Diverse Hedge Funds

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Abstract

Hedge fund teams with heterogeneous educational backgrounds, academic specializations, work experiences, genders, and races, outperform homogeneous teams after adjusting for risk and fund characteristics. An event study of manager team transitions, instrumental variable regressions, and an analysis of managers that simultaneously operate solo- and team-managed funds address endogeneity concerns. Diverse teams deliver superior returns by arbitraging more stock anomalies, avoiding behavioral biases, and minimizing downside risks. Moreover, diversity allows hedge funds to circumvent capacity constraints and generate persistent performance. Our results suggest that diversity adds value in asset management.

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1. Introduction

Investment funds are often managed by teams of portfolio managers. Anecdotal evidence suggests that driven by homophily (Lazarsfeld and Merton, 1954; McPherson, Smith-Lovin, and Cook, 2001), portfolio managers prefer working alongside other managers with similar backgrounds. For instance, it is not uncommon for investment firms to be staffed by portfolio managers who all attended the same university, chose the same major in college, worked at the same investment bank, identify with the same gender, or belong to the same race.[1] To address the diversity issues confronting asset managers, industry associations have commissioned reports that seek to improve diversity and inclusion practices.[2] Moreover, institutional investors such as the Yale University Endowment fund, the California Public Employees Retirement System, and the MacArthur Foundation now require that investment firms reveal the diversity of their leadership and workforce, in an effort to compel them to improve diversity.[3] These developments beg the question: what are the implications of team diversity for investment performance? While a nascent literature has investigated diversity in asset management, strong and broad-based evidence of the investment benefits of diversity has proven elusive, and the mechanisms by which diversity affects value remain unclear.[4]

In this study, we examine the value of diversity for management teams operating hedge funds. The hedge fund industry is an important laboratory in which to study diversity for four reasons. First, as some of the most sophisticated investors in financial markets (Brunnermeier and Nagel, 2004), hedge funds typically employ complex and unconstrained strategies. This should allow them to fully exploit the heterogeneous skills of a diverse team, especially in contrast to mutual funds, which pursue relatively simple and constrained

[1] For example, the vast majority of the partners at the now defunct Long-Term Capital Management worked at Salomon Brothers and studied at the Massachusetts Institute of Technology (Lowenstein, 2000). Similarly, all the founding partners at Domeyard, a high-frequency trading hedge fund, graduated from the Massachusetts Institute of Technology and belong to the same race (Cohen, Malloy, and Foreman, 2015).

[2] See, for example, "The Alternatives. A Practical Guide to How Hedge Fund Firms Large and Small Can Improve Diversity and Inclusion," commissioned by the Alternative Investment Management Association (https://www.aima.org/sound-practices/guides-to-sound-practices/the-alternatives.html).

[3] See "Hedge funds face mounting pressure with diversity questionnaire," Bloomberg, November 10, 2020.

[4] See Bär, Niessen, and Ruenzi (2009), Gompers and Wang (2021), and Evans, Prado, Rizzo, and Zambrana (2022), which we will discuss further.

strategies. Second, since hedge funds tend to be managed by small teams, which are more prone to homophily (Klocke, 2007), much of the economic benefits from diversity, if any, could be untapped. Indeed, anecdotal evidence suggests that the hedge fund industry suffers from a diversity and inclusion problem.[5] Third, diverse hedge funds by exploiting a wider range of investment opportunities could be more resilient to the capacity constraints that limit the investment gains from allocating capital to skilled managers (Berk and Green, 2004). Diversity could therefore have welfare implications for fund investors. Fourth, with the exception of shareholder activists, hedge funds do not typically appoint directors onto the boards of their portfolio companies. Therefore, by analyzing hedge funds, as opposed to venture capital or private equity funds, one can more cleanly distinguish from the widely studied board diversity effects.[6]

Theoretically, it is not clear whether diversity should create value in asset management. By harnessing the heterogeneous skill sets of their team members, diverse teams could exploit a wider array of investment opportunities, which should translate into superior investment returns (Hong and Page, 2004; Alesina and La Ferrara, 2005). Moreover, by working alongside other managers from different backgrounds, fund managers in diverse teams could become more aware of their own biases and entrenched ways of thinking (Rock and Grant, 2016), and therefore avoid costly behavioral mistakes. Similarly, members of a heterogeneous team could more effectively serve as checks and balances for each other (Phillips, Liljenquist, and Neale, 2009), which should engender more prudent risk management. Yet, based on the notion that similarity breeds connection (Ingram and Roberts, 2000; McPherson, Smith-Lovin, and Cook, 2001; Cohen, Frazzini and Malloy, 2008), members of a heterogeneous team may find it harder to communicate with one another, convey tacit information, or make joint decisions in a timely fashion relative to members of a homogeneous team. Such operational challenges could lead to execution problems that adversely affect fund performance.

