Identity, Diversity, and Team Performance: Evidence from U.S. Mutual Funds *

Richard B. Evans[†] Melissa Porras Prado[‡]

A. Emanuele Rizzo[§] Rafael Zambrana[¶]

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Abstract

We examine team diversity and performance in the asset management industry through the lens of identity. Focusing on political ideology as the relevant dimension of identity, we find that diverse teams outperform homogeneous teams. The mechanism involves both improved decision-making due to more diverse perspectives and increased monitoring by heterogeneous team members. The benefits of ideological diversity are undone when political polarization is higher, consistent with increased intra-team conflict. In examining why less diverse teams are prevalent in asset management, we find entrenched managers prefer homogeneous teams, and the local labor market supply of ideologically diverse managers is constrained.

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[†]Corresponding Author. Darden School of Business at the University of Virginia. E-mail: evansr@darden.virginia.edu. Address: 100 Darden Blvd., Charlottesville, VA 22903.

[‡]Nova School of Business and Economics, CEPR. Email: melissa.prado@novasbe.pt

[§]Nova School of Business and Economics. Email: emanuele.rizzo@novasbe.pt

[¶]Mendoza College of Business at Notre Dame University. Email: rzambra2@nd.edu

1 Introduction

There is a growing literature on identity, an individual's sense of self, and its impact on the choices of economic agents within organizations (e.g., Akerlof and Kranton (2000), Akerlof and Kranton (2005) and Bénabou and Tirole (2011)). One important application of this literature is understanding the relationship between diversity and team performance.[1] Because identity can be related to perspective, knowledge, and expertise, a diverse team (i.e., one comprised of individuals whose identities differ) can be more effective.[2] At the same time, differences in identity among group members, either real or perceived, can hinder productivity through mistrust, increased conflict, or decreased effort.[3] Recognizing that an individual's identity is multi-faceted, one approach to mitigating this potential conflict is to "prime" the facet of identity that the team has in common (e.g., team-building exercises to create a work-team identity). By making a given facet more salient, perceived differences and intra-team conflict are reduced.[4] Similarly, when a dimension of identity that differs among group members (e.g., political ideology) becomes more salient, increased discord can result.

In this paper, we examine the relation between diversity and team performance through the lens of identity. Focusing on political ideology as the relevant facet of identity, we examine the performance of diverse portfolio manager teams.[5] While different dimensions of identity, including both functional (e.g., differing job expertise) and demographic (e.g., race and gender), have been studied in the literature, we focus on political ideology for several reasons. First, different political ideologies are associated with different economic perspectives and information sets. As a result, a team comprised of individuals with diverse political views plausibly exhibits complementarities necessary to generate superior team performance.[6]

Second, political ideology is both a salient dimension of identity in the workplace and when "primed" is likely to generate intra-team conflict. Unlike race, religion, and gender, where social norms dictate behavior, there are fewer constraints on the expression of hostility toward people

[1]See Charness and Chen (2020) for a partial review of this literature.

[2]See Lazear (1999), Hong and Page (2001), Hamilton et al. (2003), Rockenbach et al. (2007)

[3]See Hjort (2014), Coffman (2014), Glover et al. (2017)

[4]See Eckel and Grossman (2005), Charness et al. (2007), Chen and Chen (2011) and Chen et al. (2014)

[5]While our exclusive use of team-managed funds is necessitated by our focus on team diversity, several papers within the mutual fund literature examine the role of individual versus team management. Bliss et al. (2008), for example, find that team-managed funds have less performance dispersion and greater similarity in their portfolio factor loadings than their individual-managed counterparts consistent with Adams and Ferreira (2009).

[6]For example, Hutton et al. (2014) show a manager's political affiliation affects firm policies such as corporate debt levels, R&D spending and the riskiness of firm investments. More specific to our asset management context, Hong and Kostovetsky (2012) show that the investment strategies of Democratic and Republican money managers exhibit statistically and economically significant differences broadly consistent with the tenets of these different ideologies.

who adhere to opposing political ideologies.[7] Using national-level and state-level variation in political polarization as political identity priming, we are able to examine the potential trade-offs between the value-added from incorporating diverse perspectives and the conflicts raised as a result of increased perceived differences due to polarization.[8]

Lastly, there is a third and perhaps even more important reason to focus on political ideology. The implicit assumption in using demographic facets of identity to measure diversity is that these observables proxy for individuals' values or perspectives (e.g., Hambrick and Mason (1984)). Unlike many of these demographic dimensions, political identity is a choice and one that is based on an individual's view of the world. As such, political affiliation provides a plausibly more precise reflection of an individual's values and perspective. Several studies show that the strength of people's attachment to their political parties surpasses affiliations with their own race, religion, and other social categories (Westwood et al. (2018), Sunstein (2016), and Iyengar and Westwood (2015)).

To measure diversity in political identity, we follow a well-established strand of the literature that uses political contributions to classify an individual's political orientation.[9] Using this methodology, we obtain information on the political contributions of around 2,500 money managers between 1992 and 2016 from the Center for Responsive Politics (CRP) website. We then use this data to measure how heterogeneous or homogeneous these political beliefs are within a fund management team.

The U.S. mutual fund industry provides an extremely useful setting to study how team diversity affects performance for several reasons. First, human capital plays a crucial role in the asset management industry, and the industry is increasingly reliant on teams to manage capital on behalf of investors. Second, the output of the team's decision-making process is directly observable both in the investment return and the holdings of the fund, which allows us to determine how homogenous teams differ in their portfolio choices from ideologically diverse teams. Third, as a result of the prevalence of teams in asset management, the fund manager

[7]Mutz and Mondak (2006), for example, find that the workplace is the most common setting for discussions about political differences. At the same time, Westfall et al. (2015) show that individuals who identify strongly as a Democrat or Republican, as measured in part by campaign contributions, are more sensitive to and perceive greater political polarization than other individuals. Sunstein (2016) and Iyengar and Westwood (2015) demonstrate that polarization is stronger for partisan affiliations than for racial or social class affiliations. Klar (2013) also documents the effect of identity "priming" on political preferences.

[8]Empirical evidence suggests there is time-series variation in political polarization in the U.S. (e.g., Iyengar et al. (2012), Mason (2013), Mason (2015), Boxell et al. (2017)).

[9]See, e.g., Hong and Kostovetsky (2012), Di Giuli and Kostovetsky (2014), Lee et al. (2014), Hutton et al. (2014). For example, looking at differences in corporate policies among CEOs with different political ideologies, Hutton et al. (2014) validate the use of donations by showing a strong correlation between revealed versus self-reported political orientation.

can be observed working on different teams of the same investment advisor at the same time. In this highly granular setting it is not uncommon to observe managers working simultaneously in both homogeneous and heterogeneous teams, which, as detailed below, provides us with a unique opportunity to draw causal evidence on the effect of team diversity on performance.

Consistent with a competitive advantage of diverse perspectives, we find that teams composed of money managers with different political identities outperform homogeneous teams by about 1.8% risk-adjusted return per year. Using the dollar value-added measure of Berk and Van Binsbergen (2015), we find an average difference of approximately $2 million per year between heterogeneous and homogeneous teams. We perform a host of robustness tests for this baseline result. Two of them may be of particular interest to readers. First, we include in our regressions a set of alternative measures of diversity based on gender, race, experience, and education. These additional tests show that the impact of political identity on fund performance exists over and above the role played by other demographic and functional dimensions of diversity. Indeed, these results are strongly supportive of our conjecture that political ideology is superior to these alternative measures in capturing differences in individuals' information sets and views of the world. Second, we examine in depth the sensitivity of our results to the inclusion of managers for whom we do not observe political donations (which we refer to as 'Grey' managers). This set of tests unequivocally leads to the conclusion that including Grey managers does not bias our results towards finding the outperformance of diverse teams. Instead, these results suggest that our classification of Grey managers as individuals without a strong political identity is correct, providing useful variation in our tests of the impact of team ideological diversity.

We also perform two additional analyses to strengthen the causal interpretation of our results. First, we show that the positive impact of fund diversity on performance is robust to controlling for unobserved managerial heterogeneity through the inclusion of high dimensional manager-by-time fixed effects. Results of these manager-level regressions show that the same manager, at the same point in time, performs better if she operates in an ideologically diverse team compared to a homogeneous one. Therefore, these results demonstrate that the outperformance of diverse teams cannot be explained by systematic differences in the characteristics of managers operating in those teams, but must be a feature of the interaction among team members. In the second analysis, we use exogenous changes to team diversity that result from M&A activity in the asset management industry. To eliminate any concern about possible ex-ante differences between the sample of acquired funds and those funds whose investment advisor is not acquired, we limit our analysis to acquired funds and focus on the variation in political differences across our treatment sample for identification. In a difference-in-differences (DID) setting we confirm our baseline results, an increase in the diversity of the acquired funds is associated with higher fund performance post-acquisition, thus addressing concerns that the matching of managers with different political identities is endogenous to fund-level outcomes. Jointly considered, these two analyses indicate that the documented relation between diversity and fund performance is causal.

While the performance results suggest potential complementarities in diverse teams, we also explore the potential trade-off of increased conflict due to differing political ideologies. Using different measures of political polarization, both at the national and the state level, we examine the impact of "priming" this dimension of fund manager identity. The prior literature shows that in times of high political polarization, differences in political beliefs can be exacerbated, creating conflict, limiting communication, and paralyzing decision-making.[10] We rerun our baseline analysis separately in times of low and high polarization. We find that consistent with a trade-off between the costs and benefits of diversity, the priming of group political differences associated with increased polarization undoes diverse teams' performance advantage. In addition to providing important evidence regarding the underlying team diversity mechanism, the sensitivity of the performance results to national or state-level polarization is also important because it rules out concerns about the existence of unobserved characteristics correlated with both political diversity and fund performance. As the same diverse team performs well in times of low polarization and poorly in times of high polarization, these potentially unobserved characteristics are held constant. Any alternative explanation based on such characteristics would have to explain why the relation between our diversity variable and team performance varies precisely when political identity is primed.

Next, we examine possible mechanisms for the observed outperformance. The literature on diversity suggests that an improved decision-making process might be the reason why diverse teams outperform their homogeneous counterpart. The cognitive process of a diverse team benefits from multiple different perspectives, broader information sets and expertise. To assess the potential role of this channel, we revisit an important insight from Pollet and Wilson (2008). They examine the response of mutual funds to additional investment inflows and find that the average manager responds to flows by increasing their holdings of an existing position instead of adding new positions, negatively impacting performance. We believe this result is a natural

[10] See Jehn et al. (1999), Ely and Thomas (2001), De Dreu and Weingart (2003), Klar (2013), and Westfall et al. (2015).

place to start because the authors interpret this behavior, and the resulting diseconomies of scale, as a manifestation of constraints on human capital (see also Chen et al. (2004) for a similar argument). By revisiting their analysis accounting for teams' ideological diversity, we test whether those constraints are less binding in diverse teams. Consistent with their results, we find that managers disproportionately increase their ownership share in existing positions in response to fund flows, rather than adding new positions. However, diverse teams are significantly more likely to add new positions in response to flows compared to homogeneous teams, a result that is consistent with broader information sets and improved decision-making of diverse teams.

We strengthen the link between the mechanism outlined above and our performance results with three additional tests. First, we document that both active share and tracking error increase when fund diversity is higher, which suggests that diverse funds are concentrated stock pickers, and that they generate outperformance through their superior ability to place concentrated bets (Cremers and Petajisto (2009)). Second, we explore the performance of the new positions added by diverse teams both using calendar-time portfolio returns and studying the decisions made by a team around changes in team composition (e.g., when a diverse manager joins the team). These tests confirm that the new positions added by diverse teams in response to inflows generate superior performance compared to the investment choices of homogeneous teams.

In the third set of tests, we zoom in on a specific aspect of the new stocks selected by diverse teams. Specifically, we examine one dimension of stock selection that previous literature suggests may differ across Democratic and Republican-leaning managers: ESG stocks. Hong and Kostovetsky (2012) show that Democratic managers are more likely to hold high ESG stocks, while Republican managers are more likely to hold low ESG or so-called "sin" stocks. The different holdings across these two types of managers are consistent with an implicit bias or lack of expertise regarding certain investments, leading to restrictions on the investment opportunity set (e.g. Democratic managers avoiding investment in gun manufacturers). Heterogeneous teams, however, may combine the two different information sets of Democratic and Republican managers, lifting the restrictions and resulting in improved performance. We find evidence consistent with this hypothesis: when a new manager addition makes a team more diverse, a former Democrat fund increases its positions in low ESG stocks, while a former Republican fund tilts its portfolio toward high ESG stocks. Moreover, we document that diverse teams have a superior ability to select low (high) ESG stocks compared to Democrat (Republican) teams, as testified by the superior performance of their selected assets.

While the broader diversity literature emphasizes the potential for different perspectives and information sets of the diverse team members to result in better decision-making, the economics literature also highlights an alternative mechanism: mutual monitoring (Akerlof and Kranton (2008)). The synergy among agents, which is precisely the reason for the team's existence (Alchian and Demsetz (1972)), implies that each member's contribution to the team's output is not distinguishable. Thus, it would not be possible to remunerate team members according to individual productivity. This setting generates the free-rider problem suggested by Holmstrom (1982), which arises when the joint output is the only observable indicator of each team member's input, making it impossible to identify agents who shirk. One solution to this team production problem relies on the peer pressure associated with mutual monitoring. Given the inherent unobservability of individuals' contributions by the principal, the monitoring is performed by the very members of the team, who mete out punishments to those agents who fail to perform adequately. In a theoretical work, Kandel and Lazear (1992) show that if the cost of such monitoring to the agents is sufficiently low, peer pressure can offset the free-riding incentives.

To test this second potential mechanism of mutual monitoring and peer pressure, we examine the determinants of fund manager promotions and demotions. While we expect promotions and demotions to be driven by manager performance, the mutual monitoring hypothesis suggests that there would be more intense monitoring in heterogeneous teams. As a result, we would expect managers in heterogeneous teams with higher performance to have an incrementally higher probability of promotion. At the same time, those with poor performance will also have an incrementally higher probability of being demoted. In studying the determinants of promotions and demotions of portfolio managers, we show evidence consistent with this hypothesis.

Last of all, we study potential frictions that might prevent investment advisors from adopting more diverse teams. To this end, we examine two possible hypotheses. The first is that entrenched managers may prefer to avoid any additional monitoring associated with a heterogeneous team. As a result, they may influence the allocation of managerial talent to ensure they are only involved in homogeneous teams. The second is that the supply of ideologically diverse managers may be constrained by geography. We argue that if the labor market in which the investment advisors are hiring new managers is largely homogeneous relative to the ideological bent of the investment advisors, then they will be less likely to make diversifying hires.

To examine the first hypothesis, we use tenure at the firm and assets under management for each manager to measure entrenchment and negotiating leverage. Consistent with the hypothesis that entrenched managers prefer homogeneous teams, team homogeneity is strongly positively correlated with these measures. To examine the second hypothesis, we calculate state-level time-series measures of ideological diversity. Using these measures, we find that those investment advisors operating in less ideologically diverse states are more likely to have homogeneous manager teams.

Our paper contributes to the literature in three major ways. First, we contribute to the growing literature on identity economics (i.e. Akerlof and Kranton (2000), Akerlof and Kranton (2005), Akerlof and Kranton (2008), Kranton (2016), and Kranton et al. (2020)) by providing strong empirical evidence of how identity influences decision-making in the workplace. Specifically, we provide evidence of the value of ideological diversity that arises when teams include individuals with differing political identities. We also find evidence that when these differences in their political identities are primed, the value associated with diverse teams disappears. Our results on mutual monitoring also speak to important implications of group identity for manager incentives (Kranton et al. (2020)).

