
| | (0.001) | (0.001) |
| Expense Ratio | -0.056 | 0.077 |
| | (0.101) | (0.097) |
| Direct Sold | -0.002 | -0.002 |
| | (0.001) | (0.001) |
| Category Flow | 0.002 | 0.002 |
| | (0.000) | (0.000) |
| Return STD | -0.053 | -0.507 |
| | (0.031) | (0.062) |
| Morningstar Style Category FE | Yes | Yes |
| Month FE | No | Yes |
| Observations | 141,239 | 141,239 |
| Adjusted $R^2$ | 0.019 | 0.022 |

Table 9: Fund Manager Race and Flow to Performance Sensitivity: Subsamples by Fund Size, Age, and Distribution Channel

This table reports the results of the piece-wise regression defined in table 8 for subsamples by distribution channel, fund age, and fund size. For the fund's distribution channel, we classify a fund as broker sold if it has a share class that charges a front load, rear load, or 12b-1 fee greater than 25bs, following Sun (2014). The remaining funds are classified as direct sold. For the fund age and fund size, we separate funds based on the median values in each year. Standard errors (shown in parentheses) are clustered at the fund and month level.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable: | Fund monthly flow | | | | | |
| | Distribution Channel | | Fund Age | | Fund Size | |
| | Direct-Sold | Broker Sold | Below Median | Above Median | Below Median | Above Median |
| Bottom Performance | 0.098 | 0.128 | 0.154 | 0.088 | 0.113 | 0.126 |
| | (0.030) | (0.018) | (0.026) | (0.021) | (0.020) | (0.026) |
| Medium Performance | 0.014 | 0.023 | 0.024 | 0.017 | 0.023 | 0.018 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Top Performance | 0.319 | 0.330 | 0.367 | 0.286 | 0.406 | 0.239 |
| | (0.047) | (0.035) | (0.044) | (0.038) | (0.047) | (0.030) |
| Bottom Performance × Minority Fund | -0.079 | -0.103 | 0.001 | -0.169 | -0.068 | -0.188 |
| | (0.082) | (0.097) | (0.100) | (0.074) | (0.080) | (0.139) |
| Medium Performance × Minority Fund | 0.009 | 0.002 | 0.004 | 0.004 | 0.002 | 0.005 |
| | (0.007) | (0.006) | (0.008) | (0.005) | (0.007) | (0.005) |
| Top Performance × Minority Fund | -0.217 | -0.115 | -0.271 | -0.075 | -0.188 | -0.143 |
| | (0.082) | (0.084) | (0.102) | (0.085) | (0.103) | (0.067) |
| Minority Fund | 0.002 | 0.009 | -0.003 | 0.015 | 0.005 | 0.017 |
| | (0.009) | (0.008) | (0.007) | (0.007) | (0.006) | (0.014) |
| Female Fund | -0.005 | 0.003 | 0.005 | -0.003 | -0.0001 | 0.005 |
| | (0.003) | (0.003) | (0.004) | (0.002) | (0.003) | (0.004) |
| Fund Size | -0.002 | -0.002 | -0.003 | -0.001 | -0.005 | -0.001 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| Fund Family Size | 0.002 | 0.002 | 0.002 | 0.001 | 0.002 | 0.002 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Fund Age | -0.0002 | -0.0001 | -0.001 | -0.00002 | -0.0003 | -0.0001 |
| | (0.0001) | (0.0001) | (0.0002) | (0.0000) | (0.0001) | (0.0000) |
| Turnover Ratio | 0.001 | 0.002 | 0.003 | -0.0001 | 0.003 | -0.001 |
| | (0.001) | (0.002) | (0.003) | (0.001) | (0.002) | (0.001) |
| Expense Ratio | 0.208 | 0.028 | 0.18 | 0.017 | 0.106 | -0.028 |
| | (0.205) | (0.110) | (0.162) | (0.102) | (0.112) | (0.151) |
| Direct Sold | | | -0.001 | -0.003 | -0.0003 | -0.003 |
| | | | (0.001) | (0.001) | (0.001) | (0.001) |
| Category Flow | 0.001 | 0.002 | 0.002 | 0.001 | 0.002 | 0.001 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Return STD | -0.480 | -0.508 | -0.664 | -0.337 | -0.525 | -0.459 |
| | (0.087) | (0.074) | (0.092) | (0.072) | (0.078) | (0.076) |
| Morningstar Style Category FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 42,277 | 98,962 | 70,768 | 70,471 | 70,624 | 70,615 |
| Adjusted $R^2$ | 0.025 | 0.023 | 0.026 | 0.02 | 0.027 | 0.02 |