[5]See "Hedge funds fall flat when it comes to diversifying their ranks," Bloomberg, October 7, 2020.

[6]For example, Adams and Ferreira (2009) and Ahern and Dittmar (2012) show that gender diversity in the board reduces firm value while Kim and Starks (2016) argue that gender diversity can increase firm value when the inclusion of women increases the heterogeneity in functional expertise at the board. Moreover, Chidambaran, Liu, and Prabhala (2022) show that boards tend to value skill diversity more than age or ethnic diversity.

In this paper, we study diversity based on educational institution, academic specialization, work experience, gender, and race.[7] A large body of work in sociology documents the prevalence of homophily along these dimensions (Marsden, 1987; Kalmijn, 1998; Louch, 2000; Goodreau, Kitts, and Morris, 2009). The advantage of focusing on educational institution, academic specialization, and work experience is that they more likely relate to managerial functional expertise. Moreover, these three dimensions are less confounded by the gender and racial discrimination-induced selection issues that complicate inferences about the value of diversity. For example, if women face greater barriers to entry in asset management, including a female in an all-male team should elevate performance as the female manager would likely be of higher quality than the men (Chuprinin and Sosyura, 2018).

Our results suggest that team diversity is associated with superior investment performance. We show via multivariate regressions that after accounting for backfill bias (Jorion and Schwarz, 2019), fund incentives (Agarwal, Daniel, and Naik, 2009), fund shareholder restrictions (Aragon, 2007), fund age (Aggarwal and Jorion, 2010), fund size (Getmansky, 2012; Ramadorai, 2013), fund manager quality (Chevalier and Ellison, 1999), and team size, diverse teams outpace homogeneous teams by a risk-adjusted 1.96% to 5.59% per annum. Moreover, relative to homogeneous funds, diverse funds deliver higher Sharpe ratios, information ratios, Goetzmann, Ingersoll, Spiegel, and Ross (2007) manipulation-proof performance measures, and Berk and van Binsbergen (2015) value-added skill. Diverse hedge funds also demonstrate savvy stock selection skills. The stocks they hold earn greater raw returns, Daniel, Grinblatt, Titman, and Wermers (1997) alphas, and Carhart (1997) 4-factor alphas.

To further gauge the economic significance of the impact of diversity, we conduct portfolio sorts that analyze the residuals from regressions of fund returns on a host of fund and team controls. The portfolio sorts indicate that diverse teams outperform homogeneous teams by 4.44% to 6.00% per annum after adjusting for co-variation with the Fung and Hsieh (2004) factors and the explanatory power of fund and team covariates. The findings are robust to allowing for a myriad of possible omitted factors including the Fama and French (1993) value factor, the Carhart (1997) momentum factor, the Pástor and Stambaugh (2003)

[7] In an earlier draft of the paper, we also study diversity based on fund manager nationality and obtain qualitatively similar results.

liquidity factor, the Agarwal and Naik (2004) call and put equity option-based factors, the Frazzini and Pedersen (2014) betting-against-beta factor, the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Fama and French (2015) profitability and investment factors, and an emerging markets equity factor.

Endogeneity does not explain the superior performance of diverse teams. To address concerns that *time-invariant* differences between homogeneous and diverse funds simultaneously explain diversity differences and variation in fund performance, we conduct an event study analysis of the transition to a more diverse team. Specifically, we study scenarios whereby a fund management team improves diversity by hiring a new manager from a different background. To allay concerns that *observable time-varying* differences in fund characteristics drive our results, we employ a difference-in-differences methodology and analyze the residuals from regressions of fund performance on a host of fund and team characteristics. Relative to other comparable teams and to the prior 36-month period, we find that teams that enhance diversity increase their risk- and characteristics-adjusted fund returns by 3.19% to 5.69% per annum in the following 36-month period. Inferences remain qualitatively unchanged when we (i) vary the length of the event window, (ii) match treatment to control funds based on propensity score, (iii) match treatment to control funds based on team characteristics in addition to fund performance, (iv) study manager additions that diminish diversity, or (v) limit the sample of treatment funds to those that hire managers who are of lower quality relative to the existing members of the respective teams.