Second, we relate to the broad empirical literature on diverse teams, which includes studies that focus on the effects of gender diversity on boards (e.g., Adams and Ferreira (2009), Ahern and Dittmar (2012), Kim and Starks (2016)); or among mutual fund managers (e.g., Niessen-Ruenzi and Ruenzi (2019)); the effect of differences in individual ancestries (Giannetti and Zhao (2019)); and studies that analyze several dimensions of diversity (e.g., Adams et al. (2018), Bernile et al. (2018)). Our paper is among the first to explore the role of political identity, as the relevant measure of diversity. This focus is important because political ideology is an important aspect of identity and has been shown to be a more informative measure of attitudes and beliefs. We show that political diversity is relevant over and above more common demographic or functional dimensions of diversity. Moreover, through our use of political polarization as an exogenous exacerbating shock to differences in political identity, we show that the increased conflict associated with this polarization can undo the potential value-added through diversity. When differences in political identity become more polarizing, consistent with increased conflict, limited communication, and paralyzed decision-making, the observed beneficial effect of diverse teams is mitigated. Finally, because we observe the same manager simultaneously in different teams, we can address the endogeneity concerns that plague much of the prior literature.

Finally, our findings are also relevant to the literature on the role of human capital allocation for mutual fund performance. Existing studies explore characteristics of individual managers (e.g., Chevalier and Ellison (1999)), or compare the performance of single- versus team-managed funds (e.g., Prather and Middleton (2002), Bar et al. (2011), and Patel and Sarkissian (2017)). We add to this literature by providing causal evidence of the impact of team ideological diversity on fund performance and more importantly we can show what diverse teams decide differently from homogeneous teams. We provide evidence consistent with both an improved decision-making and increased monitoring mechanisms for the observed increase in team productivity.

The remainder of the paper is structured as follows: Section 2 describes the data and how we construct our measure of political identity. Section 3 presents evidence consistent with team ideological diversity being associated with superior performance. In Section 4, we study the mechanism underlying the outperformance of diverse teams by looking into the portfolio choices of heterogeneous versus homogeneous teams and explore increased monitoring mechanisms for the observed increase in team productivity. Section 5 explores the effect of political polarization on diverse team performance. Section 6 tests two possible hypotheses for the lack of ideological diversity in asset management. Section 7 provides a detailed discussion of the robustness of the performance results. Section 8 concludes.

2 Data

This section describes the databases used in our analysis and the construction of our political diversity measures.

2.1 Data sources

To construct our dataset, we combine data from several sources. We use the Center for Research in Security Prices (CRSP) Survivorship Bias-Free Mutual Funds Database for fund-level information. The Thomson Reuters/CDA Spectrum database to obtain quarterly mutual fund holdings. We obtain the educational and professional background of portfolio managers from Morningstar.

We start from the list of actively managed U.S. funds from January 1992 through December 2016, belonging to five different asset classes: domestic and international equity, domestic and international bonds, and balanced portfolios. Because we are interested in studying the active behavior of team members, we drop index funds and funds managed by a single portfolio manager. After applying these filters, our sample contains 12,387 managers, 5,305 funds, and 583 management companies.

We obtain political contribution data from the Center for Responsive Politics (CRP), which serves to identify the political identity of the managers from their contributions. CRP is a non-profit organization that directly collects the information from the Federal Election Commission's political contributions reports. The CRP database covers all contributions from Political Action Committees (PACs) and individual contributions from the 1992 cycle through the 2016 cycle. The database includes information on the individual's name, individual's location (state/zip), individual's occupation/employer, donation amounts, recipients of their donations, and recipients' party affiliation.[11]

To determine a match between a manager in our data and an individual within the CRP data, we adopt a conservative approach consisting of two steps. First, we require that the individual in the CRP database has the same full name as the portfolio manager. Second, for individuals with the same full name as the manager, we require that the individual's employer is one of the management companies that characterize the manager's employment history in our sample. We obtain individual contributions to political candidates and political committees for 2,428 portfolio managers that are part of 4,123 team-managed funds from 1992 through 2016. The total campaign contributions by the average portfolio managers over our entire sample period was \$19,222, with the average Republican manager donating \$22,632 and the average Democratic manager donating \$14,726.[12]

We label each individual donation as Republican ("Red") or Democratic ("Blue") if the recipients' party affiliation is Republican (Democrat). If the individual contributed to a PAC, to be as conservative as possible, we label the donation Red (Blue) only if the PAC to which the manager contributed has donated 100% of the total dollar amount contributed in that election cycle to a Republican (Democrat) candidate.

2.2 Political diversity measures

Using each manager's full donation history, we construct a manager-level measure of political orientation. First, we compute the total dollar amount of political donations made by the manager to the Republican (R_i) and Democratic (D_i) Parties over the entire sample period.

[11]The CRP data can be accessed at http://www.opensecrets.org/

[12]Before the Bipartisan Campaign Reform Act of 2002 (BCRA), the individual contribution limits to a political candidate was \$1,000 per election cycle and \$25,000 to political committees per calendar year. Beginning with the 2003-2004 election cycle, the BCRA increased the limits on contributions made by individuals and political committees. As of 2016, the cap on individual donations to a political candidate was \$2,700 per election cycle and \$33,400 to political committees per calendar year.

Then, we calculate the proportion of the manager's donations towards the Republican party net of Democratic donations as a function of total donations as follows:

$$Mgr\ Rep_i = \frac{R_i - D_i}{R_i + D_i} \tag{1}$$

By construction, $Mgr\ Rep_i$ is a continuous measure between -1 for Blue managers (Democratic) and 1 for Red (Republican) managers. If a manager is not politically involved and does not donate to any candidate, we classify her as "Grey" and assign a value of zero to $Mgr\ Rep_i$.

An empirical choice that we make in classifying managers is to use each individual's full donation history to more accurately describe her dominant political identity. While it is certainly possible that an individual changes political beliefs, our choice minimizes the risk of misclassifying individuals who, for reasons unrelated to their political views (e.g., relationships with candidates or variation in party popularity), contribute to the other party in a single election cycle. This choice, driven by the desire to minimize measurement error, follows existing literature using political donations data (e.g., Hong and Kostovetsky (2012), Lee et al. (2014), Hutton et al. (2014)). There are two reasons why we believe this choice does not significantly affect our results. First, for most managers, political contributions reveal a unique political inclination; only 6.7% of managers display two different dominant political views over the sample period. Second, we also calculate a time-varying definition of manager donations in which we allow political beliefs to vary by political cycle. In Section 7.3 we show the robustness of our findings to the use of this and other alternative ways to construct our main independent variable.

In the next step, we construct a variable that reflects the distance in political beliefs between manager i and the rest of the fund's team at time t. Specifically, we compute the normalized Euclidean distance between manager i and the other managers of the fund:

$$Manager\text{-}Fund\ Distance_t = \frac{|Mgr\ Rep_i - Fund\,Rep_{-i}|}{2} \tag{2}$$

where $Fund\,Rep_{-i}$ is the average value of $Mgr\ Rep$ among the other fund managers, excluding manager i. A $Manager\text{-}Fund\ Distance$ value of zero indicates perfect agreement in political beliefs between the manager and the rest of the team members, while a value of one (the maximum distance) indicates they have complete opposing views.

As a final step, we aggregate $Manager\text{-}Fund\ Distance$ at the fund level by taking the average at time t. We compute:

$$Fund\ Diversity_t = \frac{1}{N} \times \sum_{i=1}^{N} \left(\frac{|Mgr\ Rep_i - Fund\ Rep_{-i}|}{2} \right) \tag{3}$$

where the sum is calculated across all the team members at time t. In Internet Appendix Table A4, Panel A, we also aggregate at the fund level by weighting the views of each manager by the ratio of manager's dollar donations to the fund's total dollar donation, and we document that our main results are robust to the use of this alternative weighting measure.

2.3 Grey Managers

We also make another important empirical choice. Since the decision of not making contributions to any political party is informative in itself about the strength of an individual's beliefs, we do not drop Grey managers when we compute *Fund Diversity*. Specifically, the decision of not making contributions to any political party suggests that the degree of political involvement of such an individual is lower than an individual who donates. Importantly, this information separates managers who do not donate from both Blue and Red managers and therefore contributes to the diversity in ideologies within a fund (e.g., a team composed of a Red and a Grey manager is more diverse than a team with two Red managers or two Grey managers).

If some managers with strong political views do not contribute, our empirical approach to Grey managers could result in measurement error. If such measurement error exists, it would introduce noise to our diversity measure, biasing our results toward the null hypothesis of no effect associated with ideological fund diversity. To elucidate this argument, consider that the political ideology of a misclassified Grey manager could tilt either Democratic or Republican. As a result, the manager's true value of $MgrRep_i$ could fall anywhere between -1 and $+1$, and the true diversity of the fund could be lower or higher.[13]

While we believe it is unlikely that potential misclassification of Grey managers is driving our results, we nonetheless demonstrate robustness in several different ways in Section 3.1 and, more extensively, in Section 7.3.

[13]Any argument in support of a positive association between the potential misclassification of Grey managers and fund performance would have to simultaneously explain two effects: i) why funds with misclassified managers whose actual views imply higher fund diversity are systematically associated with better fund performance; ii) why funds with misclassified managers whose actual views imply lower fund diversity are systematically associated with worse fund performance.

2.4 Summary statistics

Panel A of Table 1 reports the average number of team funds and fund families of our sample over three different sample periods. The number of funds managed by teams grew from 800 during 1992-2000 to 3,115 during the period 2010-2016. We observe a similar pattern for the number of fund families, with 178 in the earlier period of our sample and 403 during the latest period. We report summary statistics for our team diversity variables in Panel B. *Fund Diversity* is 0.15, on average, and 0.28 in the 75th percentile of the distribution. *Manager-Fund Distance* is 0.14, on average, and 0.25 in the 75th percentile of the distribution. We compute a similar diversity variable at the state level, where the average is 0.61, suggesting more heterogeneity at the state level, albeit with a lower standard deviation. Panel C shows that the median number of managers in a team is 3, with 2 in the 25th percentile and 4 in the 75th percentile of the distribution. In the other rows of Panel C, we report the distribution of the control variables used in our regression specifications.

[Insert Table 1 here]

3 Fund performance

This section examines whether team diversity in terms of political identity is related to fund performance.

3.1 Baseline Results

As a starting point for our analysis, in Table 2 we use calendar-time portfolios to study the performance of politically diverse teams. We divide the funds in our sample into the following six portfolios: a portfolio of funds with a value of diversity equal to zero (column *D=0*); four portfolios based on quartiles of diversity computed excluding funds with diversity values equal to zero or one (columns *Q1* through *Q4*); and a portfolio of funds with a value of diversity equal to one (column *D=1*). Next, we regress the time-series of gross returns of each portfolio on Fama-French-Carhart's 4-factor model. We report the resulting monthly average risk-adjusted return in Panel A. We find a nearly monotonic increase in risk-adjusted returns as we move from the low diversity to the high diversity portfolios. The portfolio of funds with zero diversity and those in column *Q1* are the only two portfolios that display returns that are not statistically different from zero. In addition, their returns are statistically indistinguishable from each other. We show positive and significant risk-adjusted returns starting from the portfolio in column

Q2, with the portfolio of funds in column *Q4* displaying average monthly risk-adjusted returns equal to 0.14%. The portfolio of funds with a value of diversity equal to one shows the highest average monthly alpha, equal to 0.19% (i.e., 2.3% risk-adjusted returns per year).

In Panel B of the table, we report the risk-adjusted returns of four long-short portfolios. In the column labeled *[D=1] - [D=0]*, we construct a portfolio that buys funds with a value of diversity equal to one and sells funds with diversity values equal to zero. Results show a positive and significant average monthly alpha of 0.15% (i.e., 1.8% risk-adjusted returns per year). In the column labeled *[D=1] - [Q1]*, we contrast funds with a diversity value of one and funds with the lowest, strictly positive diversity values. The monthly average alpha sums up to 1.7% per year, which indicates that the superior performance of diverse funds survives even excluding the set of funds with zero diversity. In column *[Q4] - [D=0]*, we exclude funds with a diversity value equal to one, thus comparing funds with the highest diversity values strictly below 1 and funds with zero diversity. We still observe a positive and significant average monthly risk-adjusted return amounting to 1.2% per year. This exercise is important as it shows that the superior performance of diverse funds does not depend upon funds with extreme values of our diversity measure (i.e. $Fund\ Diversity = 0$ or 1), but it is a feature of the entire distribution of diversity values. Similarly, these results rule out the concern that the outperformance of diverse teams stems solely from the presence in the sample of Grey funds, as our results are robust to excluding funds with zero diversity.[14] Finally, in the last column we report the risk-adjusted return of a long-short portfolio that buys funds with high values of diversity (columns *D=1* and *Q4* of Panel A) and sells funds with low values (columns *D=0* and *Q1* of Panel A). The monthly average alpha sums up to 1.2% per year, and it is highly significant.

[Insert Table 2 here]

Next, we test whether the outperformance of teams comprised of members with different political identities is robust to a fund-level multivariate regression setting, where we can explicitly control for several other determinants of performance, as well as for time-varying unobservable heterogeneity common to all funds following the same style. Moreover, in this setting we use five different performance measures, thus making sure our results are not specific to any one of them. More in detail, we run the following fund-level regression:

$$R_{it} = \alpha_{st} + \beta Fund\ Diversity_{it-1} + \gamma X_{it-1} + \epsilon_{it} \tag{4}$$

[14]In section 7 and the related Internet Appendix Table A3, we perform several additional tests to rule out potential biases introduced by the presence of Grey managers.

where the dependent variable R_{it} is either the gross return of the fund i, or the fund's alpha over the CAPM (*Alpha 1F*), the Fama-French 3-factor (*Alpha 3F*), the Fama-French-Carhart's 4-factor (*Alpha 4F*), or the difference between the fund's gross return and the return of the fund's Morningstar benchmark (*Benchmark-Adjusted*), all measured as of month t.[15] X_{it-1} is a matrix of fund characteristics, including fund size, expense ratio, load fee, turnover, fund age, and the number of fund managers, all measured at the end of month $t-1$. We also add style-by-time fixed effects (α_{st}), which absorb any time-varying differences across styles that may correlate with fund performance. To account for cross-sectional correlation of fund returns, we cluster standard errors by time (year-month).[16] We find that, regardless of the specification used, the coefficient on *Fund Diversity* is positively and significantly related to fund performance.[17]

[Insert Table 3 here]

In Section 7.1, we show that the relation between fund diversity and performance survives the inclusion of several high-dimensional fixed effects. For instance, since many managers serve simultaneously in different teams, we can introduce manager-by-time fixed effects, which absorbs any time-varying unobservable differences across managers and provide causal evidence of the impact of diversity on performance. Moreover, in Section 7.2, using a quasi-experimental design based on M&A activity in the asset management industry, we further strengthen our confidence that the documented relation between diversity and performance is causal.

To gain further insight into the economic magnitude of our documented results, in Internet Appendix Table A1 we study the difference in value-added between homogeneous and diverse teams. Following Berk and Van Binsbergen (2015), we compute value-added by multiplying the difference between the gross return of the fund and the return of the fund's corresponding Vanguard index by the total assets under management of the fund at the end of the previous period. Assets under management are inflation-adjusted by expressing them in 2016 dollars. We find that teams in the top quartile of diversity generate about \$2.3 million per year in value-added compared to those in the bottom quartile. When looking at the relation between *Fund Diversity* and value-added in a multivariate regression setting, we find that the difference

[15] The factors SMB (size factor), HML (book-to-market factor), and WML (momentum factor) are obtained from Kenneth French's website. Morningstar benchmark returns are obtained from Morningstar Direct.

[16] Our results are robust to different clustering methods, such as clustering by fund, clustering by fund and time, or using Newey-West standard errors in a Fama-Macbeth specification. Results with fund and time clustering are presented in Table A4 in the Internet Appendix

[17] We find similar results when we repeat the analysis using returns after deducting fees and expenses. The results are presented in Table A5 in the Internet Appendix.

in the value extracted from markets between a homogeneous team (bottom quartile, *Fund Diversity = 0*) and a diverse team (top quartile, *Fund Diversity = 0.28*) is about $1.8 million per year.

3.2 Demographic and functional diversity

In addition to our metric of ideological diversity based on political views, a growing literature also explores the impact of demographic and functional diversity (e.g., Bar et al. (2011), Bernile et al. (2018)). In this section, we test whether our political diversity measure contributes to fund performance above and beyond these other dimensions of diversity.