# A Online Appendix

## A.1 Algorithm for name-based classification of racial affiliation

Our approach to inferring the racial affiliation of individuals relies on two databases. First, we rely on the 2010 U.S. Census data, which provides the Frequency of Surnames in the U.S. population by racial affiliation. The second dataset is obtained from the Harvard Dataverse, which provides a list of first names by race based on information from three distinct proprietary mortgage datasets.[25]

For each first or last name, these two data sets provide a tool for identifying the probability that a particular individual is affiliated with a particular ethnic group.

### A.1.1 Illustrative examples

To introduce our procedure for identifying racial/ethnic affiliation from first and last names, we provide two illustrative examples.

**Example 1.** Consider La Toya Jackson, a well-known Black singer. The Harvard Dataverse data shows that the first name La Toya is 4.3% White, 4.3% Hispanic, and 91.4% Black. The Census dataset shows that the last name Jackson is 39.9% White, 2.5% Hispanic, and 53% Black. It follows that the probability of making a type I error of identifying La Toya Jackson as White from her first name is 1-0.043=0.957, and the probability of a type I error of identifying her as White from her last name is 1-0.399=0.601. Thus, if first and last names are chosen independently, the total type I probability (p-value) of erroneously identifying La Toya Jackson as White based on her first and last names is

$$p_{White} = (1-0.043)(1-0.399) = 0.575.$$

25. The three distinct mortgage datasets include: (1) mortgage applications from a lender in 2010; (2) a merged dataset between HMDA and DataQuick for 2010 that excludes any loans from the lender in the first dataset; and (3) mortgage applications from a subprime lender in 2007. The data is from **DVN/TYJKEZ˙2018**, which includes 4,250 unique first name and their classifications on six mutually exclusive racial and Hispanic origins in US. The link to the data is here: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/TYJKEZ

It is important to note that first and last names are not chosen independently. We will maintain the independence assumption for this discussion and explain how we deal with it later on. In a parallel manner, the type I probability of erroneously identifying La Toya Jackson as Black from her first name is $1-0.914 = 0.086$, and the probability of erroneously identifying her as Black from her last name is $1-0.53 = 0.47$. Thus, assuming independence, the p-value of erroneously identifying her as Black is

$$p_{Black} = (1-0.914)(1-0.53) = 0.04.$$

The p-value of 4% identifying La Toya Jackson as Black is the smallest among all p-values associated with all possible races. We thus correctly identify La Toya Jackson as Black.

**Example 2.** Consider Lucy Liu, a famous actress of Asian descent. The Harvard Dataverse dataset shows that the first name Lucy is 68.91% White, 15.29% Hispanic, 5.38% Black, 9.75% Asian, and 0.67% American Indian. The Census dataset indicates that the last name Liu is 1.77% White, 0.69% Hispanic, 0.36% Black, 95.74% Asian, and 0.02% American Indian. It follows that the race which minimizes the type I error probability is Asian, with a p-value of

$$p_{Asian} = (1-0.0975)(1-0.9574) = 0.0384.$$

We thus correctly identify Lucy Liu as Asian.

These two examples illustrate the essence of the idea behind the algorithm we are using. For each possible race we use the data sets to calculate the probability of a type I error of erroneously identifying a specific combination of first and last names as of a specific race. We then assign the name the racial affiliation that minimizes the p-value under the assumption of independent draws of first and last names. It is important to note that in some cases the first name is more informative about racial affiliation, while in other cases it is the last name that helps identify race. For example, La Toya Jackson's first name is highly informative about her being Black, while her last name is quite generic. By contrast, in the case of Lucy Liu, it is the last name that allows us to identify her as Asian. Overall, as we will demonstrate below, the combination of first and last names significantly increases the power of our identification algorithm as compared to using just one or the other.