To cater for *unobserved time-varying* differences between diverse and homogeneous funds, we run an instrumental variable analysis with the racial diversity of the inhabitants at the hedge fund founding partner's hometown as the instrument. We posit that due to imprinting (Marquis and Tilcsik, 2013; Simsek, Fox, and Heavey, 2015) during childhood, hedge fund firm founders who grew up in diverse cities are more likely to set up diverse teams. As in Acemoglu, Johnson, and Robinson (2001) and Glaeser, Kerr, and Kerr (2015), we rely on the separation of time to motivate the exclusion restriction. In support of the conceptual underpinnings of our instrumental variable approach, we show that the racial compositions of fund management teams reflect the racial compositions of the respective cities (as reported in 1980 U.S. Census data) where their founders grew up . Consistent with the relevance condition of our instrument, we show that team diversity positively relates to the demographic diversity of the founder's hometown. Using founder hometown demographic diversity as an instrument in two-stage least squares regressions, we find strong support for the idea that team diversity engenders superior investment performance. Our choice of instrument is robust to alternative specifications. Moreover, our results are driven neither by differences in founders' access to resources or education quality during childhood directly affecting fund performance nor by possible correlation between hometown demographic diversity and size.

To further address endogeneity concerns related to differences in manager quality between diverse and homogeneous funds, we focus on the subset of fund managers that simultaneously operate both solo- and team-managed hedge funds. To explicitly control for manager quality, we analyze the relation between team diversity and the performance of team-managed hedge funds *relative to* the average performance of the solo-managed funds concurrently operated by the individual members of the respective teams. The aforementioned performance difference likely understates the benefits from diversity since managers have strong incentives to import any best practices that they learn from teams to their solo-managed funds. Nonetheless, we find using this difference-in-differences model that diverse teams continue to outperform homogeneous teams after adjusting for fund manager quality in this way. These results, together with those from the event study and instrumental variable analysis, provide strong and compelling evidence that endogeneity explanations do not drive our findings.

Next, we provide insights into the mechanisms underlying the superior performance of diverse hedge funds. The diversity story posits that by leveraging the heterogeneous skill sets of their team members, diverse teams exploit a wider range of investment opportunities. Consistent with this view, diverse teams arbitrage a greater variety of the prominent stock anomalies identified by Stambaugh, Yu, and Yuan (2015). Dovetailing with the notion that working alongside other managers from different backgrounds helps fund managers become more aware of their own biases, diverse teams are less susceptible to behavioral biases such as the disposition effect (Odean, 1998), overconfidence-induced excessive trading (Barber and Odean, 2000; 2001), and the preference for lottery stocks (Bali, Cakici, and Whitelaw, 2011).

The diversity story also predicts that hedge funds with long-term capital are better placed to overcome the operational challenges associated with managing a diverse team. In line with this view, diverse teams outpace homogeneous teams more when they impose longer redemption, notice, and lock-up periods. Finally, consistent with the idea that members of a heterogeneous team can more effectively monitor each other, diverse teams bear lower downside risk, exhibit lower operational risk, and report fewer suspicious returns.

We also explore through the lens of diversity the well-publicized capacity constraints (Naik, Ramadorai, and Strömqvist, 2009; Getmansky, 2012; Ramadorai, 2013) and performance persistence (Agarwal and Naik, 2000; Kosowski, Naik, and Teo, 2007) effects in hedge funds. We find that diverse teams, by exploiting more varied investment opportunities, sidestep capacity constraints at the fund level. Consequently, capacity constraints mainly affect funds operated by homogeneous teams. In line with the logic of Berk and Green (2004), we show that performance strongly persists among diverse teams but not among homogeneous teams as the former are better able to accommodate additional capital from fund investors without sacrificing future performance. These results resonate with those of Harvey, Liu, Tan, and Zhu (2021) who show that relative to solo-managed mutual funds, team-managed mutual funds are less susceptible to capacity constraints, which they ascribe to "experience" diversity or the inverse of the average pairwise correlation in prior fund returns between the managers in the team.[8]

Do investors value team diversity? We show that investors allocate more capital to diverse funds even after controlling for past fund performance. The additional capital does not completely erode away the superior alphas of diverse funds, which is unsurprising as they are less affected by capacity constraints. Given the value of team diversity, why do fund founders not set up teams that are more diverse? We find that search frictions constrain team diversity at fund inception. Teams set up opportunistically to manage funds in hot investment strategies (Cao, Farnsworth, and Zhang, 2021) or established by founders with limited industry experience tend to be more homogeneous.