We use the Teachman's Entropy index based on managers' gender and ethnicity to measure team diversity based on gender and ethnicity. We measure tenure diversity as the standard deviation of managers' tenure, where tenure is the number of years since the manager is recorded in the Morningstar Direct database. Style-experience diversity is the standard deviation of the number of years each fund's manager has worked on a given style. Lastly, we measure functional diversity using the Teachman's Entropy index based on the degree level and field of studies of the manager.

As a first step in the analysis, in Internet Appendix Table A2 we report correlations and regression results examining the relationship between the average political views of a fund and other fund-level demographic measures. Specifically, we compute the political view of the fund management team by taking the average of Equation (1) across the fund's managers. This variable captures how Republican-leaning is the average member of the team (*Fund Republican Index*). We then compare this variable to *Female Managers*, computed as the fraction of female managers working for a fund at date t; *Non-White Managers*, computed as the proportion of managers working for a fund that is not White/Caucasian; *Average Tenure*, computed as the mean tenure of funds' managers; *Average Style-Experience*, computed as the mean number of years each manager has worked on her fund's style; *Graduate Managers*, computed as the fraction of managers with graduate studies; and *Business Major*, the fraction of managers with a business major.

We find that funds with a greater proportion of male, white/Caucasian, longer-tenured, without a graduate degree, and with a business major are more likely to exhibit Republican views. These results accord well with prior literature and anecdotal evidence and thus provide a point of validation for our measure of funds' political identity. For example, the Pew Research Center (2018) examines demographic differences in Republican and Democratic voters.

Consistent with our results, they find, women, African American, Latino, Millennial voters, and college graduates are more likely to identify as Democrats or lean Democratic.

While these results provide a point of verification for our measure of manager political views, they also point to a possible alternative causality. Due to the correlation between manager political views and these other managers' characteristics, our measure of team ideological diversity may proxy for other dimensions of diversity. To determine what role, if any, these other diversity variables play relative to ideological diversity, we rerun our baseline performance analysis (Equation (4)), including alternative diversity variables based on gender, ethnicity, tenure, specialization on a given fund style, and education. The results are presented in Panel A of Table 4.

Overall, the results indicate that using political ideology diversity as the relevant facet of identity matters over and above functional and demographic diversity measures. Some of the other measures, such as functional diversity and diversity based on managers' experience in an investment style, seem to impact team performance positively. Interestingly, for measures of demographic diversity, the results are more mixed: in some specifications, gender diversity negatively affects performance, while ethnicity diversity does not seem to have any significant effect. These results are consistent with Bar et al. (2011), who construct measures of team diversity based on age, gender, tenure, and education, and find no significant impact of any of the diversity dimensions on the team behavior of portfolio managers. We conclude that none of the demographic and functional diversity measures are as strongly and consistently associated with outperformance as our measure of political identity diversity.

Given these results, a question that might arise is: what makes diversity in political identity superior in predicting performance compared to the other diversity measures? While a complete answer to this question is outside the scope of this paper, we propose a potential explanation. The implicit assumption behind the use of demographic and functional characteristics to study the impact of diversity on team performance is that differences in such characteristics reflect differences in team members' preferences and views (see, e.g., Hambrick and Mason (1984) for a discussion of this assumption). However, characteristics like gender, ethnicity, and education are only imperfect proxies for an individual's views of the world, and thus diversity measures based on such characteristics likely capture with significant error intra-team dispersion in beliefs. On the other hand, political identities provide a more precise reflection of an individual's views. We, therefore, argue that using a diversity metric based on political identities reduces measurement error and allows higher statistical power to study the impact of dispersion in value systems and preferences on performance.

3.3 Political connections

A second plausible alternative explanation for our main results is that fund diversity proxies for a team's political connections. Such political connections could provide a comparative advantage in access to information, which, in turn, might give managers an edge to generate outperformance. The argument is similar, for example, to the one in Cohen et al. (2008), which shows that a manager's social network provides valuable information advantages. In our setting, diverse teams are those in which managers contribute to different political candidates. Thus, these teams might mechanically have a larger network of political connections. If managers benefit from collecting information based on their political identity, they could capitalize on the abnormal returns related to this information, generating higher performance (Grossman and Stiglitz (1976)).

To rule out that the outperformance arises because diverse teams capitalize on their political network, we rerun our baseline model (4), including variables that control for the intensity of funds' political connections. These variables are: *Fund Contributions*, a fund's total dollar value of political contributions; *Fund Candidates*, computed as the total number of unique candidates that received a contribution by the fund's managers in the election cycle; and *Fund Winners*, computed as the total number of unique winning candidates that received a contribution by the fund's managers in the election cycle. Because funds might benefit from their political network by investing in politically connected stocks, where they arguably possess superior information, we also explore the degree of political bias that the fund displays in its holdings. We use the Thomson Reuters mutual fund holdings database to compute the average political views of stocks included in the portfolio of funds in our sample. We measure the political views of fund holdings using the political contributions of the firms' executives. We then add *Holdings' Political Similarity*, computed as the Euclidean distance between the average political views of the fund managers and the value-weighted average political views of the fund holdings. Lastly, we also add *Percent Aligned*, computed as the fraction of fund holdings invested in politically aligned stocks, as in Wintoki and Xi (2019).

The results are shown in Panel B of Table 4. While both *Fund Contributions* and *Holdings' Political Similarity* have a positive impact on fund performance, our *Fund Diversity* variable remains virtually unchanged. We confirm that across different specifications, the relation between *Fund Diversity* and performance is robust to the inclusion of these additional controls.

These results suggest that the outperformance we observe for diverse teams is independent of any additional outperformance they generate through increased political connections on both sides of the aisle.

[Insert Table 4 here]

4 Potential channels

In this section, we explore two potential mechanisms for the superior performance of diverse teams, based on: i) improved decision-making in diverse teams; and ii) enhanced monitoring and peer pressure by team members in diverse teams.

4.1 Improved decision-making

First, borrowing from the literature on team diversity, we entertain the hypothesis that diverse teams benefit from an improved decision-making process. With different perspectives, information sets and expertise, a diverse team may consider a wider set of possibilities and through considering more dimensions of the analysis make better decisions on that wider set. The mutual funds setting allows us to observe teams' decision-making at a very granular level, and thus uncover what makes heterogeneous teams different from homogeneous teams.

4.1.1 Portfolio diversification and scaling

In exploring the first mechanism, we start from an important insight from Pollet and Wilson (2008) and examine a potential direct consequence of diverse teams' improved decision-making. Pollet and Wilson (2008) show that fund managers disproportionately respond to asset growth by increasing their investments in existing positions rather than increasing the number of investments in their portfolios. At the same time, the paper documents that funds that do increase the number of distinct holdings in their portfolios in response to flows display higher subsequent performance. Thus, the observed limited ability of fund managers to generate additional (equally good) investment ideas might explain the well-known negative relation between fund size and fund returns (Chen et al. (2004)). Faced with growing fund size, manager teams are unable to augment the number of investment ideas at a sufficient rate. Interestingly, both Pollet and Wilson (2008) and Chen et al. (2004) suggest that the slow growth in the number of new stocks might be due to constraints on human capital. We hypothesize that team ideological diversity may alleviate these constraints, as the addition of a diverse manager to a team is more likely to enrich the information set used by the team to make investment decisions.

To test this hypothesis, we study whether the relation between fund flows and the growth in the number of new stocks in funds' portfolios is affected by the political diversity of the fund. We use the same regression framework provided by Pollet and Wilson (2008) adding *Fund Diversity* as well as the interaction between *Fund Diversity* and fund flows. Results are reported in Table 5. Columns (1) and (5) replicate the baseline results of Pollet and Wilson (2008), and document that a 1% increase in Total Net Assets (TNA) raises the number of stocks in a portfolio by about 6%, and leads to an increase in average ownership share of approximately 50%. However, the coefficient of interest is the interaction between *Fund Diversity* and *Fund Flows*. Our results show that politically diverse funds respond to a 1% increase in TNA by raising the number of stocks in their portfolio by an additional 1.2/1.4%. In contrast to this, *Fund Diversity* plays no role in fund scaling decisions in response to fund flows. These results are consistent with the notion that diverse teams benefit from additional information, perspectives, styles, and insights, which manifest in their enhanced ability to generate new investment ideas in response to the growth in their assets under management.

[Insert Table 5 here]

4.1.2 Active management

Results in the previous subsection indicate that funds with diverse teams are better than homogenous funds at enlarging their universe of investment ideas, suggestive of reduced human capital constraints in diverse teams. Results so far, however, do not allow to go beyond that conclusion and learn about the type of investment strategy followed by diverse teams. Specifically, we do not know whether the addition of new stocks leads to the outperformance of diverse teams through a better portfolio diversification, or whether their higher ability to generate new investment ideas allows diverse team to more successfully engage in stock picking.

Cremers and Petajisto (2009) provide a framework that, by studying a fund's active share and tracking error, enables us to infer a fund's approach to active management and thus its source of outperformance. In our second set of tests, therefore, we aim to study the type of investment strategy followed by diverse teams by examining the relationship between portfolio active management measures and team diversity. In Table 6, Column (1) we regress funds' active share on *Fund Diversity* and other controls, while in Column (2) we use tracking error as dependent variable. We follow Cremers and Petajisto (2009) to construct active share for our sample of funds. The tracking error is measured as the standard deviation of the residuals obtained from a 36-month rolling window regression of fund performance on the Fama-French-Carhart 4-factor model.

[Insert Table 6 here]

Table 6 documents that there is a significant positive relation between *Fund Diversity* and both active share and tracking error. The fact that diverse teams display both higher active share and tracking error suggests that diverse funds are concentrated stock pickers, and that they generate outperformance through their superior ability to place concentrated bets.

4.1.3 New investment ideas

In this section, we further explore the higher ability of diverse funds to generate new investment ideas. The analyses in this subsection follow from the observation that, if the outperformance of diverse teams derives from their stock-picking ability, then we should observe that the new stocks diverse funds add to their portfolios exhibit superior performance. The analyses below are also useful as they provide a closer point of connection to our baseline performance results of section 3.1.

In Panel A of Table 7, we follow a calendar-time portfolios approach. We construct four different portfolios of stocks: i) a portfolio of new stocks in which diverse teams invest in response to fund inflows; ii) a portfolio of existing stocks in which diverse teams invest in response to fund inflows; iii) a portfolio of new stocks in which homogeneous teams invest in response to fund inflows; iv) a portfolio of existing stocks in which homogeneous teams invest in response to fund inflows. We compute value-weighted returns for each portfolio, and we regress them on the Fama-French 4-factor model.

We observe that the portfolio of new stocks selected by diverse teams exhibits the highest alpha across the four portfolios, about 0.7% in monthly risk-adjusted returns. In the last two columns of Panel A, we test the performance differences between the portfolio of new stocks selected by diverse teams and the portfolios of homogeneous teams. First, we compare the performance of new stocks selected by diverse teams and those selected by homogeneous funds (Column *[1] - [3]*). We show that the former outperform the latter by more than 0.3% risk-adjusted returns per month. The last column of Panel A shows that new stocks selected by diverse teams outperform the overall portfolio of homogeneous teams by about 0.53% risk-adjusted returns per month.[18]

[18]Given that on average the new stocks in the portfolio of column (1) account for 11% of the portfolios of

In Panel B of Table 7 we test whether these results survive in a multivariate setting, where we can control for additional covariates as well as for fund and firm unobservable characteristics. First, we identify all the fund-date pairs in which a new manager joins a team. Second, we classify the new manager as diverse (i.e., the new manager's views are opposite to the average views of the existing team) or as homogeneous (i.e., the new manager shares the same views as the existing team). We also classify the holdings of funds in each date into new stocks or existing ones. Finally, armed with these classifications, we estimate the following model:

$$\begin{aligned} R_{ijt+1} = \delta + \beta_1 New\ Stocks_{ijt} + \beta_2 New\ Manager_{it} \\ + \beta_3 New\ Stocks_{ijt} \times New\ Manager_{it} + \gamma\ X_{ijt} + \epsilon_{ijt+1} \end{aligned} \quad (5)$$

where i indexes funds and j indexes fund holdings. The dependent variable is the Fama-French 4-factor alpha of stock j held by fund i over quarter $t+1$, weighted by the percentage of fund i assets that are invested in stock j. We estimate stocks' alpha using the previous 36 months leading to quarter $t+1$. *New Stocks* is an indicator variable with value 1 if stock j has been added for the first time in the portfolio of fund j in quarter t. δ represents fixed effects. In columns (1) and (3), we report results of a specification that includes firm and style-time fixed effects as well as firm and fund controls ($\gamma\ X_{ijt}$). In Columns (2) and (4), we report results of a specification with firm-time and fund-time fixed effects. In the first two columns of the table, we focus on the addition of diverse managers: we define *New Diverse Manager* as an indicator variable with value 1 starting from the quarter in which a new manager arrives in fund i and the new manager has different political views from the views of fund i ($Mgr\,Rep_m$ and $Fund\,Rep_{-m}$ have opposite signs, using the notation of equation (2)). Estimates for coefficient β_3 in both columns are positive and significant. Our results, therefore, suggest that new diverse managers who join homogeneous teams are able to contribute with new and profitable investment ideas, which is consistent with our proposed channel.

As a comparison, in the last two columns of Panel B, we perform the same analysis focusing on the addition of a homogeneous manager. *New Homogeneous Manager* is an indicator variable with value 1 starting from the quarter-year in which a new manager joins the fund i and the new manager has the same political views as fund i ($Mgr\,Rep_m$ and $Fund\,Rep_{-m}$ have the same sign). In contrast with our previous results, a new homogeneous manager does not appear to provide the team with profitable new investment ideas.

diverse funds, the alpha of column *[1] - [3+4]* indicates that roughly 57% ($0.525 \times 11\%/0.102$) of the diverse teams' monthly outperformance (0.102%) can be attributed to their superior ability to select new stocks.

[Insert Table 7 here]

4.1.4 ESG investing

As a last step in our analysis of the mechanism underlying the outperformance of diverse teams, we investigate the characteristics of the new stocks selected by these teams. Specifically, we examine one salient dimension of stock selection that previous literature suggests may differ across Democratic and Republican-leaning managers: the ESG score or leaning of stocks. Hong and Kostovetsky (2012) show that Democratic managers are more likely to hold high ESG stocks, while Republican managers are more likely to hold low ESG or so-called "sin" stocks. The different holdings across these two types of managers are consistent with an implicit bias or lack of expertise regarding certain investments. We hypothesize that as Democrat and Republican teams become more ideologically diverse, their respective biases are mitigated, helping them to develop new skills and broaden their expertise. As a consequence, the set of potentially profitable investment ideas grows larger. The increase in the investment opportunity set aligns well with the results of section 4.1.1, providing a plausible mechanism for the observed reduction in diseconomies of scale for diverse teams.

To test the hypothesis outlined above, we employ holdings-level panel regressions. Our first step is to identify all the fund-date pairs in which a new manager holding diverse views joins the fund. This time, however, we distinguish between a new Republican manager joining a Democrat team and a new Democrat manager joining a Republican team. Next, we study the ESG characteristics of the new stocks that funds buy after the new managers have joined the team.

Results are reported in Panel A of Table 8. The dependent variable is constructed as stock i ESG score weighted by the percentage of fund i assets invested in stock j at quarter t. The ESG score is the industry-adjusted score reported in the MSCI ESG rating data. Our sample period for these ESG-related tests is limited to the years between 2002 and 2016, and is dictated by the availability of MSCI ESG data. The first two columns focus on cases in which a new Republican manager joins the team. We use as a comparison group the sample of homogeneous Democrat teams. Thus, we study how the ESG investment preference of homogeneous Democrat teams changes when a Republican manager joins the team. Coefficients on the interaction term *New Stocks*$\times$*New Republican Manager* are negative and statistically significant, which indicates that when a Republican manager is added to a team, the fund tilts its portfolio away from ESG stocks.

In the last two columns of Panel A of Table 8, we repeat the same analysis focusing on the addition of Democrat managers. We examine how the ESG investment preference of homogeneous Republican teams changes when a Democrat manager joins the team. Consistent with our hypothesis, we find positive and statistically significant coefficients on the interaction term *New Stocks*×*New Democrat Manager*. We conclude that Republican teams tilt their portfolios towards ESG stocks when a new Democrat manager arrives.