We next turn to providing a formal description of the algorithm, validating its empirical merit, and evaluating the influence of the independence assumption.

### A.1.2 Algorithm description

We begin with a set of possible racial/ethnic affiliations.

$$E = \{White, Black, American\ Indian, Asian, Hispanic, Multi\text{-}races\}$$

For each race $e \in E$, let $\phi(e)$ be the unconditional frequency of race $e$ in the U.S. population as of the census of 2010.[26]

Consider a name denoted by $N$, consisting of a first and last name, $N = (F, L)$. For each first name $F$, we have two possible cases. First, if the name is included in the first names database, then we can look up the conditional probability, which is the frequency of race $e$ among people with first name $F$, denoted by $\phi(e|F)$. Second, if $F$ is not included in the database, then we cannot update our prior based on the first-name database. Thus, the probability of a first name $F$ being affiliated with $e$ is given by

$$q_e(F) = \begin{cases} \phi(e|F) & F \text{ is in first names data set} \\ \phi(e) & F \text{ is not in first names data set} \end{cases}$$

Similarly, let $\phi(e|L)$ be the frequency of race $e \in E$ given last name $L$ based on the last names

26. The prior distribution of race from 2019 census estimates: 1) White: 60.1% 2) Black or African-American: 13.4% 3) American Indian or Alaskan Native: 1.3% 4) Asian, Native Hawaiian, and Other Pacific Islander: 6.1% 5) Non-White Hispanic: 18.5% 6) Two or more races: 2.8%. (Data Source: https://www.census.gov/quickfacts/fact/table/US/PST045219)

database. Then, the probability of $L$ being affiliated with $e$ is given by

$$q_e(L) = \begin{cases} \phi(e|L) & L \text{ is in last names data set} \\ \phi(e) & L \text{ is not in last names data set} \end{cases}$$

Now, assuming that first and last names are chosen independently (see discussion of this assumption below), the probability of $N = (F, L)$ not being affiliated with $e \in E$ – the probability of a Type I error – is given by

$$p_e(F, L) = (1 - q_e(F))(1 - q_e(L)). \tag{7}$$

Let $e^*$ be the race that minimizes the type I error for a name $N = (F, L)$, i.e.,

$$e^* = \arg\min_{e \in E} p_e(F, L).$$

We set a threshold significance level $\alpha$. If $p_{e^*}(F, L) \le \alpha$ we set the race of the name $N = (F, L)$ to be $e^*$. Otherwise, we set the race to be "unidentified." Intuitively, $e^*$ is the race that is the least likely to be a false identification. We maintain $e^*$ as our identified race so long as the probability of type I error it induces falls below $\alpha$.

To implement the algorithm, we set the threshold significance level to $\alpha = 10\%$. As we will demonstrate, the actual error rate in our data is much smaller. Table A1 lists a few examples of prominent household names. The algorithm correctly identifies Joe Biden, Donald Trump, Marco Rubio, and Andrew Yang. The algorithm fails to identify Michael Jackson as Black due to the popularity of the name 'Michael' among Whites.

### A.1.3 Evaluation of the algorithm's accuracy

To evaluate the accuracy of the algorithm and whether the independence assumption has any bite, we randomly draw 500 names covering both the fund managers and the C-suite executives from our manual search sample. We then identify their racial/ethnic affiliation using the algorithm. We consider the race identified by the algorithm to be accurate if it coincides with the manual search. Column (1) in Panel A of Table A2 describes the accuracy rate of the algorithm. The bottom line of this analysis is that the accuracy rate is extremely high at 98.7%. Evidently, the probability of a type I error is much smaller than the threshold of 10%. Critically, our manual search procedure does not hinge on the independence assumption. Thus, the very low error rate shows that our independence assumption is effectively innocuous.

We also compare the accuracy rate of the algorithms with alternative algorithms that use only the first or last name to define the race (Panel A of Table A2). Using the full name increases the number of identifiable individuals while keeping a low type I error compared to the alternative algorithms. We find that using only the first name and keeping the threshold of 10% will only identify 74% of individuals in the sample. Similarly, using only the last name will identify 45% of individuals in the sample. Conditional on being identified, the type I errors of the three algorithms are all very small, less than 1.5%.