[8]Unlike Harvey et al. (2021), we analyze differences in capacity constraints among team-managed funds, thereby circumventing the host of other possible confounding differences between solo- and team-managed funds. Moreover, we relate capacity constraints to a much broader spectrum of simple and relatable diversity measures based on educational institution, college major, work experience, gender, and race.

Our work complements the nascent literature on team diversity in asset management.[9] Bär, Niessen, and Ruenzi (2009) study the implications of heterogeneity in manager industry tenure, length of education, age, and gender for mutual fund performance but obtain mixed results, Gompers and Wang (2021) find that gender diversity improves performance for venture capital funds. Evans et al. (2022) show that ideologically diverse mutual funds outperform ideologically homogeneous mutual funds by 1.80% per year. By analyzing hedge funds, which are better positioned to harness the value of diversity given the complex and relatively unconstrained strategies that they employ, we obtain more consistent and substantially larger estimates of the investment performance benefits from diversity than those in Bär, Niessen, and Ruenzi (2009) and Evans et al. (2022), respectively. Since hedge funds, unlike venture capital funds, do not typically appoint directors onto the boards of their portfolio companies, compared to those of Gompers and Wang (2021), our results are less confounded by board diversity effects. Moreover, relative to these papers, we provide new insights into the mechanisms through which team diversity shapes fund performance by relating diversity to stock anomalies, behavioral biases, shareholder restrictions, risk management, and capacity constraints.[10]

[9]Our study also relates to the body of work that analyzes the performance of female- or minority-led hedge funds. In general, this literature has found mixed results about the investment ability of women and minorities. On one hand, Lerner, Leamon, Sessa, Dewan, and Holt (2019) do no observe superior performance among female- and minority-led hedge funds and Aggarwal and Boyson (2016) do not find that female hedge funds managers outperform. On the other hand, Barclays Capital (2011) and Bloomberg News (2020, 2021) report that hedge funds run by women and minorities outperform. It is worth noting that our results are robust to controlling for the fraction of women and the fraction of racial minorities in the team. Aggarwal and Boyson (2016) also investigate mixed gender teams and show that they underperform all-male and all-female hedge funds. However, they analyze a much smaller sample of 195 mixed gender teams. In contrast, we study 2,207 mixed gender teams and find that they outperform single gender teams.

[10]While Evans et al. (2022) also show, using U.S. mutual fund data, that diverse teams exploit more investment opportunities, we offer novel insights into the nature of those investment opportunities, i.e., prominent stock anomalies, and the implications of such investment behavior, i.e., lower capacity constraints and greater performance persistence.

2. Data and methodology

2.1. Hedge fund data

We study the relation between team diversity and hedge fund performance using monthly net-of-fee returns and assets under management (henceforth AUM) data of live and dead hedge funds reported in the Lipper TASS, Morningstar, Hedge Fund Research (henceforth HFR), and BarclayHedge commercial databases from January 1994 to June 2016. We focus on data from January 1994 onward as the hedge fund commercial databases do not track dead funds prior to January 1994 and, therefore, contain survivorship bias.

In our fund universe, we have a total of 43,083 hedge funds comprising 17,368 live funds and 25,715 dead funds. In view of concerns that funds with multiple share classes could cloud the analysis, we exclude duplicate share classes from the sample. This leaves a total of 27,751 hedge funds, of which 10,228 are live funds and 17,523 are dead funds. While 6,996 funds appear in multiple databases, many funds belong to only one database. Specifically, there are 7,085, 3,336, 5,512, and 4,822 funds that appear only in the Lipper TASS, Morningstar, HFR, and BarclayHedge databases, respectively, highlighting the advantage of collecting hedge fund data from multiple databases. In addition to fund returns and AUM, the hedge fund databases contain information on fund manager names, fund fees, redemption terms, inception dates, investment strategies, and other fund characteristics.

As per Agarwal, Daniel, and Naik (2009), we classify funds into four broad investment styles: Security Selection, Multi-process, Directional Trader, and Relative Value. Security Selection funds take long and short positions in undervalued and overvalued securities, respectively. They typically take positions in equity markets. Multi-process funds employ multiple strategies that take advantage of significant events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks. Directional Trader funds wager on the direction of market prices of currencies, commodities, equities, and bonds in the futures and cash markets. Relative Value funds bet on spread relations between prices of financial assets while aiming to minimize market exposure.