Next, we again aim to provide a tighter link to our baseline performance results. Thus, we examine how diverse teams perform when it comes to ESG choices. If diverse teams outperform because they enjoy access to a larger investment opportunity set, we should observe a superior performance of ESG stocks by diverse teams. More specifically, we hypothesize that diverse teams have a superior ability to select low (high) ESG stocks compared to Democrat (Republican) teams.

We bring this hypothesis to the data in a calendar-time portfolios setting. We construct six portfolios of stocks: i) portfolio of low ESG stocks selected by diverse teams; ii) portfolio of high ESG stocks selected by diverse teams; iii) portfolio of low ESG stocks selected by Democrat teams; iv) portfolio of high ESG stocks selected by Democrat teams; v) portfolio of low ESG stocks selected by Republican teams; vi) portfolio of high ESG stocks selected by Republican teams. We report the value-weighted risk-adjusted returns of these portfolios in Panel B of Table 8. Portfolios alphas show that diverse teams earn positive and significant risk-adjusted returns in portfolios of low ESG stocks (0.6%) and high ESG stocks (0.3%). Consistent with a specialization of Democrat teams on ESG stocks, Democrat funds display positive and significant risk-adjusted returns only when they invest in high ESG stocks. On the other hand, Republican funds do not exhibit significant alphas in either of the two portfolios. Interestingly, in the last two columns of the panel we show evidence of superior performance when we compare the performance of portfolios of low (high) ESG stocks purchased by diverse teams and low (high) ESG stocks selected by Democrat (Republican) teams.

[Insert Table 8 here]

Overall, results in the previous four subsections support the hypothesis that diverse teams, thanks to their broader information sets and expertise, are able to generate a larger universe of profitable investment ideas. This is reflected in the investment behavior of these teams, which, in response to additional inflows, are able to select new concentrated stock picks. These new stock picks, on average, display superior performance.

4.2 Mutual monitoring and peer pressure

An alternative mechanism for the observed relation between *Fund Diversity* and outperformance is that, in diverse teams, managers exert more effort due to increased monitoring by other team members. The free-rider problem associated with team production proposed by Holmstrom (1982), Kandel and Lazear (1992) suggests that peer pressure can offset free-riding incentives within teams. Specifically, given the inherent unobservability of individuals' contributions by the principal, monitoring is performed by the very members of the team, who mete out punishments to those agents who fail to perform adequately. At the same time, both the broader diversity literature and the finance literature (e.g., Lee et al. (2014)) provide evidence that greater homogeneity in a group or team may result in reduced monitoring. We hypothesize that in more diverse teams, however, the incentive to monitor would be higher.

To test whether increased monitoring is a plausible mechanism for the observed diversity and performance relation, we examine the determinants of manager promotion and demotion decisions. Similar to the demotion analysis of Chevalier and Ellison (1999), in this section we examine how the probability of being either demoted or promoted within the fund family is affected by a manager's past performance and the distance between a manager's political beliefs and the average political beliefs of other managers in the fund.

We employ data at the manager-fund-date level and run the following regression:

$$\begin{aligned} Y_{mt} = \alpha_i + \alpha_m + \alpha_t + \beta_1 \textit{ Manager Performance}_{mt-1} + \beta_2 \textit{ Manager-Fund Distance}_{imt-1} \\ + \beta_3 \textit{Manager Performance}_{mt-1} \times \textit{Manager-Fund Distance}_{mt-1} + \gamma\ X_{imt-1} + \epsilon_{imt} \end{aligned} \tag{6}$$

Here i indexes fund, m indexes managers, and t indexes time. In the first set of specifications, the dependent variable Y_{mt} equals one if a given manager m is promoted in month t, or 0 otherwise. The second set of specifications examines manager demotions using a similar setup. We define a promotion (demotion) as an increase (decrease) in both the number of funds and total assets under management (AUM) overseen by the portfolio manager. *Manager Performance* is measured as the value-weighted average of the past 36-month style-adjusted gross returns across all funds in which the manager operates, where the weights are computed as the portion of fund AUM attributed to the manager. Since both the dependent variables and *Manager Performance* change at the manager-time level, we cannot include manager-by-time fixed effects as in Equation (8) because they would absorb all the relevant variation. Thus, we include fund fixed effects (α_i), time fixed effects (α_t), and manager fixed effects (α_m). The set of covariates is the same as in Table 3. Using this specification, we compare the promotion and demotion decisions of portfolio managers when they work with team members with similar beliefs compared to a situation when they work with colleagues with different political beliefs. Table 9 present the results.

As expected, manager promotions (demotions) are positively (negatively) related to past performance. At the same time, while we expect promotions and demotions to be driven by good and bad manager performance, respectively, the mutual monitoring hypothesis predicts that the greater the ideological differences between the manager and the funds where she operates, the greater the monitoring. Consistent with such a hypothesis, in the promotion regressions, we find that the coefficient on the interaction term between *Fund Diversity* and *Manager Performance* is positive and significant, indicating a higher sensitivity of promotions to performance when the distance between the manager's political view and that of other team members is greater. Similarly, in the demotion regressions, the point estimate on the interaction term is negative and significant, consistent with higher sensitivity of demotions to performance.

[Insert Table 9 here]

Overall, these results suggest that career incentives are enhanced in ideologically diverse teams, where promotion and demotion decisions are more sensitive to objective measures like performance. In turn, stronger career incentives might elicit additional managers' efforts, leading to increased fund performance.

5 Political polarization

One of the reasons to focus on political ideology to measure team diversity is the availability of plausibly exogenous variation in the priming of this dimension of identity. In this section, we study the within-team conflicts that may arise from negative identity priming due to increased political polarization.

On *average*, diversity in political identity is beneficial for fund performance. Diverse teams benefit from both larger information sets and enhanced monitoring within teams. However, the literature on identity suggests that when differences in identity become more salient, diversity may also have a detrimental effect on team performance. Such negative consequences arise since diversity might exacerbate conflicts among team members and disrupt the team's decision-making process. (see e.g., Jehn et al. (1999), Ely and Thomas (2001), De Dreu and Weingart (2003)).

We use different measures of political polarization as a proxy for the priming of differences in political identity across team members and examine how they affect team performance. Using this exogenously determined variation in political polarization, we are able to examine the potential tradeoffs between the value-added from incorporating diverse perspectives and the conflicts raised due to greater perceived differences in identity.

Our first measure of political polarization is defined at the national level as the absolute distance between the contribution-weighted-average campaign finance scores of Democratic and Republican congressional election winners (see Autor et al. (2020)). We borrow our second political polarization metric from McCarty et al. (2006). This national-level metric is the average distance between the mean ideology of Republican and Democratic parties in the House and the Senate, computed using legislative roll call data. In Table 10 we use both metrics to determine if polarization influences the relation between team ideological diversity and performance. Specifically, we rerun our baseline analysis (Equation (4)) on two subsamples of dates characterized by low (bottom quartile) and high (top quartile) levels of polarization. Results relative to periods of low polarization are reported in Panel A, while Panel B reports results for high polarization dates.

Across performance metrics, and for both measures of political polarization, the benefits of diversity appear to be concentrated only in times of low polarization. In times of high polarization we observe that the effect of *Fund Diversity* on performance disappears.

[Insert Table 10 here]

To further validate our results, in Table A6 we test whether the sensitivity of fund performance to political polarization that we document in Table 10 is robust to two additional polarization metrics. The first three columns of Table A6 use a state-level measure of political polarization, borrowed from Shor and McCarty (2011). They measure the average distance between the median ideology of Republican and Democratic parties in the House and the Senate using state legislative roll call data. The last three columns of the Table use the Partisan Conflict Index provided by the Federal Reserve Bank of Philadelphia and developed by Azzimonti (2018). This measure tracks the degree of political disagreement among U.S. politicians at the federal level by measuring the frequency of newspaper articles reporting disagreement in a given month. The use of these alternative measures does not change the results of Table 10: the outperformance of diverse teams is concentrated in periods of low political polarization.

To sum up, in this section we uncover evidence of the potential costs of team diversity. Differences in political identities may cause teams to be more prone to conflicts, especially in polarized times, and this may negatively affect intra-team communication and decision-making.

It is worth noting that, in addition to characterizing the potential downsides of diversity, this section also lends credence to our interpretation of the baseline results of the paper as the effect of *political* diversity on performance. Evidence that the relation between *Fund Diversity* and performance is sensitive to the degree of political polarization suggests that our results in Section 3.1 are driven by differences in *political* identity. At the same time, the sensitivity of our results to levels of political polarization is not consistent with alternative explanations based on unobserved variables that correlate with both political diversity and team performance, for example, the complementarity of team managers' different skills (e.g., people skill vs. analytical skill). If the outperformance of a politically diverse team is in fact driven by the team managers possessing both people and analytical skills, it is not clear why the outperformance should disappear precisely when political identity is primed.

6 Bargaining power and supply of diversity

Given the potential of diverse teams to add value in the asset management industry, there is an important final question: why aren't all asset management teams ideologically diverse? In this section, we explore two potential constraints facing asset management companies that may explain the prevalence of more homogeneous teams: entrenched managers and local labor supply.

6.1 Bargaining power and entrenchment

One plausible determinant of the observed homogeneity in fund manager teams is manager entrenchment if managers have a strong preference to be in a like-minded group. Being in a homogeneous team offers managers important advantages. The similarity-attraction paradigm of Byrne (1971) suggests that individuals are attracted to others who are similar to themselves and gain utility from working with like-minded colleagues. Consistent with this view, Wiersema and Bird (1993) show that heterogeneous teams are the most likely to have higher turnover rates. Moreover, being in a homogeneous team relaxes the incentives to monitor each other and might make communication and decision-making easier (Jehn et al. (1999)).

If a team's composition is the product of bargaining between the asset management firm and the individual portfolio manager, individuals with high bargaining power may be more likely to surround themselves with like-minded managers. To test this, we regress our measure of team diversity on variables reflecting fund managers' bargaining power within the fund. The first measure of bargaining power uses the dollar value ($ million) of the assets controlled by the manager (*Manager AUM*). For a given fund-date observation, this variable reflects the AUM of the manager who oversees the greatest dollar value of assets across all funds overseen. Our second measure uses the tenure of the manager (*Manager Tenure*). For a given fund-date observation, this variable reflects the manager's tenure who has worked in the mutual fund industry for the highest number of years.

Table 11 provides evidence consistent with the entrenchment hypothesis. Managers with greater bargaining power as measured by more assets under management or longer tenure, are more likely to manage funds with less ideologically diverse teams.[19]

[Insert Table 11 here]

6.2 Local labor supply of ideologically diverse managers

Our second possible explanation relies on exogenous constraints imposed by a limited local supply of ideologically diverse managers. To determine whether a labor supply that is not perfectly elastic could partially explain why we observe homogeneous teams, we construct a state-level diversity measure akin to our main fund-level dispersion variable. Then, we relate this variable to the diversity of the funds headquartered in that state. *State-Level Diversity* is computed as the average Euclidean distance among all donors in a state based on their political identities. The assumption underlying the use of this state-level variable is that the state where funds are headquartered constitutes the most relevant labor market for the management companies. Columns (3) and (6) of Table 11 show that *State-Level Diversity* is positively and significantly related to *Fund Diversity*, which suggests that a limited supply of diverse managers at the state level plays a role in determining the degree of diversity observed in the funds in our sample.

7 Endogeneity and robustness checks

In Sections 7.1 and 7.2, we address potential endogeneity concerns for the relation between fund diversity and performance. In Section 7.3, we perform a battery of robustness tests on our main performance results.

[19]Note that to make sure our results are not driven by a manager's potential preference for solo-managing a fund, we exclude single-managed funds in our analysis.

7.1 *Fund and manager unobserved heterogeneity*

While our results provide compelling evidence that the performance relation we document is not driven by demographic and functional diversity or political connections of the managers, there may be plausible alternative explanations that we have not explicitly addressed. These alternative explanations can be related to unobserved family, fund, or portfolio manager-level heterogeneity.

A first concern is that our main variable *Fund Diversity* might be persistent, and thus cross-sectional differences in our variable might be capturing time-invariant heterogeneity across funds. This concern originates from the fact that we use a time-invariant classification of managers' political identity (as detailed in section 2.2), so variation in our *Fund Diversity* measure comes solely from changes in the composition of the team. To address this concern, we include fund fixed effects in our regressions, and we run the following specification:

$$R_{it} = \alpha_i + \alpha_t + \beta \ \textit{Fund Diversity}_{it-1} + \gamma \ X_{it-1} + \epsilon_{it} \tag{7}$$

where the difference with equation (4) is the substitution of style-time fixed effect with fund and time fixed effects. Results in Panel A of Table 12 show that the positive and significant relation between *Fund Diversity* and performance survives the inclusion of fund fixed effects. Since coefficients are now estimated using within-fund variation, these results indicate that time-invariant fund-level drivers of performance cannot explain the positive impact of *Fund Diversity* on performance.

Given the economics of the asset management industry, family-level unobserved factors are also a relevant concern,[20] thus we add family-by-time fixed effect to our performance analysis of Equation (7) and report results in Panel B of Table 12. The coefficient on *Fund Diversity* remains positive and highly statistically significant, which indicates that our results are not induced by family-level drivers, even if those drivers are unobservable and time-varying.

A potentially more serious concern for the interpretation of our baseline results is that they are driven by unobserved omitted variables at the manager level. For example, managers operating in diverse teams might simply be better managers. Similarly, there might be systematic differences in idiosyncratic personal preferences between managers operating in diverse and homogeneous teams, such as those stemming from wealth differences (e.g., Pool et al. (2019)).

[20] Potential examples of such factors are family-level competitive/cooperative incentives, which are known to predict fund performance (Evans et al. (2020)); the political views of the top executives of a family, which prior work suggests may shape the contribution of lower-level employees (Babenko et al. (2020)); or the existence of insurance pools within fund families (Bhattacharya et al. (2013)).

In such a case, those differences would be the actual driver of the outperformance of diverse funds, rather than the political diversity per se. The richness of our data offers us a powerful way to deal with this concern. To control for unobserved managerial characteristics, we exploit the fact that we observe managers in our sample operating in multiple funds simultaneously, which allows us to hold fixed any factor that changes across managers at any point in time.

Operationally, in this section, we use a manager-fund-date panel, and we run the following regression:

$$R_{imt} = \alpha_i + \alpha_{mt} + \beta_1 \ \textit{Manager-Fund Distance}_{imt-1} + \gamma \ X_{it-1} + \epsilon_{imt} \tag{8}$$

where i indexes fund, m indexes managers, and t indexes time. *Manager-Fund Distance* is the Euclidean distance between a manager's political beliefs and the average political beliefs of the other managers in the same team. The key element of this regression is the high-dimensional manager-by-time fixed effects α_{mt}, which absorb any difference across managers, irrespective of whether they are unobservable and time-varying. α_i indicates fund fixed effects. The set of controls included in X_{it-1} is the same as in our baseline regression (4) with the addition of an indicator variable for single-manager funds. Since most managers who serve simultaneously in different teams do that also as solo-managers, we also add these observations to reflect the other extreme of complete ideological agreement (i.e., in a single-manager fund, the manager only needs to agree with him/herself). The results in Table 12 Panel C are compelling. They show that the same manager, at the same time, performs better if she operates in an ideologically diverse team compared to a homogeneous team. These results rule out any alternative explanation based on manager-level heterogeneity.