## Table A1: Examples of Names and Algorithm Implementation

This table provides additional examples of well-known first and last names and their corresponding race frequencies from the US Census Database and the Harvard Dataverse. Fields suppressed for confidentiality in the U.S. Census data are assigned with NA. Algo-based Race represents the ethnicity from our identification algorithm. True Race is the person's actual race.

| Name | Correctly Identified | Algo-based Race | True Race | | Non-White Hispanic(%) | White(%) | Black or African American(%) | Asian, Native Hawaiian and Other Pacific Islander(%) | American Indian or Alaska Native(%) | Two or More Races(%) |
|---|---|---|---|---|---|---|---|---|---|---|
| Joe Biden | Yes | White | White | First Name | 18.57 | 69.013 | 6.874 | 5.155 | 0.222 | 0.166 |
| | | | | Last Name | NA | 91.19 | NA | NA | NA | 4.4 |
| | | | | Type I Error Rate | 66% | 3% | 81% | 89% | 98% | 95% |
| Donald Trump | Yes | White | White | First Name | 0.722 | 95.057 | 3.251 | 0.722 | 0.166 | 0.083 |
| | | | | Last Name | 1.34 | 95.6 | 0.82 | 0.69 | 0.23 | 1.31 |
| | | | | Type I Error Rate | 98% | 0% | 96% | 99% | 100% | 99% |
| Marco Rubio | Yes | Non-White Hispanic | Non-White Hispanic | First Name | 63.056 | 33.828 | 1.78 | 1.335 | 0 | 0 |
| | | | | Last Name | 92.04 | 5.35 | 0.28 | 1.8 | 0.27 | 0.25 |
| | | | | Type I Error Rate | 3% | 63% | 98% | 97% | 100% | 100% |
| Andrew Yang | Yes | Asian | Asian | First Name | 1.882 | 93.212 | 1.69 | 3.07 | 0.11 | 0.037 |
| | | | | Last Name | 0.45 | 1.03 | 0.2 | 96.81 | 0.02 | 1.5 |
| | | | | Type I Error Rate | 98% | 7% | 98% | 3% | 100% | 98% |
| La Toya Jackson | Yes | Black | Black | First Name | 4.301 | 4.301 | 91.398 | 0 | 0 | 0 |
| | | | | Last Name | 2.5 | 39.89 | 53.04 | 0.39 | 1.06 | 3.12 |
| | | | | Type I Error Rate | 93% | 58% | 4% | 100% | 99% | 97% |
| Michael Jackson | No | White | Black | First Name | 1.693 | 94.363 | 2.142 | 1.592 | 0.092 | 0.118 |
| | | | | Last Name | 2.5 | 39.89 | 53.04 | 0.39 | 1.06 | 3.12 |
| | | | | Type I Error Rate | 96% | 3% | 46% | 98% | 99% | 97% |
| Lucy Liu | Yes | Asian | Asian | First Name | 15.294 | 68.908 | 5.378 | 9.748 | 0.672 | 0 |
| | | | | Last Name | 0.69 | 1.77 | 0.36 | 95.74 | 0.02 | 1.43 |
| | | | | Type I Error Rate | 84% | 31% | 94% | 4% | 99% | 99% |

Table A2: Identification Rate and Accuracy Rate of Different Algorithms

This table reports the identification rate and accuracy rate of the race identification algorithm using a sample of 500 randomly drawn names of mutual fund managers and C-suite executives. We have manually identified the race of each randomly drawn name using sources such as LinkedIn, company websites, and Wikipedia, among others. Columns (1)-(3) report statistics for three variations of the identification algorithm using first and last name, first name only, and last name only. Number of identified names indicates the number of names for which a race is identified using the corresponding algorithm. Number of correctly identified names is the number of names for which the manual search yields an identical race to that obtained by the algorithm. Identification rate is the ratio of the number of names identified by the algorithm out of the 500 randomly drawn names. Accuracy rate is the ratio of the number of correctly identified names out of the number of identified names. Panel A considers the case of $\alpha = 10\%$, which is the baseline case used throughout the paper. Panel B considers the the case of $\alpha = 5\%$; Panel C considers the case of no threshold, i.e., $\alpha = 100\%$.