As listing on commercial databases is not mandatory for hedge funds, hedge fund data are susceptible to self-selection biases. For example, hedge funds often include returns prior to fund listing dates onto the databases. Because funds that have good track records tend to go on to list on databases to attract investment capital, the backfilled returns tend to be higher than non-backfilled returns, which leads to a backfill bias (Liang, 2000; Fung and Hsieh, 2009; Bhardwaj, Gorton, and Rouwenhorst, 2014). To alleviate concerns about backfill bias, throughout this paper, we analyze hedge fund returns reported post fund database listing date. For funds from databases that do not provide listing date information, we rely on the Jorion and Schwarz (2019) algorithm to back out fund database listing dates.

We estimate hedge fund performance relative to the Fung and Hsieh (2004) seven factors. These factors are S&P 500 return minus the risk-free rate (SNPMRF), Russell 2000 return minus the S&P 500 return (SCMLC), change in the constant maturity yield of the 10-year U.S. Treasury bond appropriately adjusted for the duration (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodity PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Fung and Hsieh (2004) show that their model captures up to 84% of the variation in hedge fund index returns.

2.2. Measuring diversity

Our decision to study diversity based on educational institution, academic specialization, work experience, gender, and race is motivated by work in sociology on homophily.[11] According to Lazarsfeld and Merton (1954) homophily refers to the "tendency for friendships to form between those who are alike in some designated aspect." A large body of work documents the prevalence of homophily along the dimensions of education (Marsden, 1987; Louch, 2000; Flap and Kalmijn, 2001), occupation (Laumann, 1973; Kalmijn, 1998), gender

[11] Research in finance has shown that homophily can reduce the monitory effectiveness of corporate boards (Hwang and Kim, 2009), increase the likelihood of outside appointees to the board (Berger, Kick, Koetter, and Schaeck, 2013), improve communication and coordination between venture capitalists and start-up executives (Hegde and Tumlinson, 2014), and increase the propensity by retail bank clients to follow financial advice (Stolper and Walter, 2018).

(Marsden, 1987; Shrum, Cheek, and Hunter, 1988), and race (McPherson, Smith-Lovin, and Cook, 2001; Quillian and Campbell, 2003; Goodreau, Kitts, and Morris, 2009). Consistent with those findings, anecdotal evidence suggests that hedge fund management teams often share commonalities along these specific dimensions.

While one can measure diversity over a wide range of dimensions, we focus on dimensions directly impacted by homophily. By curtailing the formation of diverse teams, homophily should ultimately increase the value of diversity for investment management. Moreover, homophily is a key driver underlying some of the mechanisms by which diversity could affect investment performance. Specifically, members in homophilious teams can more effectively communicate with each other but are also more prone to group think and less likely to call attention to or ameliorate the personal biases of other team members.

An advantage of studying diversity based on educational institution, academic specialization, and work experience is that, relative to gender and race, they more closely relate to manager functional expertise. For example, managers who enrolled in the same university likely took the same courses. Similarly, managers who majored in the same subject in college likely possess similar skill sets. Likewise, managers who worked at the same investment bank likely attended the same training program for junior analysts and traders. That said, differences in functional expertise could exist between the different genders and races due to societal, familial, and innate factors (Catsambis, 1994). Moreover, by analyzing diversity in educational institution, academic specialization, and work experience, we sidestep the gender and racial discrimination-induced selection issues that create barriers to entry for underrepresented groups (i.e., females and minorities), and therefore complicate inferences about the value of diversity (Chuprinin and Sosyura, 2018). The advantage of studying diversity based on gender and race is that, as we shall show, investment management teams tend to be more homogeneous (and hence more homophilious) when evaluated along such dimensions.

Following the network literature (United States Department of the Army, 2014), we define team network density as the number of shared connections due to manager educational institutions, college majors, work experiences, genders, or races scaled by the maximum number of possible shared connections within a team. For example, for the educational institution-based measure, we define two members of the team as having a shared connection if they attended the same school (or schools). In a team of N, the maximum number of shared connections C_i that a team member i can have with the rest of the team is $N-1$. Therefore, we define network density as $\frac{1}{N}\sum_i \frac{C_i}{N-1}$. Diversity is simply one minus network density. Consider a five-person team where three members went to Harvard and two members attended Stanford. The educational institution-based network density is $(2/4+2/4+2/4+1/4+1/4)/5 = 2/5$ and diversity equals to $1-2/5 = 3/5$. For another five-person team where all five members studied at MIT, the educational institution-based network density is 1 and diversity equals to 0. The college major-, work experience-, gender-, and race-based diversity measures are defined analogously.