[Insert Table 12 here]

7.2 Investment advisor mergers and acquisitions

In this section, we address remaining concerns for the causal interpretation of the positive effect of fund diversity on fund performance. A plausible alternative explanation for that relation is based on endogenous team formation. While it is true that our tests (especially our analyses in Table 12, Panel C) control for unobserved managerial heterogeneity, it is still possible that the matching of managers with different political identities is endogenous to fund-level outcomes. Our strategy to address these concerns is to use a quasi-experimental design focused on M&A activity in the asset management industry to shock diversity at the fund level.[21]

Specifically, our identification strategy is based on a difference-in-differences setting and exploits information on a total of 545 funds managed by 35 management companies that were involved in M&A activity over the 1995–2016 period. For each deal we measure the political views of the acquired funds ($Fund\,Rep_j$) as the average political ideology of the funds' managers at the M&A announcement date; similarly, the political views of the acquirer family ($Fam\,Rep_k$) are measured as the average political ideology across all the family managers at the M&A announcement date. We then use the normalized Euclidean distance between fund j and the acquirer family k (*Fund-Family Distance* $= (|Fund\,Rep_j - Fam\,Rep_k|)/2$) at the M&A announcement date as a shock to team diversity of acquired funds. Importantly, the distance in political views between each individual fund and the acquirer family is plausibly endogenous to the motives driving the M&A deal, as well as to fund-level outcomes. Therefore, using that shock to team diversity addresses potential concerns about endogenous team formation. In our tests below we examine how this shock to the diversity of the acquired funds relates to the performance of the funds.

To eliminate any concern about possible ex-ante differences between the sample of acquired funds and those funds whose investment advisor is not acquired, we limit our analysis to acquired funds and add fund fixed effects. Instead of the standard bivariate treatment/control framework, our setting relies on variation in "dosing" across our treatment sample for identification. Because there is wide variation in the differences in political views between the acquiring investment advisors and the acquired funds, we include this difference in political views as a continuous variable in our analysis. The mean *Fund-Family Distance* in our sample is 0.19, with a median of 0.06, and a standard deviation of 0.21. Additionally, we find that the distance in political ideology between the acquirer investment advisor and the acquired fund at deal announcement date is a strong predictor (coefficient of 0.175 with a t-statistic of 3.75) of the change in fund diversity of the acquired fund from the period before the acquisition (as measured at the M&A announcement date) to the period after the acquisition (average over the next 5 years).[22]

In Table 13 we show the results. The dependent variables are the gross return of the fund, the fund's alpha over the CAPM (*Alpha 1F*), the Fama-French 3-factor (*Alpha 3F*), the Fama-French-Carhart's 4-factor (*Alpha 4F*), and the difference between the fund's gross return and

[21] To identify possible investment advisor mergers, we use the same methodology employed by Evans et al. (2020).

[22] Results are reported in the Internet Appendix Table A7.

the return of the fund's Morningstar benchmark (*Benchmark-Adjusted*). In addition to the standard fund and family controls, the specification also includes fund and time fixed effects absorbing any unobservable fund-specific effects or any time-series variation that may have otherwise affected our results. We include an indicator variable for the post-merger period (*Post Merger*), and we interact the dosage variable (*Fund-Family Distance*) with this post-event indicator. Table 13 shows results that are strongly consistent with our baseline Table 3: across all performance measures, an increase in the diversity of the acquired funds is associated with higher fund performance post-acquisition.

[Insert Table 13 here]

7.3 Additional robustness tests

Our results that fund diversity is associated with better fund performance survive several additional robustness tests based on alternative sample choices or variations in the baseline measure of political diversity.

We start by studying more closely our classification of Grey managers. The presence of Grey managers poses a concern for our results if, for some reason and as a group, they are systematically associated with lower performance. It is important to note that those reasons must be different from the simple benefits coming from being a donor as opposed to not donating, such as the value of political connections, as we directly address these alternative explanations in Table 4, Panel B. To deal more generally with the potential biases introduced by Grey managers, in Panel A of Table A3 we start from a different angle: we test whether Grey managers are systematically linked to lower performance compared to donor managers. To do that, we use a calendar portfolio approach. In the first three columns, we focus on solo-manager funds, which have zero diversity by definition. In these columns, we contrast the portfolio of Grey solo-manager funds with the portfolio of solo-manager funds for which we observe the political donations of the manager. As the third column of the table clearly shows, we do not find any difference in their performance. In the last three columns, we perform a similar exercise using team-managed funds. We compare teams fully composed of Grey managers with teams that also have a value of diversity equal to zero, but in which we observe the political donations of at least two managers. Again, we do not find any difference in the performance of these two portfolios.[23] To sum up, these results provide evidence against the view that Grey managers are systematically associated to lower performance and thus bias our results.

[23]The absence of statistical significance for the alphas is unlikely to be due to the low statistical power of the test, as many of the loadings on the factors display high statistical significance.

Quite the contrary, they indicate that our classification of Grey managers as individuals with no political identity is borne out by the data.

Nonetheless, in Panel B of Table A3 in the Internet Appendix we repeat our baseline test of Table 3 including as an additional variable the fraction of Grey managers in a team. This addition serves to controls for any systematic difference in performance between funds with a larger proportion of Grey managers and funds with a larger proportion of either Red or Blue managers. Coefficients in Panel B show that the positive effect of political diversity on fund performance survives even holding fixed the proportion of Grey managers in a team.

Finally, in Table Panel C we further study the sensitivity of our results to the choice of including Grey managers in the computation of *Fund Diversity*. In column (1), we drop funds whose managers are all Grey, i.e., do not make donations to any candidate. In column (2), we restrict the sample to funds with at least two managers donating to political parties. In column (3), we restrict the sample to funds with at least 50% of team members who make political contributions. Across the different columns, the coefficient on *Fund Diversity* remains positive and significant. In all columns, the point estimates of the diversity coefficient grow larger compared to the baseline coefficients of Table 3. For example, the last column indicates that diverse teams (*Fund Diversity* = 1) outperform homogeneous teams (*Fund Diversity* = 0) by 1.6% style-adjusted returns per year. We interpret this as supporting our conjecture that if including Grey managers in our diversity metric introduces measurement error, such a measurement error is either inconsequential or biases our estimates toward zero.

In Panel A of Table A4, we study the robustness of our results to variations in the baseline measure of political diversity. In column (1), we use a version of *Fund Diversity* constructed, allowing the political beliefs of managers to vary by political cycle. In column (2), we use a version of *Fund Diversity* constructed weighting the views of each manager by the ratio of manager's dollar donations to fund's total dollar donations. In column (3), we use a version of *Fund Diversity* constructed considering political beliefs only of those who give more than $2,000 in net contributions and a value of zero to all others. In column (4), we use a version of *Fund Diversity* computed as the standard deviation of political beliefs among the managers of a fund. Regardless of how we define *Fund Diversity*, the results indicate a positive and significant impact of diversity on performance.

In Panel B of Table A4, we restrict the sample to domestic equity funds. This panel clearly shows that our baseline result of a positive impact of *Fund Diversity* on performance does not hinge critically on our inclusion of multiple asset classes in the analysis, but it survives when we focus exclusively on U.S. domiciled equity funds.

Another plausible alternative explanation is that our diversity measure proxies for managerial incentives, known to affect fund performance and risk-taking (e.g., Agarwal et al. (2009), Agarwal et al. (2020)). To ensure that managers are not just responding to different explicit incentives provided by the investment advisor, in Table A8, we run our baseline model (4), including fund-level incentive variables. We use the following five manager compensation variables hand collected from each fund's Statement of Additional Information (SAI) filings: *Bonus-fund performance*, *Bonus-fund revenue*, and *Bonus-paid in fund shares*. Khorana et al. (2007) show that manager fund ownership is positively related to performance. Thus, we control for the impact of manager ownership on performance by including the portfolio managers' ownership range data, which rank manager ownership from one to seven, with a higher rank corresponding to higher ownership.[24] Finally, we also use the shape of the fund advisory contract, Cole's incentive rate (CIR) (see Coles et al. (2000)). A higher CIR results in higher performance and risk-taking (Massa and Patgiri (2008)). We document that the effect of our *Fund Diversity* variable remains unchanged even after controlling for fund-level differences in the provision of contractual incentives.

8 Conclusion

In this paper, we examine the impact of team diversity on performance through the lens of identity for a sample of about 2,500 U.S. mutual fund managers from 1992 to 2016. Using fund manager political donations to characterize their political identity, we find that teams composed of money managers with different political identities outperform homogeneous teams. In economic terms, the outperformance corresponds to a difference of about to \$2 million per year between homogeneous and heterogeneous teams. These results are robust to adding fund, investment advisor, and manager-by-time fixed effects. In the specification with manager-by-time fixed effects, thus, we confirm that a manager in a team composed of members with differing political convictions generates higher value than her performance in another team with like-minded members. We also show that our results are robust to the use of a quasi-experimental design focused on M&A activity in the asset management industry.

We also provide evidence that the result is not driven by other dimensions of identity (i.e., gender, ethnicity, tenure, experience on a given fund style and education), manager political connections, or managerial compensation incentives. In trying to assess the mechanism for this

[24] The SEC requires managers to disclose the value of their fund ownership across 7 ranges: None; \$1-\$10,000; \$10,001-\$50,000;\$50,001-\$100,000; \$100,001-\$500,000; \$500,001-\$1,000,000; or more than \$1,000,000.

observed outperformance, we find evidence of both improved decision-making due to combining different information sets and increased monitoring associated with more diverse teams.

While our evidence suggests a realization of the potential complementarities of diverse teams –namely improved decision-making through incorporating different perspectives and information sets– we are also mindful that team composed of individuals with differing identities may negatively affect performance if those differences become more salient. Using a measure of political polarization as a plausibly exogenous "priming" shock to political identity and the associated within-team conflicts, we find that polarization has a significant limiting effect of team diversity on performance. Moreover, consistent with reduced ability to reach consensus, portfolios managed by heterogeneous teams become less active in politically polarized times.

In examining why less diverse teams are prevalent in asset management, we find entrenched managers prefer homogeneous teams, and the local labor market supply of ideologically diverse managers is constrained. These results shed light on how team composition can influence productivity, and they highlight the importance of diverse perspectives as a fundamental driver of human behavior within teams.

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Table 1: Summary Statistics

Panel A of the table reports the average number of team funds and fund families of our sample over three different sample periods. Panel B, C report summary statistics for our fund diversity variables and fund characteristics for the sample, respectively. The sample period runs from 1992 through 2016. A complete list of definitions for these variables is provided in the Data appendix.

Panel A: Sample Descriptive Statistics

	1992 − 2000	2000 − 2010	2010 − 2016
Team Funds	800	2905	3115
Fund Families	178	392	403

Panel B: Diversity Variables

	Obs.	Mean	Std. Dev.	25%	50%	75%
Fund Diversity	589,316	0.15	0.19	0.00	0.00	0.28
Manager-Fund Distance	2,359,246	0.14	0.20	0.00	0.00	0.25
State Diversity	589,316	0.61	0.05	0.58	0.61	0.63

Panel C: Other Variables

	Obs.	Mean	Std. Dev.	25%	50%	75%
Size (log TNA)	589,316	5.77	2.17	4.35	5.86	7.30
Expense Ratio	589,316	0.01	0.01	0.01	0.01	0.01
Load Fee	589,316	0.04	0.04	0.01	0.03	0.08
Turnover	589,316	0.97	1.12	0.34	0.64	1.14
Fund Age (log)	589,316	2.25	0.84	1.73	2.34	2.82
Fund Managers	589,316	3.51	2.51	2.00	3.00	4.00

Table 2: Team Diversity and Performance: Calendar Portfolios

This table presents risk-adjusted monthly portfolio returns for different portfolios of funds. Fund returns are calculated before (gross) deducting fees and expenses. Panel A reports the risk-adjusted monthly returns of six portfolios: i) portfolio of funds with zero diversity (column *D=0*); ii) four portfolios based on quartiles of diversity computed excluding funds with diversity equal to zero or one (columns *Q1* through *Q4*); portfolio of funds with diversity equal to one (column *D=1*). Panel B reports the risk-adjusted monthly returns of the portfolio that buys funds with diversity equal to one and sells funds with zero diversity (column *[D=1]-[D=0]*); the monthly returns of the portfolio that buys funds with diversity equal to one and sells funds in the bottom quartile by the distribution of diversity values that exclude zeros and ones (column *[D=1]-[Q1]*); the monthly returns of the portfolio that buys funds with diversity in the top quartile by the distribution of diversity values that exclude zeros and ones and sells funds with zero diversity (column *[Q4]-[D=0]*); the monthly returns of the portfolio that buys funds with high diversity (columns *D=1* and *Q4*) and sells funds with low diversity (columns *D=0* and *Q1*). We calculate the average portfolio return across funds in each month by equal-weighting funds in a portfolio. The sample period runs from 1992 through 2016. *t*-statistics based on robust standard errors are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Diversity Portfolios

	D=0	Q1	Q2	Q3	Q4	D=1
Alpha	0.037	0.052	0.086*	0.076*	0.135*	0.191**
	(0.74)	(1.05)	(1.80)	(1.71)	(1.85)	(2.36)
MKT	0.698***	0.753***	0.703***	0.722***	0.722***	0.659***
	(42.74)	(46.95)	(43.01)	(49.82)	(31.21)	(28.61)
SBM	0.118***	0.146***	0.106***	0.140***	0.096***	0.131***
	(7.62)	(7.51)	(6.12)	(9.08)	(3.44)	(5.91)
HML	0.054**	0.030	0.042*	0.044**	0.162***	0.031
	(2.55)	(1.36)	(1.93)	(2.16)	(4.66)	(1.02)
WML	-0.006	0.006	-0.019	-0.007	-0.039**	0.021
	(-0.48)	(0.45)	(-1.45)	(-0.63)	(-2.48)	(1.32)

Panel B: Long-Short Portfolios

	[D=1] - [D=0]	[D=1] - [Q1]	[Q4] - [D=0]	[D=1 + Q4] - [D=0 + Q1]
Alpha	0.154**	0.139**	0.099**	0.102***
	(2.34)	(2.09)	(1.99)	(2.82)
MKT	-0.039**	-0.093***	0.024	0.001
	(-2.00)	(-5.05)	(1.65)	(0.08)
SBM	0.013	-0.015	-0.023	-0.009
	(0.67)	(-0.66)	(-1.06)	(-0.61)
HML	-0.023	0.001	0.108***	0.072***
	(-1.02)	(0.04)	(4.90)	(4.58)
WML	0.026*	0.015	-0.034**	-0.021**
	(1.83)	(1.00)	(-2.38)	(-2.06)

Table 3: Team Diversity and Performance: Multivariate Analysis

This table reports results from regressions of fund monthly performance variables on *Fund Diversity* and other fund characteristics lagged one month. Fund returns are calculated before (gross) deducting fees and expenses. These returns are also adjusted using the CAPM model (Alpha 1F), the Fama-French model (Alpha 3F), the Carhart model (Alpha 4F), or computed as the difference between the fund gross return and the return of the fund benchmark, as provided by Morningstar. *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. t-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. A complete list of definitions for these variables is provided in the Data appendix.