| | Full Name<br>(1) | First Name Only<br>(2) | Last Name Only<br>(3) |
|---|---|---|---|
| Panel A: $\alpha = 10\%$ (Baseline) | | | |
| Number of total sample | 500 | 500 | 500 |
| Number of identified names | 466 | 370 | 227 |
| Number of correctly identified names | 460 | 365 | 226 |
| Identification rate | 93.2% | 74.0% | 45.4% |
| Accuracy rate | 98.7% | 98.6% | 99.6% |
| Panel B: $\alpha = 5\%$ (Robustness) | | | |
| Number of total sample | 500 | 500 | 500 |
| Number of identified names | 439 | 126 | 87 |
| Number of correctly identified names | 433 | 124 | 87 |
| Identification rate | 87.8% | 25.2% | 17.4% |
| Accuracy rate | 98.6% | 98.4% | 100.0% |
| Panel C: $\alpha = 100\%$ (Robustness) | | | |
| Number of total sample | 500 | 500 | 500 |
| Number of identified names | 500 | 500 | 500 |
| Number of correctly identified names | 485 | 465 | 476 |
| Identification rate | 100.0% | 100.0% | 100.0% |
| Accuracy rate | 97.0% | 93.0% | 95.2% |

## Table A3: Performance of Minority-dominant (White-dominant) Funds and Holdings: Subsample Analysis

This table reports the return spreads ($S^M$ for minority-dominant funds and $S^W$ for white dominant funds) as well as the difference-in-differences measure ($D = S^M - S^W$) defined in Table 7 for subsamples of funds based on fund size, fund age, and the tendency of funds to hold minority-led firms. For the fund age and fund size, we separate funds based on the median values in each year. For the tendency of funds to hold minority-led firms, we separate funds based on the median allocation in minority-led firms in each year. We report the raw returns, CAPM, and 4-factor alpha. The standard errors are summarized in parentheses.

| | Minority Funds ($S^M$) | | | White Funds ($S^W$) | | | Diff ($D = S^M - S^W$) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Raw | CAPM | 4-factor | Raw | CAPM | 4-factor | Raw | CAPM | 4-factor |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Fund Size | | | | | | | | | |
| Below Median | 0.023 | -0.065 | -0.059 | 0.080 | 0.028 | 0.005 | -0.057 | -0.093 | -0.063 |
| | (0.127) | (0.121) | (0.121) | (0.114) | (0.112) | (0.109) | (0.082) | (0.081) | (0.080) |
| Above Median | 0.148 | 0.081 | 0.091 | 0.098 | 0.037 | 0.025 | 0.049 | 0.044 | 0.060 |
| | (0.140) | (0.138) | (0.133) | (0.124) | (0.122) | (0.120) | (0.072) | (0.073) | (0.073) |
| Fund Age | | | | | | | | | |
| Below Median | 0.066 | -0.021 | -0.014 | 0.037 | -0.019 | -0.040 | 0.029 | -0.002 | 0.017 |
| | (0.145) | (0.140) | (0.133) | (0.116) | (0.114) | (0.113) | (0.088) | (0.088) | (0.088) |
| Above Median | 0.082 | 0.009 | 0.013 | 0.141 | 0.085 | 0.069 | -0.059 | -0.075 | -0.052 |
| | (0.126) | (0.122) | (0.124) | (0.122) | (0.121) | (0.118) | (0.081) | (0.082) | (0.080) |
| Fund Allocation in Minority-Led Firms | | | | | | | | | |
| Below Median | 0.068 | -0.048 | -0.025 | 0.087 | 0.030 | 0.012 | -0.020 | -0.078 | -0.042 |
| | (0.150) | (0.140) | (0.138) | (0.118) | (0.116) | (0.114) | (0.084) | (0.079) | (0.076) |
| Above Median | 0.071 | 0.034 | 0.030 | 0.087 | 0.030 | 0.012 | -0.017 | 0.004 | 0.016 |
| | (0.134) | (0.135) | (0.132) | (0.118) | (0.116) | (0.114) | (0.098) | (0.099) | (0.100) |