Our simple measure focuses on the paucity of shared connections established across managers within a team, thereby avoiding some of the problems associated with other alternative measures of diversity. Specifically, a diversity measure based on the negative of the Herfindahl-Hirschman concentration index or on the Teachman (1980) entropy-based index may not accurately characterize team diversity for dimensions such as educational institution and work experience whereby multiple universities and past employers could be assigned to the same manager. For instance to compute the Herfindahl-Hirschman index-based diversity measure for work experience, one would have to focus on say the most recent past employer, ignoring valuable information from connections forged via other past employers. It is comforting to note that our findings are qualitatively unchanged when we employ the Herfindahl-Hirschman and Teachman (1980) index-based diversity measures.

We focus on hedge funds operated by teams, i.e., funds with two or more managers, although we also analyze solo-managed funds in some of our tests.[12] There are 16,307 team-managed funds, comprising a substantial 58.76% of the funds in our combined hedge fund database. We obtain undergraduate and postgraduate educational institution information for 3,385 managers operating 5,250 funds, college major information for 3,092 managers

[12]Hedge fund teams are not large. Of the funds managed by teams, 40.61% are managed by two people, 30.29% are managed by three people, 16.97% are managed by four people, and 12.13% are managed by five or more people. Inferences remain qualitatively unchanged when we redo our baseline analysis after including solo-managed hedge funds in the sample, which we classify as fully homogeneous funds. We thank Marcin Kacperczyk for suggesting this interpretation for solo-managed hedge funds.

running 4,514 funds, and prior employment information for 3,315 managers managing 5,019 funds by manually searching manager LinkedIn pages and matching based on manager and fund management company names.

To determine manager gender, and race, we rely on genderize.io (https://genderize.io) and NamSor (https://www.namsor.com) application programming interfaces (APIs) for predicting gender and race from name. We obtain manager gender and race information for 8,546 and 7,564 managers running 11,681 and 11,651 funds, respectively. The gender and racial classifications do not rely on LinkedIn data and, therefore, the analyses of the gender- and race-based diversity measures circumvent any sample selection concerns related to the LinkedIn data. An advantage of the LinkedIn dataset is that it includes the dates for which fund managers joined and/or exited from their respective fund management companies, thereby allowing us to analyze the implications of changes in the composition and diversity of teams over time. Table IA1 of the Internet Appendix reveals that the differences in fund characteristics (except for lockup period) between funds with and without LinkedIn information are all statistically indistinguishable from zero. Therefore, we cannot reject the null that the LinkedIn sample is representative of the broader fund sample.

To mitigate concerns about measurement error induced by the aforementioned APIs, we redo our baseline tests after using NamSor to ascertain gender and using the Ye et al. (2017) or the Imai and Khanna (2016) methodology to determine race, and obtain virtually identical results. To further address measurement error concerns, we manually classify managers based on race and gender for the subset of 1,826 managers with facial profile photos from LinkedIn and obtain qualitatively similar baseline results. These findings are available upon request.

Panel A of Table 1 provides information on the universities, college majors, former employers, genders, and races of the hedge fund managers in our sample. The top five universities are Harvard, University of Pennsylvania, Columbia, New York University, and University of Chicago. The top five college majors are Finance, Economics, Accounting, Computer Science, and Mathematics. The top five former employers are Goldman Sachs, Morgan Stanley, Merrill Lynch, JP Morgan, and UBS. It is unsurprising that the majority of the managers are male (94.12%) and white (64.83%).

[Insert Table 1 here]

Panel B of Table 1 presents summary statistics of the diversity measures, fund returns, and fund characteristics from our hedge fund sample. We observe relatively greater heterogeneity in the universities attended by members of the same team and their college majors, less heterogeneity in their races and former workplaces, and even less heterogeneity in their genders. The respective means for the diversity measures based on educational institution, college major, work experience, gender, and race are 0.789, 0.742, 0.560, 0.112, and 0.584.[13]

Panel C reports summary statistics of the diversity measures broken down by investment style. It shows that the diversity measures do not vary significantly across investment styles although there is some evidence that relative value funds tend to be more homogeneous.