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.128***	0.097***	0.076***	0.069***	0.082***
	(5.40)	(5.70)	(5.73)	(6.24)	(4.27)
Size (log TNA)	-0.032***	-0.012***	-0.003	-0.007**	-0.007*
	(-2.68)	(-2.66)	(-0.95)	(-2.22)	(-1.87)
Expense Ratio	4.485	2.971	3.558***	2.083*	3.200
	(1.47)	(1.60)	(2.74)	(1.76)	(1.49)
Load Fee	0.341	0.269**	0.165**	0.233***	0.118
	(1.38)	(2.35)	(2.01)	(2.91)	(1.07)
Turnover	-0.015	0.000	-0.003	-0.007	-0.003
	(-1.31)	(0.02)	(-0.44)	(-1.39)	(-0.42)
Fund Age (log)	0.031	-0.018**	-0.030***	-0.035***	-0.019***
	(1.52)	(-2.15)	(-4.22)	(-4.64)	(-2.72)
Fund Managers (log)	0.020	0.009	0.010	0.014*	0.010
	(1.41)	(0.96)	(1.33)	(1.91)	(1.19)
Style x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	589,316	589,316	589,316	589,316	589,316
Adjusted r^2	0.107	0.067	0.070	0.068	0.021

Table 4: Team Diversity and Performance: Alternative Explanations

This table reports results from regressions of fund performance variables on *Fund Diversity* and other fund characteristics lagged one month. Panel A includes demographic and functional diversity variables as: *Gender Diversity*, computed using the Teachman's Entropy index based on managers' gender; *Ethnicity Diversity*, using the Teachman's Entropy index based on managers' ethnic groups; *Tenure Diversity*, the standard deviation of tenure of a fund's managers; *Style-Experience Diversity*, the standard deviation of the number of years each fund's manager has worked on a given style; *Functional Diversity - Degree*, the Teachman's Entropy index based on managers' degree level; *Functional Diversity - Major*, the Teachman's Entropy index based on managers' major of studies. In Panel B, we include variables to control for political connections. *Fund Contributions*, a fund's total dollar value of political contributions; *Fund Candidates*, the total number of unique candidates that received a contribution from the fund's managers; *Fund Winners*, the total number of unique winning candidates that received a contribution by the fund's managers; *Holdings' Political Similarity*, the Euclidean distance between the average political views of the fund managers and the average political views of the fund holdings; *Percent Aligned*, the fraction of fund holdings invested in politically aligned stocks (Wintoki and Xi (2018)). In both, panels the list of controls is the same as in our baseline Table 3. t-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Demographic and Functional Diversity

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.127***	0.097***	0.075***	0.069***	0.086***
	(5.53)	(5.69)	(5.77)	(6.02)	(4.51)
Gender Diversity	-0.009	-0.003	-0.006*	-0.006*	0.000
	(-1.24)	(-0.76)	(-1.92)	(-1.83)	(0.01)
Ethnicity Diversity	0.007	0.008	0.004	-0.012	0.004
	(0.39)	(0.52)	(0.33)	(-1.17)	(0.32)
Tenure Diversity	-0.002	-0.002	0.006	0.001	-0.013
	(-0.13)	(-0.20)	(0.69)	(0.18)	(-0.75)
Style-Experience Diversity	0.009***	0.005**	0.002	0.003	0.005*
	(3.18)	(2.21)	(1.19)	(1.57)	(1.67)
Functional Diversity - Degree	0.006	-0.006	-0.006	-0.001	0.000
	(0.42)	(-0.53)	(-0.71)	(-0.11)	(0.01)
Functional Diversity - Major	0.035	0.025**	0.021**	0.023**	0.041***
	(1.63)	(2.11)	(2.04)	(2.58)	(2.94)
Controls	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	561,276	561,276	561,276	561,276	561,276
Adjusted r^2	0.107	0.067	0.070	0.067	0.021

Panel B: Political Connections

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.132***	0.110***	0.085***	0.072***	0.088***
	(4.06)	(6.09)	(5.75)	(5.61)	(4.46)
Fund Contributions	0.008***	0.006**	0.005***	0.006***	0.004*
	(3.01)	(2.38)	(2.89)	(3.25)	(1.91)
Fund Candidates	0.048	0.013	-0.005	-0.021	-0.057
	(0.81)	(0.28)	(-0.13)	(-0.59)	(-1.35)
Fund Winners	-0.113	-0.041	0.001	0.029	0.108
	(-1.09)	(-0.55)	(0.02)	(0.50)	(1.56)
Holdings Political Similarity	0.032	0.043***	0.037***	0.031***	0.035***
	(0.83)	(3.69)	(3.51)	(2.95)	(3.38)
Percent Aligned	0.000	0.001	-0.000	-0.003	-0.003
	(0.02)	(0.28)	(-0.08)	(-1.45)	(-1.15)
Controls	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	551,634	551,634	551,634	551,634	551,634
Adjusted r^2	0.107	0.067	0.070	0.068	0.021

Table 5: Portfolio Diversification and Scaling

This table reports results from regressions of log growth rate in the number of stocks and the annual change in the portfolio weighted log ownership share on *Fund Flows*, *Fund Diversity*, and other fund characteristics lagged one month. *Fund Flows* is defined as the difference between the log growth rate for TNA and the log return for the fund between year t-1 and t. *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. The dependent variable is either the change in log number of stocks from year t-1 to t for fund i (Δ LogS, in columns (1) through (4)) or the change in portfolio-weighted average log ownership share from year t-1 to t for fund i (Δ LogOwn, in columns (5) through (8)). The list of controls is the same as in our baseline Table 3. We also include the interaction between all our controls and *Fund Flows*. *t*-statistics based on standard errors clustered by fund are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. A complete list of definitions for these variables is provided in the Data appendix.

	Δ LogS				Δ LogOwn			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fund Flows	0.058***	0.055***	0.056***	0.049***	0.519***	0.517***	0.522***	0.481***
	(6.65)	(6.45)	(6.71)	(5.96)	(11.67)	(11.66)	(11.91)	(11.35)
Fund Diversity		0.003	0.003	-0.003		0.017	0.018	0.009
		(0.40)	(0.46)	(-0.34)		(0.97)	(1.02)	(0.44)
Fund Flows × Fund Diversity		0.014**	0.012**	0.012**		-0.015	-0.013	-0.012
		(2.56)	(2.36)	(2.41)		(-0.70)	(-0.60)	(-0.60)
Controls Interacted	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes			Yes	Yes		
Style x Time FE			Yes	Yes			Yes	Yes
Family FE				Yes				Yes
Observations	276,612	276,612	276,612	276,612	276,612	276,612	276,612	276,612
Adjusted r^2	0.019	0.020	0.049	0.067	0.090	0.091	0.114	0.137

Table 6: Team Diversity and Active Management

This table reports results from regressions of active management variables on *Fund Diversity* and other fund characteristics lagged one month. *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. Activeness variables are *Active Share* and *Tracking Error*, computed as in Cremers and Petajisto (2009). The results reported for Active Share are based on the sample where the Active Share metric is available and use quarterly observations. The list of controls is the same as in our baseline Table 3. t-statistics based on standard errors clustered by fund are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Active Share	Tracking Error
Fund Diversity	0.025***	0.146***
	(2.73)	(5.19)
Size (log TNA)	-0.005***	-0.004
	(-4.72)	(-1.43)
Expense Ratio	2.653***	23.715***
	(5.28)	(15.29)
Turnover	-0.001	0.038***
	(-0.75)	(6.51)
Fund Age (log)	-0.012***	-0.091***
	(-4.26)	(-10.29)
Fund Managers (log)	-0.037***	-0.096***
	(-7.24)	(-6.73)
Style x Time FE	Yes	Yes
Observations	141,409	589,316
Adjusted r^2	0.412	0.721

Table 7: Team Diversity and Performance: New Ideas

This table studies the performance of new stocks added by diverse and homogenous teams. Panel A presents risk-adjusted monthly portfolio returns for different portfolios of stocks. We report the risk-adjusted monthly returns of the following four portfolios: i) portfolio of new stocks added by diverse funds (column [1]); ii) portfolio of old stocks held by diverse funds (columns [2]); iii) portfolio of new stocks added by homogenous funds (column [3]); iv) portfolio of old stocks held by homogenous funds (columns [4]). We also report: the risk-adjusted monthly returns of the portfolio that buys new stocks added by diverse funds and sells new stocks added by homogenous funds (column *[1]- [3]*); the risk-adjusted monthly returns of the portfolio that buys new stocks added by diverse funds and sells the portfolio of stocks selected by homogenous funds (column *[1]-[3+4]*). Diverse funds are defined as those included in the portfolios of columns *D=1* and *Q4* of Table 2, while homogenous funds are funds included in the portfolios of columns *D=0* and *Q1*. The sample period runs from 1992 through 2016. t-statistics based on robust standard errors are shown in parentheses. Panel B shows the results of regressions at the holding level described by equation (5). The dependent variable is the Fama-French 4-factor alpha of stock j over quarter $t+1$ weighted by the percentage of fund i assets invested in stock j at quarter t. *New Stocks* is an indicator variable with value 1 if stock j has been added for the first time in the portfolio of fund j in quarter t. *New Diverse Manager* is an indicator variable with value 1 starting from the quarter in which a new manager arrives in fund i and the new manager has different political views from the views of fund i. The list of fund-level controls is the same as in our baseline Table 3. Stock-level controls include market capitalization, book-to-market, previous 12-month return, and ROA. t-statistics based on standard errors clustered by fund are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Calendar Portfolios

	Diverse Funds		Homogenous Funds		Difference	
	New Stocks	Old Stocks	New Stocks	Old Stocks		
	[1]	[2]	[3]	[4]	[1]-[3]	[1]-[3+4]
Alpha	0.693***	0.127*	0.375**	0.121	0.318*	0.525***
	(4.64)	(1.84)	(2.52)	(1.42)	(1.81)	(3.50)
MKT	1.071***	1.099***	1.057***	1.114***	0.014	-0.003
	(38.33)	(67.09)	(29.12)	(56.23)	(0.37)	(-0.10)
SBM	0.258***	0.122***	0.206***	0.156***	0.052	0.047
	(4.46)	(4.47)	(3.88)	(5.41)	(0.95)	(0.93)
HML	0.016	0.082**	0.025	0.080***	-0.009	-0.058
	(0.30)	(2.22)	(0.54)	(2.87)	(-0.17)	(-1.37)
WML	-0.101**	-0.058***	-0.091***	-0.079***	-0.011	-0.010
	(-2.16)	(-2.41)	(-3.27)	(-2.82)	(-0.23)	(-0.31)

Panel B: Multivariate Analysis

	(1)	(2)	(3)	(4)
New Stocks	0.010	-0.131***	-0.004	-0.125***
	(0.31)	(-3.90)	(-0.10)	(-3.19)
New Diverse Manager	-0.005			
	(-0.07)			
New Stocks × New Diverse Manager	0.159***	0.149**		
	(2.79)	(2.26)		
New Homogenous Manager			0.035	
			(0.46)	
New Stocks × New Homogenous Manager			0.062	0.017
			(1.14)	(0.28)
Controls Funds	Yes		Yes	
Controls Stocks	Yes	Yes	Yes	Yes
Style x Time FE	Yes		Yes	
Stock FE	Yes		Yes	
Fund FE	Yes		Yes	
Fund x Time FE		Yes		Yes
Stock x Time FE		Yes		Yes
Observations	15,623,089	15,623,089	15,813,540	15,813,540
Adjusted r^2	0.050	0.155	0.050	0.155

Table 8: Team Diversity and ESG Investing

This table examines diverse teams' ESG choices and their performances. In Panel A we present results of equation (5). The dependent variable is stock j ESG score weighted by the percentage of fund i assets invested in stock j at quarter t. *New Stocks* is an indicator variable with value 1 if stock j has been added for the first time in the portfolio of fund j in quarter t. In the first two columns of the table we interact *New Stocks* with *New Republican Manager*, an indicator variable with value 1 starting from the quarter in which a new Republican manager arrives in a team. In performing the analysis reported in columns (1) and (2), we use as comparison group the sample of homogenous Democrat funds in quarter $t-1$. In the last two columns of the table we interact *New Stocks* with *New Democrat Manager*, an indicator variable with value 1 starting from the quarter in which a new Democrat manager arrives in a team. In performing the analysis reported in columns (3) and (4), we use as comparison group the sample of homogenous Republican funds in quarter $t-1$. The ESG score is the industry-adjusted score reported in the MSCI ESG Ratings data. The list of fund-level controls is the same as in our baseline Table 3. Stock-level controls include market capitalization, book-to-market, previous 12-month return, and ROA. t-statistics based on standard errors clustered by fund are shown in parentheses. Panel B presents risk-adjusted monthly portfolio returns for different portfolios of stocks. We report the risk-adjusted monthly returns of the following six portfolios: i) portfolio of new low ESG stocks added by diverse funds (column [1]); ii) portfolio of new high ESG stocks added by diverse funds (columns [2]); iii) portfolio of new low ESG stocks added by Democrat funds (column [3]); iv) portfolio of new high ESG stocks added by Democrat funds (columns [4]); v) portfolio of new low ESG stocks added by Republican funds (columns [5]); vi) portfolio of new high ESG stocks added by Republican funds (columns [6]). We define low and high ESG stocks using the bottom and top quartiles of the distribution of the industry-adjusted score reported in the MSCI ESG Ratings data. In both panels, our sample period is restricted to the years between 2002 and 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ESG investing

	(1)	(2)	(3)	(4)
New Stocks	-0.089**	-0.092***	-0.296***	-0.266***
	(-2.46)	(-2.60)	(-8.27)	(-8.04)
New Republican Manager	-0.046			
	(-0.20)			
New Stocks × New Republican Manager	-0.090**	-0.091**		
	(-2.23)	(-2.31)		
New Democrat Manager			-0.215**	
			(-2.07)	
New Stocks × New Democrat Manager			0.153***	0.122***
			(3.59)	(3.15)
Controls Funds	Yes		Yes	
Controls Stocks	Yes		Yes	
Style x Time FE	Yes		Yes	
Stock FE	Yes		Yes	
Fund FE	Yes		Yes	
Fund x Time FE		Yes		Yes
Stock x Time FE		Yes		Yes
Observations	11,280,820	11,280,820	7,166,481	7,166,481
Adjusted r^2	0.471	0.573	0.460	0.554

Panel B: Calendar Portfolios

	Diverse		Democrat		Republican		Difference	
	Low	High	Low	High	Low	High		
	[1]	[2]	[3]	[4]	[5]	[6]	[1]-[3]	[2]-[6]
Alpha	0.645***	0.327**	0.041	0.473***	0.163	-0.026	0.604*	0.353*
	(3.21)	(2.38)	(0.12)	(2.93)	(0.96)	(-0.10)	(1.86)	(1.73)
MKT	1.054***	0.996***	1.045***	1.005***	1.054***	0.997***	0.010	-0.001
	(20.83)	(21.57)	(12.27)	(7.83)	(17.61)	(15.34)	(0.10)	(-0.01)
SBM	0.125*	0.146**	0.225**	0.078	0.234***	-0.013	-0.100	0.159*
	(1.94)	(2.49)	(2.08)	(0.48)	(3.08)	(-0.16)	(-0.88)	(1.72)
HML	-0.028	-0.002	0.052	0.272*	-0.010	0.004	-0.080	-0.005
	(-0.44)	(-0.03)	(0.47)	(1.66)	(-0.13)	(0.04)	(-0.068)	(-0.06)
WML	-0.047	-0.083**	-0.196***	-0.059	-0.106**	-0.045	-0.149**	-0.038
	(-1.19)	(-2.30)	(-2.95)	(-0.59)	(-2.26)	(-0.89)	(-2.08)	(-0.66)

Table 9: Team Diversity and Monitoring

This table reports results from regressions of portfolio manager promotions and demotions on performance, diversity, and other fund characteristics lagged one month. In the first two columns the dependent variable is Promotion, a dummy variable that equals one if a portfolio manager increases both the number of funds and total assets under management (AUM) in the next month. In the last two columns the dependent variable is Demotion, a dummy variable that equals one if a portfolio manager decreases both the number of funds and total assets under management (AUM) in the next month. *Manager Performance* is measured as the value-weighted average of the 36 past months style-adjusted gross returns across all funds in which the manager operates, where the weights are computed as the portion of a fund AUM attributed to the manager. *Manager-Fund Distance* is computed as the Euclidean distance between a manager's political beliefs and the average political beliefs of the other managers in the fund. The list of controls is the same as in our baseline Table 3. t-statistics based on standard errors clustered by fund are shown in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

	Promotion		Demotion	
	(1)	(2)	(3)	(4)
Manager Performance	0.234***	0.228***	-0.149***	-0.148***
	(8.18)	(7.95)	(-6.88)	(-6.79)
Manager-Fund Distance	-0.016	-0.017	0.023	0.078
	(-0.12)	(-0.13)	(0.19)	(0.66)
Manager Performance $\times$ Manager-Fund Distance	0.370***	0.357***	-0.183**	-0.176**
	(3.03)	(2.94)	(-2.16)	(-2.09)
Controls		Yes		Yes
Manager FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	2,359,246	2,359,246	2,359,246	2,359,246
Adjusted-r^2	0.072	0.072	0.035	0.035

Table 10: Team Diversity and Performance: The Impact of Polarization

This table reports results from regressions of fund performance variables on *Fund Diversity* and other fund characteristics lagged one month. *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. We split our sample into low (Panel A) and high polarization periods (Panel B). In the first three columns of each panel, *Polarization* is computed as the distance in the contribution-weighted campaign finance scores for Democratic and Republican congressional election winners, using the data made available by Autor et al. (2020). We define low and high values of *Polarization* using quartiles of the *Polarization* variable in the current year, respectively. In the last three columns of each panel, *Polarization* is computed as the average distance in the ideology of the House and the Senate, using the methodology of McCarty et al. (2006). We define low and high values of *Polarization* using the bottom and top quartiles of the *Polarization* variable in the current year, respectively. The list of controls is the same as in our baseline Table 3. *t*-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Low Polarization Sample