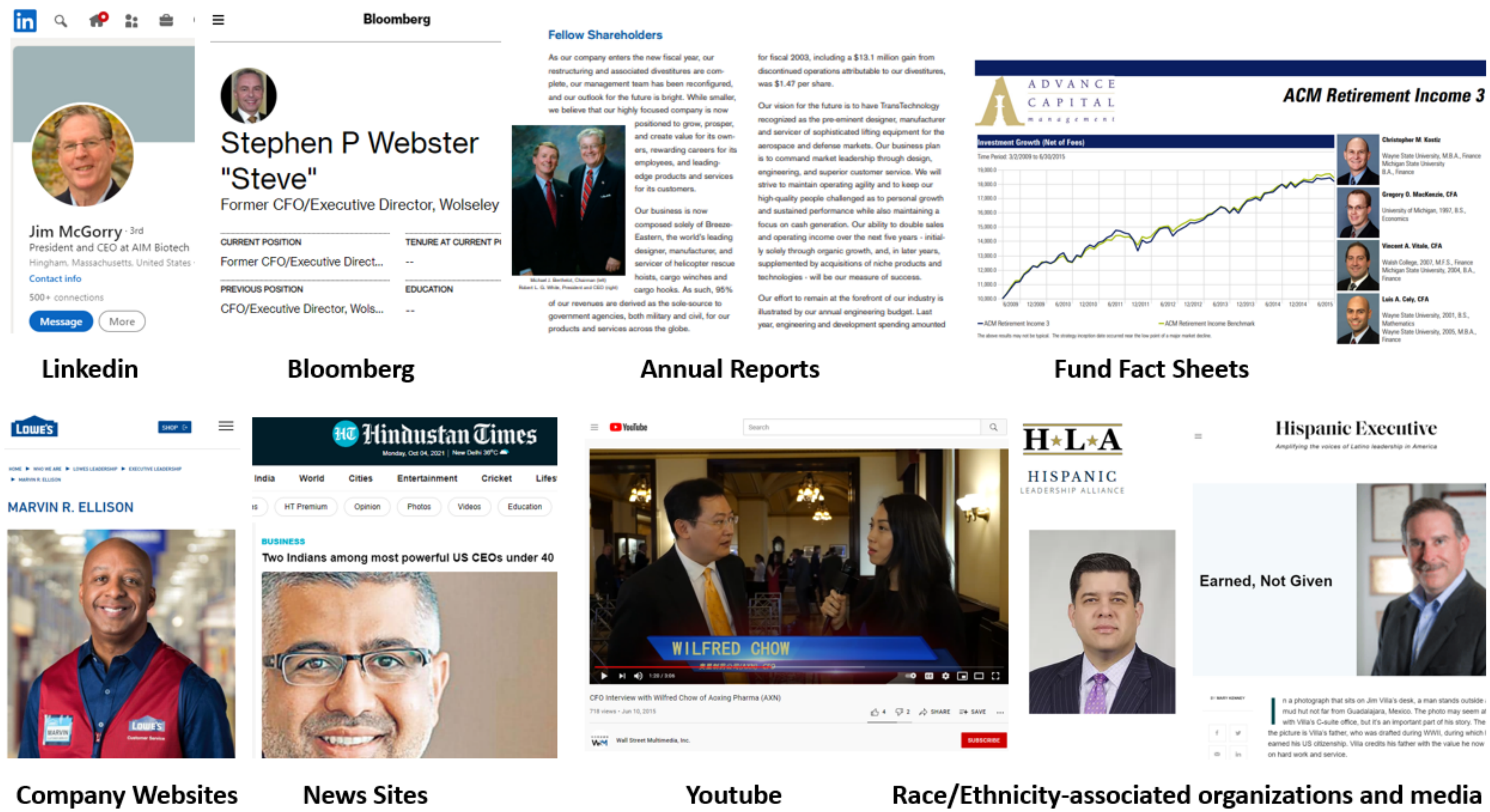
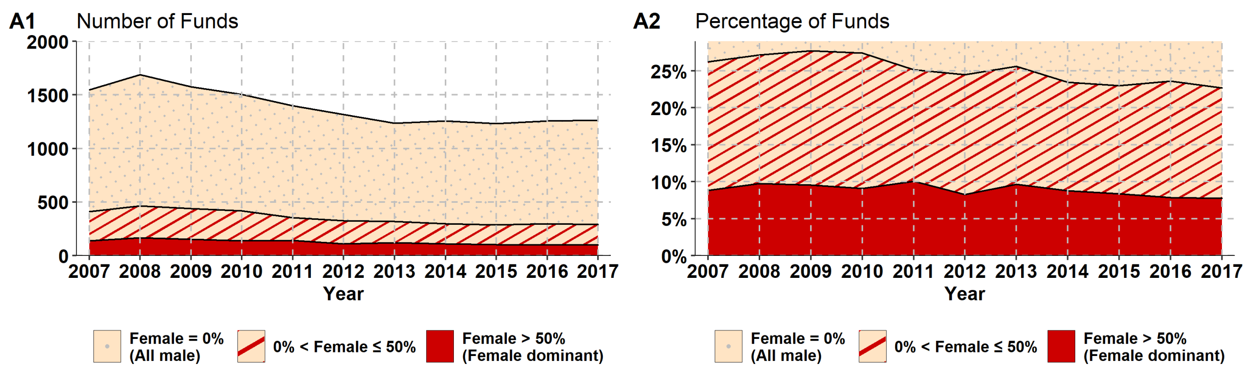