Panel D reveals the correlations between the diversity measures, fund returns, and fund characteristics. It indicates that, team diversity based on educational institution, college major, and work experience more positively relate to fund returns, which is in line with the view that these three dimensions more closely relate to functional expertise. Manager college median SAT score and fund age also positively relate to diversity, which suggests that diverse funds tend to comprise higher quality managers and survive longer in our sample. The other fund characteristics do not display a consistently positive or consistently negative correlation with our diversity measures. In our analysis of fund performance, we will carefully control for the explanatory power of these fund characteristics in a multivariate regression setting.

[13]Based on the educational institution, college major, work experience, gender, and race team diversity measures, there are 435 (8.29%), 388 (8.59%), 1,200 (22.86%), 9,474 (81.10%), and 4,912 (35.80%) homogeneous funds, as well as 3,553 (67.68%), 1,832 (40.58%), 2,056 (39.16%), 0 (0%), and 6,405 (46.68%) diverse funds, respectively.

3. Empirical results

3.1. Fund investment performance

To determine the incremental explanatory power of team diversity on fund performance, we first estimate the following pooled OLS regression:

$$\begin{aligned}
ALPHA_{im} = \alpha &+ \beta_1 DIVERSITY_{im-1} + \beta_2(SAT_i/100) + \beta_3 MGTFEE_i + \beta_4 PERFFEE_i \\
&+ \beta_5 HWM_i + \beta_6 LOCKUP_i + \beta_7 LEVERAGE_i + \beta_8 AGE_{im-1} \\
&+ \beta_9 REDEMPTION_i + \beta_{10} log(FUNDSIZE_{im-1}) + \sum_k \beta_{11}^k YEARMTHDUM_m^k \\
&+ \sum_l \beta_{12}^l STRATEGYDUM_i^l + \sum_o \beta_{13}^o TEAMSIZEDUM_i^o + \epsilon_{im},
\end{aligned} \tag{1}$$

where $ALPHA$ is fund alpha, $DIVERSITY$ is team diversity, SAT is team SAT score, $MGTFEE$ is management fee, $PERFFEE$ is performance fee, HWM is the high-water mark indicator, $LOCKUP$ is lock-up period, $LEVERAGE$ is the leverage indicator, AGE is fund age since inception, $REDEMPTION$ is redemption period, $FUNDSIZE$ is fund AUM, $YEARMTHDUM$ is the year-month dummy, $STRATEGYDUM$ is the fund strategy dummy, and $TEAMSIZEDUM$ is the team size dummy. Fund alpha is the monthly abnormal return from the Fung and Hsieh (2004) model, where the factor loadings are estimated over the prior 24 months.[14] Team SAT score is the average of the median SAT score for the undergraduate institutions attended by fund managers in the team and proxies for manager quality. We estimate five sets of regressions that correspond to the five diversity measures. We base statistical inferences on White (1980) robust standard errors clustered by fund and month and also estimate the analogous regressions on monthly fund excess returns.

Panel A of Table 2 indicates that after controlling for the explanatory power of various fund and team characteristics, team diversity positively relates to fund performance. Specifically, the coefficient estimate on $DIVERSITY\_EDU$ in column 2 shows that a one-unit increase in educational institution-based diversity (from a fully homogeneous to a fully

[14] Inferences do not change when we use factor loadings estimated over the past 36 months instead.

diverse team) is synonymous with a 5.59% per annum increase in fund alpha. Similarly, the coefficient estimates in columns 4, 6, 8, and 10 reveal that one-unit increases in college major-, work experience-, gender-, and race-based diversity are associated with 3.02%, 3.60%, 3.00%, and 1.96% per annum increases in fund alpha, respectively.[15] These results suggest that functional diversity (based on educational institution, college major, and work experience) more positively relate to investment performance than does non-functional diversity (based on gender and race).

The signs of the coefficient estimates on the fund control variables broadly agree with the extant literature. As per Aggarwal and Jorion (2010), fund age is negatively associated with fund performance. Consistent with Getmansky (2012) and Ramadorai (2013), fund size negatively relates to fund performance. In line with Aragon (2007), fund redemption period positively relates to fund performance. The positive relation between team SAT score and fund performance follows Chevalier and Ellison (1999) and Li, Zhang, and Zhao (2011).

[Insert Table 2 and Figure 1 here]

Figure 1 shows binned scatter plots that illustrate the relation between fund monthly abnormal returns and the measures of team diversity. The lines of best fit through the scatter plots corroborate the central finding from the regressions, i.e., that diversity positively relates to fund performance.