	Autor et al. (2020)			McCarty et al. (2016)		
	Gross Return	Alpha 1F	Benchmark-Adjusted	Gross Return	Alpha 1F	Benchmark-Adjusted
	(1)	(2)	(3)	(4)	(5)	(6)
Fund Diversity	0.227***	0.161***	0.163***	0.260***	0.235***	0.220***
	(4.84)	(4.57)	(4.33)	(4.26)	(4.51)	(3.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	190,859	190,859	190,859	72,381	72,381	72,381
Adjusted r^2	0.060	0.050	0.021	0.087	0.068	0.027

Panel B: High Polarization Sample

	Autor et al. (2020)			McCarty et al. (2016)		
	Gross Return	Alpha 1F	Benchmark-Adjusted	Gross Return	Alpha 1F	Benchmark-Adjusted
	(1)	(2)	(3)	(4)	(5)	(6)
Fund Diversity	0.038	0.033	-0.003	0.012	0.022	-0.057
	(1.32)	(1.25)	(-0.11)	(0.28)	(0.72)	(-1.57)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136,006	136,006	136,006	68,620	68,620	68,620
Adjusted r^2	0.086	0.111	0.019	0.129	0.098	0.017

Table 11: Bargaining Power and Supply of Diversity

This table reports results from regressions of *Fund Diversity*, on variables reflecting fund managers' bargaining power within the fund, as well as a state-level supply of individuals with different political views. *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers. In columns (1) and (4), we measure bargaining power using the dollar value ($ million) of the assets controlled by the manager (*Manager AUM*). For a given fund-date observation, this variable reflects the AUM of the manager who controls the greatest dollar value of assets. In columns (2) and (5), we measure bargaining power using the tenure of the manager (*Manager Tenure*). For a given fund-date observation, this variable reflects the manager's tenure who has worked in the mutual fund industry for the highest number of years. Finally, in columns (3) and (6), we measure the supply of individuals with diverse political beliefs using *State-Level Diversity*, computed as the average Euclidean distance among all donors in a state based on their political beliefs. The list of controls is the same as in our baseline Table 3. t-statistics based on standard errors clustered by fund are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Fund Diversity					
	(1)	(2)	(3)	(4)	(5)	(6)
Manager AUM	-0.518***			-0.455***		
	(-4.56)			(-3.31)		
Manager Tenure		-0.145***			-0.112***	
		(-14.48)			(-11.06)	
State-Level Diversity			0.103*			0.075*
			(1.90)			(1.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time x Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Family FE				Yes	Yes	Yes
Observations	589,316	589,316	589,316	589,316	589,316	589,316
Adjusted r^2	0.248	0.258	0.247	0.372	0.376	0.371

Table 12: Team Diversity and Performance: Fixed-Effects

This table reports results from regressions of fund performance variables on *Fund Diversity* and other fund characteristics lagged one month. Fund returns are calculated before (gross) deducting fees and expenses. These returns are also adjusted using the CAPM model (Alpha 1F), the Fama-French model (Alpha 3F), the Carhart model (Alpha 4F), or computed as the difference between the fund gross return and the return of the fund benchmark, as provided by Morningstar. In Panel A, we run specification (7), which includes fund and time fixed effects. In Panel B, we add family-by-time fixed effects to equation (7). Panel C reports results from regressions of fund performance variables on *Manager-Fund Distance* and other fund characteristics lagged one month. *Manager-Fund Distance* is computed as the Euclidean distance between a manager's political beliefs and the average political beliefs of the other managers of the same fund. We add manager-by-time fixed effects and fund fixed effects. In all panels, the list of controls is the same as in our baseline Table 3. t-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. A complete list of definitions for these variables is provided in the Data appendix.

Panel A: Fund Fixed Effects

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.172***	0.111***	0.082***	0.072***	0.104***
	(3.06)	(3.03)	(3.34)	(3.04)	(3.61)
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	589,316	589,316	589,316	589,316	589,316
Adjusted r^2	0.082	0.035	0.042	0.045	0.024

Panel B: Family Fixed Effects

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.157**	0.085**	0.091**	0.081**	0.110***
	(2.22)	(2.06)	(2.55)	(2.01)	(3.47)
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Family x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	589,096	589,096	589,096	589,096	589,096
Adjusted r^2	0.082	0.051	0.062	0.065	0.048

Panel C: Manager Fixed Effects

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Manager-Fund Distance	0.118*	0.083***	0.084***	0.073***	0.058**
	(1.97)	(3.35)	(4.34)	(3.75)	(2.06)
Sole Manager Fund	0.046	0.020	0.019	0.022	0.001
	(1.24)	(1.30)	(1.39)	(1.62)	(0.11)
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Manager x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	2,359,246	2,359,246	2,359,246	2,359,246	2,359,246
Adjusted r^2	0.089	0.077	0.091	0.092	0.058

Table 13: Team Diversity and Performance: Evidence from Investment Advisor M&A

This table presents the effect of the diversity of the acquirer company on the performance of the target funds, before and after the merger. Fund returns are calculated before (gross) deducting fees and expenses. These returns are also adjusted using the CAPM model (Alpha 1F), the Fama-French model (Alpha 3F), the Carhart model (Alpha 4F), or computed as the difference between the fund gross return and the return of the fund benchmark, as provided by Morningstar. *Fund-Family Distance* is computed as the Euclidean distance between the acquirer family and the target funds, as measured at the M&A announcement date. *Post Merger* is a dummy variable that is equal to one during the 60 months after the merger and zero during the prior 60 months. We add fund and time (year-month) fixed effects. t-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. A complete list of definitions for these variables is provided in the Data appendix.

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Post Merger × Fund-Family Distance	0.163**	0.281**	0.279**	0.277**	0.162**
	(2.08)	(2.53)	(2.29)	(2.26)	(1.99)
Fund-Family Distance	-0.087	-0.071	-0.076	-0.055	-0.040
	(-0.50)	(-0.61)	(-0.52)	(-0.39)	(-0.024)
Post Merger	-0.082*	-0.129**	-0.118**	-0.083*	-0.027
	(-1.79)	(-2.28)	(-2.36)	(-1.87)	(-0.82)
Size (log TNA)	-0.236***	-0.074**	-0.018	-0.042*	-0.043**
	(-2.76)	(-2.37)	(-0.69)	(-1.75)	(-2.55)
Expense Ratio	-31.158	-20.400*	-6.258	-10.149	-6.303
	(-0.85)	(-1.79)	(-0.65)	(-1.02)	(-0.79)
Load Fee	2.469	1.258	0.609	0.959	0.568
	(1.09)	(1.36)	(0.80)	(1.34)	(0.80)
Turnover	-0.027	0.010	-0.034	-0.018	-0.017
	(-0.70)	(0.40)	(-1.53)	(-0.82)	(-0.75)
Fund Age (log)	0.438**	0.096	-0.043	0.004	0.081
	(2.26)	(1.28)	(-0.77)	(0.08)	(1.51)
Fund Managers (log)	-0.002	-0.084	-0.122***	-0.090**	-0.049
	(-0.02)	(-1.55)	(-2.61)	(-2.12)	(-0.69)
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	55,337	55,337	55,337	55,337	55,337
Adjusted r^2	0.105	0.028	0.029	0.026	0.011

Appendix

Data appendix: Variable definitions

Variable	Definition
Political Diversity Variable	
Fund Diversity	Average Euclidean distance among all managers of a fund based on the political beliefs of managers. For each manager i of a fund, the Euclidean distance between her and the other fund managers is computed as $\lvert MgrRep_i - FundRep_{-i} \rvert/2$. Where $MgrRep_i$ captures the manager i political beliefs, and it is computed as $(R_i - D_i)/(R_i + D_i)$, with R_i and D_i denoting the total dollar amount of political donations made by manager i to the Republican and Democratic parties, respectively, over the whole sample period. $FundRep_{-i}$ is the average value of $MgrRep$ at the fund level, excluding manager i.
Manager-Fund Distance	Euclidean distance between manager i and the other managers of the same fund. Computed as $\lvert MgrRep_i - FundRep_{-i} \rvert/2$. Where $MgrRep_i$ captures the manager i political beliefs, and it is computed as $(R_i - D_i)/(R_i + D_i)$, with R_i and D_i denoting the total dollar amount of political donations made by manager i to the Republican and Democratic parties, respectively, over the whole sample period. $FundRep_{-i}$ is the average value of $MgrRep$ at the fund level, excluding manager i.
State Diversity	Average Euclidean distance among all contributors of a state based on their political beliefs. For each individual i living in state s, the Euclidean distance between her and the other individuals is computed as $\lvert IndRep_i - StateRep_{-i} \rvert/2$. Where $IndRep_i$ captures the individual i political beliefs, and it is computed as $(R_i - D_i)/(R_i + D_i)$, with R_i and D_i denoting the total dollar amount of political donations made by individual i to the Republican and Democratic parties, respectively, over the whole sample period. $StateRep_{-i}$ is the average value of $IndRep$ at the state level, excluding individual i.
Fund-Family Distance	The Euclidean distance between the acquirer family and the target funds, as measured at the M&A announcement date. For each target fund j, the Euclidean distance between the fund and the acquiring family k is computed as $\lvert Fund\,Rep_j - Fam\,Rep_k \rvert/2$. Where $Fund\,Rep_j$ captures the average political beliefs of the fund managers at the M&A announcement date. $Fam\,Rep_k$ measures the average political beliefs of the acquiring family managers at the M&A announcement date.
Other Diversity Variables	
Female Managers	Proportion of female managers working for a fund at date t. To determine the gender of a manager, we employ an algorithm written using Python that infers the gender of an individual from her first name. The algorithm relies on a dictionary containing a list of more than 40,000 first names and gender, covering the vast majority of first names in U.S., all European countries, and in some overseas countries (e.g., China, India, Japan).
Non-white Managers	Proportion of managers working for a fund at date t that are not White/Caucasian. To determine the ethnicity of a manager, we employ an algorithm written using Python that exploits the U.S. census data to predict race and ethnicity based on the first and last name of an individual. The algorithm classifies an individual in one of the following four categories: White, Black, Asian, or Hispanic.
Tenure	The average tenure of managers working for a fund at date t. We define a manager's tenure as the number of years she has worked in the mutual fund industry. Computed using the first date the manager appeared in the Morningstar database.

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Variable	Definition
Graduate Managers	Proportion of managers working for a fund at date t that completed graduate studies (M.S., MBA, or Ph.D.). To determine the education degree of a manager, we use the managerial biographies provided by Morningstar Direct, and we employ an algorithm to search for terms indicating completion of graduate studies. For example, we classify a manager as having completed graduate studies if the biography contains terms such as "mba", "master in business administration", or "phd".
Business Major	Proportion of managers working for a fund at date t that completed business studies. To determine the major of a manager's studies, we use the managerial biographies provided by Morningstar Direct, and we employ an algorithm to search for terms indicating the major type. Then we classify a manager as having completed Business studies when the biography contains terms such as "management" or "business".
Style-Experience	The average number of years each manager has worked in the specific style of the fund. Computed taking the average across all managers of a fund at time t.
Gender Diversity	Teachman's Entropy Index based on fund managers' gender. The Entropy Index is computed as $-\sum(p_k \times ln(p_k))$. Where p_k is the proportion of fund managers that are either male or female.
Ethnicity Diversity	Teachman's Entropy Index based on fund managers' ethnic groups. The Entropy Index is computed as $-\sum(p_k \times ln(p_k))$. Where p_k is the proportion of fund managers of an ethnic group k. We classify managers into four ethnic groups: Asian, black, hispanic, white.
Tenure Diversity	The standard deviation of the number of years each manager of a fund has worked in the mutual fund industry. We compute each manager's tenure using the first date the manager appeared in the Morningstar database.
Style-Experience Diversity	The standard deviation of the number of years each manager has worked in the specific style of the fund. Computed taking the standard deviation across all managers of a fund at time t.
Functional Diversity - Degree	Teachman's Entropy Index based on fund managers' degree level. The Entropy Index is computed as $-\sum(p_k \times ln(p_k))$. Where p_k is the proportion of fund managers that either completed graduate studies (MS, MBA, or PhD) or not.
Functional Diversity - Major	Teachman's Entropy Index based on fund managers' major of studies. The Entropy Index is computed as $-\sum(p_k \times ln(p_k))$. Where p_k is the proportion of fund managers either with or without a business degree
Political Connection Variables	
Fund Contributions	For each election cycle, this variable measures the total dollar amount of political donations made by the managers of the fund ($ million).
Fund Candidates	Number of individual political candidates to which the fund managers made at least one donation. Aggregated over the election cycle.
Fund Winners	Number of individual political candidates that won the elections to which the fund managers made at least one donation. Aggregated over the election cycle.
Holdings Political Similarity	Euclidean distance between the average political views of the fund managers and the average political views of the fund holdings.
Percent Aligned	Fraction of fund holdings invested in politically aligned stocks (Wintoki and Xi (2018)).
Other Fund-Level Variables	
Size (log TNA)	Natural logarithm of TNA (total net assets) under management (in US $m).
Expense Ratio	Total annual expenses and fees divided by year-end TNA (in %).
Load Fee	Total front-end, deferred, and rear-end charges divided by year-end TNA (in %). Source: CRSP.
Turnover	Minimum of aggregate purchases and sales of securities divided by average TNA over the calendar year.

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Variable	Definition
Flows	The change in log TNA not attributable to the portfolio return of the fund Pollet and Wilson (2008).
Fund Age (log)	Natural logarithm of the number of years since the fund inception date.
Fund Managers	Number of reported managers running the fund at a given date (year-month).
Grey Managers	For each election cycle, this variable measures the fraction of individual managers in a fund that does not contribute to any political candidate.
Value-Added (gross or net)	We follow Berk and Van Binsbergen (2015) in constructing the value-added of funds, using as the next-best alternative investment opportunity the set of index funds offered by The Vanguard Group as in their Table 1. We multiply the benchmark adjusted realized gross or net return by the real size of the fund (assets under management adjusted by inflation by expressing them in 2016 dollars) at the end of the previous period to obtain the realized value-added.

For Online Publication

Internet Appendix for "Identity, Diversity, and Team Performance: Evidence from U.S. Mutual Funds"

Richard Evans, Melissa Prado, Emanuele Rizzo, and Rafael Zambrana

This Internet Appendix reports the supplementary results as described below:

- Table A1: Team Diversity and Fund Value-Added
- Table A2: Team Political Views and Other Demographic Measures
- Table A3: Team Diversity and Performance: Robustness Tests Related to Grey Managers
- Table A4: Team Diversity and Performance: Alternative Measures, Samples, and Clustering
- Table A5: Team Diversity and Performance: Net Returns
- Table A6: Team Diversity and Performance: Alternative Polarization Measures
- Table A7: Investment Advisor M&A and Changes in Team Diversity
- Table A8: Team Diversity and Fund Incentives

Table A1: Team Diversity and Fund Value-Added

This table examines the relation between *Fund Diversity* and a fund's gross value added. In Panel A, we compare the average gross value added between the sample of funds characterized by low diversity and the sample of funds characterized by high diversity. We define low (high) diversity funds as funds in the bottom (top) quartile of the diversity distribution. In Panel B, we report results from regressions of fund gross value added on *Fund Diversity*, and other fund characteristics lagged one month. We follow Berk and Van Binsbergen (2015) in constructing the value-added of funds, using the set of index funds offered by The Vanguard Group as the next-best alternative investment opportunity. We multiply the benchmark adjusted realized gross return by the real size of the fund (assets under management adjusted by inflation by expressing them in 2016 dollars) at the end of the previous period to obtain the realized value-added. *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. t-statistics based on standard errors clustered by fund are shown in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. A complete list of definitions for these variables is provided in the Data appendix.