Figure A1: Examples of Sources Relied on in the Manual Search

This figure shows some examples of sources we have relied on in the manual search to identify the race/ethnicity of fund managers and firm executives. Sources are required to include the person's name, have corroborating information on where they work, and have an image, video, or textual information divulging their race/ethnicity.

Panel A: Fund Manager Gender Distribution




Panel B: Firm CEO Gender Distribution

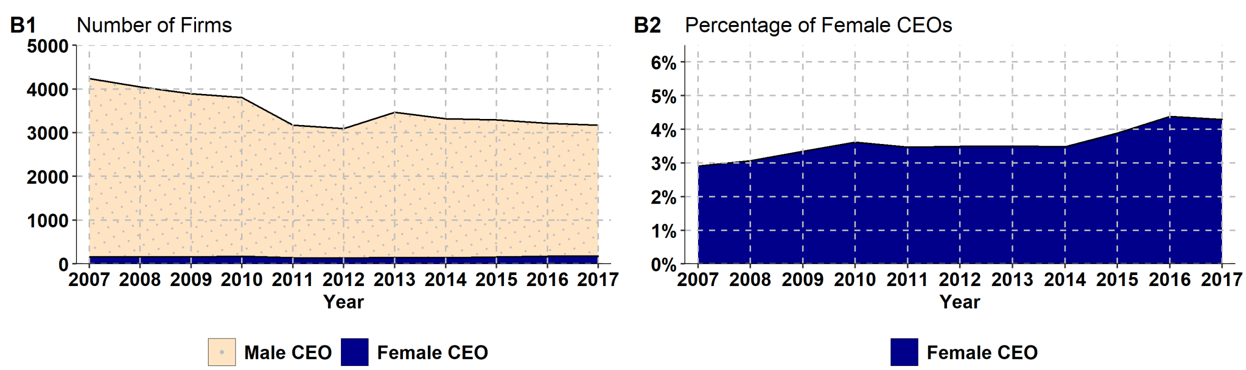



Figure A2: Fund Manager and Firm CEO Gender Distribution Through Time

These figures show the time series for the number of actively-managed US equity funds in our sample by portfolio management teams of different gender compositions, and the number of firms held by those funds by the gender of the firm's CEO. Panel A shows the number of mutual funds managed by all male, male-dominant and female-dominant portfolio management teams. Funds belong to the all male group if all of its portfolio managers are identified as male. Funds belong to the male-dominant group if 50% of its portfolio managers are identified as male, but the team also has at least one female manager. Funds belong to the female-dominant group if at least 50% of its portfolio managers in the team are female. Panel B shows the number of firms managed by male and female CEOs.