Panel A: Univariate Results

	Low Diversity	High Diversity	Difference
Value-Added	3.499***	5.829***	2.330**
	(3.66)	(7.11)	(2.03)
Observations	282,655	280,432	563,087

Panel B: Multivariate Results

	(1)	(2)	(3)	(4)
Fund Diversity	6.172***	5.833***	6.411*	6.380*
	(2.87)	(2.70)	(1.82)	(1.78)
Expense Ratio	-360.055***	-327.766***	-475.318***	-484.853***
	(-3.52)	(-3.20)	(-2.61)	(-2.65)
Load Fee	117.077***	95.725***	88.578***	88.336***
	(5.21)	(4.72)	(3.99)	(3.97)
Turnover	-1.794***	-1.955***	-0.827**	-0.823**
	(-6.57)	(-6.40)	(-2.28)	(-2.27)
Fund Age (log)	4.040***	6.076***	9.349***	9.352***
	(4.78)	(5.01)	(5.24)	(5.24)
Fund Managers (log)	6.410***	6.896***	-3.054	-3.087
	(3.70)	(3.75)	(-0.78)	(-0.79)
Time FE		Yes	Yes	Yes
Fund FE			Yes	Yes
Family FE				Yes
Observations	563,087	563,087	563,087	563,087
Adjusted r^2	0.001	0.016	0.043	0.043

Table A2: Team Political Views and Other Demographic Measures

This table relates the average political views of a fund, with the fraction of female managers in a team (*Female Managers*), the fraction of non-white managers (*Non-white Managers*), the average manager tenure (*Average Tenure*), the average style-experience of managers (*Average Style-Experience*), the fraction of graduate managers *Graduate Managers*, and the fraction of managers with a business degree *Business Major*. *Fund Republican Index* is computed as the average political views of team managers, where the views of a manager are measured as in equation (1). In Panel A, we present correlations between the six variables. In Panel B, we present results from regressions of *Fund Republican Index* on the other demographic measures. The list of controls is the same as in our baseline Table 3. t-statistics based on standard errors clustered by fund are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. A complete list of definitions for these variables is provided in the Data appendix.

Panel A: Correlation Table

Diversity Variable	Fund Republican Index	Female Managers	Non-white Managers	Average Tenure	Graduate Managers	Business Major
Female Managers	-0.072					
Non-white Managers	-0.025	0.058				
Average Tenure	0.080	-0.023	-0.009			
Average Style-Experience	0.045	-0.024	-0.044	0.482		
Graduate Managers	-0.040	0.016	-0.029	0.012	0.024	
Business Major	0.033	-0.069	0.038	0.064	0.015	0.061

Panel B: Regression Table

	Fund Republican Index											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female Managers	-0.186***						-0.098***					
	(-5.21)						(-3.01)					
Non-white Managers		-0.057						-0.089**				
		(-1.45)						(-2.47)				
Average Tenure			0.020***						0.017***			
			(5.55)						(5.54)			
Average Style-Experience				0.003***						0.002**		
				(4.63)						(2.46)		
Graduate Managers					-0.110***						-0.069**	
					(-3.18)						(-2.09)	
Business Major						0.122***						0.143***
						(3.45)						(4.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style x Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family FE							Yes	Yes	Yes	Yes	Yes	Yes
Observations	589,316	589,316	589,316	589,316	589,316	589,316	589,316	589,316	589,316	589,316	589,316	589,316
Adjusted r^2	0.038	0.035	0.038	0.038	0.037	0.036	0.268	0.267	0.269	0.267	0.267	0.268

Table A3: Team Diversity and Performance: Robustness Tests Related to Grey Managers

This table reports robustness tests for our baseline results of Table 3. In Panel A we report the risk-adjusted monthly returns of four portfolios: i) portfolio of solo-manager funds where the individual manager is a grey manager; ii) portfolio of solo-manager funds where the individual manager is a donor (either red or blue); iii) portfolio of team-managed funds where all the managers are grey managers; iv) portfolio of team-managed funds where all the managers are donors (either red or blue) but the fund's value of diversity is zero. We also report: the risk-adjusted monthly returns of the portfolio that buys donor solo-manager funds and sells grey solo-manager funds; and the monthly returns of the portfolio that buys donor team-managed funds and sells grey team-managed funds. We calculate the average portfolio return across funds in each month by equal-weighting funds in a portfolio. In Panel B, we add to the baseline specification of Table 3 the proportion of grey managers in a team (*Grey Managers*). In Panel C, the dependent variable is a fund's style-adjusted performance. In Panel C column (1), we drop funds with 100% of Grey managers. In Panel C column (2), we only use funds with at least two managers who contribute to political parties. In Panel C column (3), we only use funds with at least 50% of managers who contribute to political parties. In panels B and C, the list of controls is the same as in our baseline Table 3. In both panels, fund returns are calculated before (gross) deducting fees and expenses. *t*-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Donors vs. Grey Portfolios

	Individual Funds			Team Funds with Zero Diversity		
	Grey Managers	Donor Managers	Donor-Grey	Grey Teams	Donor Teams	Donor-Grey
Alpha	0.048	0.071	0.023	0.034	0.077	0.042
	(0.92)	(1.43)	(1.33)	(0.69)	(1.57)	(1.10)
MKT	0.723***	0.792***	0.069***	0.697***	0.717***	0.020*
	(42.83)	(46.41)	(14.12)	(42.30)	(46.75)	(1.66)
SBM	0.115***	0.138***	0.024***	0.117***	0.169***	0.052***
	(7.00)	(8.83)	(3.09)	(7.49)	(9.27)	(3.65)
HML	0.023	0.052**	0.028***	0.055**	0.061***	0.006
	(1.05)	(2.35)	(4.11)	(2.58)	(2.67)	(0.41)
WML	-0.005	-0.003	0.001	-0.006	0.010	0.016*
	(-0.37)	(-0.29)	(0.32)	(-0.52)	(0.68)	(1.71)

Panel B: Adding Grey Managers as Control

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.109***	0.107***	0.075***	0.066***	0.086***
	(4.05)	(5.30)	(4.78)	(4.44)	(4.03)
Grey Managers	-0.007	0.018	0.005	0.004	0.012
	(-0.46)	(1.52)	(0.49)	(0.45)	(0.99)
Controls	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	589,316	589,316	589,316	589,316	589,316
Adjusted r^2	0.109	0.067	0.069	0.067	0.023

Panel C: Robustness to the Number of Grey Managers in a Team

	Grey Managers < 100%	Red+Blue >= 2	Red+Blue >= 50%
Fund Diversity	0.132***	0.121**	0.136***
	(4.30)	(2.27)	(3.91)
Controls	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes
Observations	344,549	150,961	203,012
Adjusted r^2	0.106	0.106	0.103

Table A4: Team Diversity and Performance: Alternative Measures, Samples, and Clustering

This table reports results from regressions of fund performance variables on *Fund Diversity* and other fund characteristics lagged one month. Panel A deals with alternative ways of measuring *Fund Diversity*. In this panel, the dependent variable is a fund's style-adjusted performance. In Panel A column (1), we use a version of *Fund Diversity* constructed allowing the political beliefs of managers to vary by political cycle. In Panel A column (2), we use a version of *Fund Diversity* constructed weighting the views of each manager by the ratio of manager's dollar donations to fund's total dollar donations. In Panel A column (3), we use a version of *Fund Diversity* constructed considering political beliefs only of those who give more than $2,000 in net contributions and a value of zero to all others. In Panel A column (4), we use a version of *Fund Diversity* computed as the standard deviation of political beliefs among the managers of a fund. In Panel B, we repeat the analysis of Table 3 restricting the sample to domestic equity funds. In this panel *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. While in Panel A and B we report t-statistics based on standard errors clustered by time (year-month), in Panel C we report t-statistics based on standard errors clustered by fund and time (year-month). Fund performance measures are calculated using performance before deducting fees and expenses (gross). These returns are also adjusted using the CAPM model (Alpha 1F), the Fama-French model (Alpha 3F), the Carhart model (Alpha 4F), or computed as the difference between the fund gross return and the return of the fund benchmark, as provided by Morningstar. In all panels, the list of controls is the same as in our baseline Table 3. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. A complete list of definitions for these variables is provided in the Data appendix.

Panel A: Alternative Diversity Measures

	Time Varying	Value-Weighted	Large Contributors	SD Diversity
Fund Diversity	0.078***	0.226***	0.178***	0.078***
	(3.82)	(4.48)	(5.31)	(5.29)
Controls	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes
Observations	589,316	589,316	589,316	589,316
Adjusted r^2	0.107	0.107	0.107	0.107

Panel B: Restricting the Sample to Domestic Equity Funds

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.155***	0.122***	0.099***	0.090***	0.115***
	(4.97)	(4.73)	(5.58)	(5.48)	(4.66)
Controls	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	302,380	302,380	302,380	302,380	302,380
Adjusted r^2	0.098	0.049	0.043	0.040	0.020

Panel C: Standard Errors Clustered by Fund and Time

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.128***	0.097***	0.076***	0.069**	0.082**
	(4.79)	(3.22)	(2.60)	(2.38)	(2.57)
Controls	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	589,316	589,316	589,316	589,316	589,316
Adjusted r^2	0.107	0.067	0.070	0.068	0.021

Table A5: Team Diversity and Performance: Net Returns

This table reports results from regressions of fund net performance variables on *Fund Diversity* and other fund characteristics lagged one month. *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. Fund performance measures are calculated using performance after (net) deducting fees and expenses. These returns are also adjusted using the CAPM model (Alpha 1F), the Fama-French model (Alpha 3F), the Carhart model (Alpha 4F), or computed adjusting the fund gross return using the return of the fund benchmark, as provided by Morningstar. t-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. A complete list of definitions for these variables is provided in the Data appendix.

	Net Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.126***	0.106***	0.088***	0.088***	0.081***
	(5.35)	(6.07)	(6.40)	(7.50)	(4.22)
Size (log TNA)	-0.033***	-0.012***	-0.005	-0.008***	-0.008**
	(-2.75)	(-2.80)	(-1.46)	(-2.60)	(-2.09)
Expense Ratio	-3.355	-5.528***	-5.072***	-6.219***	-4.621**
	(-1.10)	(-2.70)	(-3.66)	(-4.91)	(-2.16)
Load Fee	0.320	0.226*	0.126	0.163*	0.095
	(1.29)	(1.84)	(1.41)	(1.87)	(0.86)
Turnover	-0.015	-0.001	-0.002	-0.008	-0.003
	(-1.33)	(-0.07)	(-0.32)	(-1.61)	(-0.46)
Fund Age (log)	0.031	-0.004	-0.015**	-0.016**	-0.018***
	(1.55)	(-0.44)	(-2.18)	(-2.55)	(-2.62)
Fund Managers (log)	0.021	0.009	0.009	0.014*	0.011
	(1.47)	(0.94)	(1.11)	(1.97)	(1.32)
Style x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	589,316	589,316	589,316	589,316	589,316
Adjusted r^2	0.107	0.068	0.074	0.071	0.021

Table A6: Team Diversity and Performance: Alternative Polarization Measures

This table reports results from regressions of fund performance variables on *Fund Diversity* and other fund characteristics lagged one month. *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. We split our sample into low (Panel A) and high polarization periods (Panel B). In the first three columns of each panel, *Polarization* is computed as the average distance in the ideology of the House and the Senate for a given state, using the data made available by Shor and McCarty (2011). We define low and high values of *Polarization* using quartiles of the *Polarization* variable in the current year. In the last three columns of each panel, *Polarization* is the Partisan Conflict Index computed as in Azzimonti (2018) and provided by the Federal Reserve Bank of Philadelphia. We define low and high values of *Polarization* using the bottom and top quartiles of the *Polarization* variable in the current month, respectively. The list of controls is the same as in our baseline Table 3. t-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Low Polarization Sample

	Shor and McCarty (2011)			Azzimonti (2018)		
	Gross Return	Alpha 1F	Benchmark-Adjusted	Gross Return	Alpha 1F	Benchmark-Adjusted
Fund Diversity	0.131**	0.119***	0.099*	0.121**	0.113*	0.088*
	(2.13)	(2.98)	(1.93)	(2.24)	(1.95)	(1.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	140,180	140,180	140,180	145,793	145,793	145,793
Adjusted r^2	0.112	0.061	0.026	0.179	0.091	0.037

Panel B: High Polarization Sample

	Shor and McCarty (2011)			Azzimonti (2018)		
	Gross Return	Alpha 1F	Benchmark-Adjusted	Gross Return	Alpha 1F	Benchmark-Adjusted
Fund Diversity	0.088	0.061	0.054	0.044	0.072	0.043
	(1.58)	(1.46)	(1.55)	(0.78)	(1.55)	(1.41)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	137,649	137,649	137,649	150,521	150,521	150,521
Adjusted r^2	0.107	0.064	0.023	0.131	0.096	0.023

Table A7: Investment Advisor M&A and Changes in Team Diversity

This table reports results from regressions of Δ*Fund Diversity* on *Fund-Family Distance*, and other fund characteristics lagged one month. Δ*Fund Diversity* is computed as the change in *Fund Diversity* between its value at the M&A announcement date and its average in the five years after the M&A deal. *Fund Diversity* is average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. *Fund-Family Distance* is computed as the Euclidean distance between the acquirer family and the target funds, as measured at the M&A announcement date. *t*-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Fund-Family Distance	0.175***	0.240***	0.249**
	(3.75)	(3.13)	(2.71)
Size (log TNA)	-0.003		0.018*
	(-1.40)		(2.07)
Expense Ratio	1.391		7.410*
	(0.83)		(2.05)
Load Fee	-0.112		-0.424
	(-0.82)		(-1.12)
Turnover	-0.005		0.012
	(-0.56)		(0.91)
Fund Age (log)	0.004		-0.043
	(0.70)		(-1.48)
Fund Managers (log)	-0.037**		-0.032
	(-2.26)		(-1.57)
Style × Time FE	Yes		
Fund FE		Yes	Yes
Time FE		Yes	Yes
Observations	545	545	545
Adjusted r^2	0.323	0.600	0.609

Table A8: Team Diversity and Fund Incentives

This table reports results from regressions of fund gross returns on *Fund Diversity*, fund incentives variables, and other fund characteristics lagged one month. *Fund Diversity* is computed as the average Euclidean distance among all managers of a fund based on the political beliefs of managers, as described in section 2.2. We add *Bonus-fund performance*, an indicator variable with value 1, if the manager's compensation is based on the specific fund's performance; *Bonus-paid in fund shares*, an indicator variable with value 1, if the manager's compensation includes shares from the fund; *Bonus-fund revenue*, an indicator variable with value 1, if the manager's compensation is linked to the revenues collected by the fund; *Manager ownership*, Morningstar's ownership range based on the portfolio managers ownership data reported to the SEC; *CIR measure*, the difference between the last and first marginal compensation rates divided by the effective marginal compensation rate (Massa and Patgiri (2009)). The list of controls is the same as in our baseline Table 3. t-statistics based on standard errors clustered by time (year-month) are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Gross Return	Alpha 1F	Alpha 3F	Alpha 4F	Benchmark-Adjusted
Fund Diversity	0.103***	0.069***	0.067***	0.059***	0.057**
	(3.21)	(3.22)	(3.84)	(4.16)	(2.47)
Bonus-fund performance	0.027**	0.014	0.017*	0.015*	0.017
	(2.01)	(1.40)	(1.95)	(1.89)	(1.59)
Bonus-paid in fund shares	0.038	0.053**	0.032*	0.045***	0.029
	(1.33)	(2.35)	(1.73)	(2.62)	(0.98)
Bonus-fund revenue	0.039**	0.016	0.023**	0.032***	0.010
	(2.12)	(1.12)	(2.15)	(3.14)	(0.65)
Manager ownership	0.050	0.032**	0.026**	0.020*	0.008
	(1.10)	(2.48)	(2.24)	(1.89)	(1.36)
CIR measure	0.003	0.014	-0.003	-0.003	0.021
	(0.12)	(0.71)	(-0.19)	(-0.18)	(0.59)
Controls	Yes	Yes	Yes	Yes	Yes
Style x Time FE	Yes	Yes	Yes	Yes	Yes
Observations	280,421	280,421	280,421	280,421	280,421
Adjusted r^2	0.111	0.070	0.077	0.073	0.026