Next, we gauge the robustness of our regression results. First, to address concerns that hedge fund residuals may be correlated across different funds within the same month, we estimate Fama and MacBeth (1973) regressions on fund performance. We base statistical inferences on Newey and West (1987) standard errors with lag length as per Greene (2018). Second, to verify that our findings are not affected by incubation bias (Fung and Hsieh, 2009), we rerun the regressions after excluding the first 24 months of returns for each fund. Third, to check that serial correlation in fund returns is not inflating the test statistics and

[15] Panel A in Table IA2 of the Internet Appendix reveals that a one-unit increase (from a fully homogeneous team to a fully diverse team) in aggregate diversity is associated with a 4.24% and 5.28% increase in annualized fund return and alpha, respectively. They also suggest that there are diminishing marginal returns to diversity as evidenced by the negative coefficient estimates on the square of aggregate diversity.

affecting inferences, we reestimate the regressions on unsmoothed fund returns and alphas, which are constructed as per Getmansky, Lo, and Makarov (2004). Fourth, to ensure that our results are not driven by the imputation of fund fees, we redo the analysis on gross returns and alphas. To back out prefee fund returns, we calculate high-water marks and performance fees by matching each capital outflow to the relevant capital inflow, assuming as per Agarwal, Daniel, and Naik (2009) that capital leaves the fund on a first-in, first-out basis. The results in Panel B of Table 2 and Table IA3 of the Internet Appendix reveal that our findings are robust to these adjustments.[16]

Table IA4 of the Internet Appendix shows that diverse hedge funds also exhibit higher Sharpe ratios, information ratios, manipulation-proof performance measures (Goetzmann et al., 2007), and Berk and van Binsbergen (2015) value-added skill relative to homogeneous funds. Next, Table IA5 of the Internet Appendix reveals that the stock holdings of diverse hedge funds generate higher raw returns, Daniel et al. (1997) DGTW-adjusted returns, and Carhart (1997) 4-factor alphas than do those of homogeneous hedge funds, which suggests that diverse teams possess superior stock selection skills.

To further gauge economic significance, for each of our diversity measures, we sort hedge funds into five groups based on their team diversity measures every January 1 and evaluate their residuals from regression of fund returns on the fund and team characteristics in Eq. (1). Portfolio 1 comprises hedge funds managed by diverse teams for which the diversity measure equals one. Portfolio 5 comprises hedge funds managed by homogeneous teams for which the diversity measure equals zero. Hedge funds operated by other teams are allocated to the remaining three portfolios based on team diversity.[17] Next, we link the equal-weighted post-formation residuals over the next 12 months across years to form a single series for each portfolio and evaluate performance of the residuals relative to the Fung and Hsieh (2004) seven-factor model. Statistical inferences are based on White (1980)

[16] In results available upon request, we show that the findings remain qualitatively unchanged when we control for past one-year or two-year fund alpha.

[17] Since the sort is based on team diversity, a discrete variable, the numbers of hedge funds in each of remaining three portfolios are very close but not necessarily identical to each other. For the portfolio sort on gender diversity, since there are no funds operated by teams with gender diversity equals to one, funds operated by teams with gender diversity greater than zero are sorted equally into portfolios 1 to 4 based on gender diversity.

heteroscedasticity consistent standard errors.

The results reported in Table 3 reveal that hedge funds managed by diverse teams outperform those managed by homogeneous teams. Panel A indicates that hedge fund teams with divergent education backgrounds outperform those with common education backgrounds by an economically meaningful 5.16% per annum (t-statistic = 4.91) after adjusting for co-variation with the Fung and Hsieh (2004) factors and the explanatory power of fund and team characteristics. The results in Panels B, C, D, and E suggest that hedge fund teams with disparate college majors, work experiences, genders, and races also outpace teams with matching college majors, work experiences, genders, and races by 6.00%, 4.44%, 4.92%, and 4.97% per annum, respectively, after adjusting for risk as well as fund and team covariates. Panel B in Table IA2 of the Internet Appendix reveals that the top quintile of hedge funds based on aggregate diversity, or the average of the five diversity measures, outperforms the bottom quintile of hedge funds based on aggregate diversity by 6.80% per annum (t-statistic = 3.46) after accounting for risk as well as fund and team characteristics.

[Insert Table 3 here]

Table IA6 in the Internet Appendix reports results from several robustness tests on the portfolio sorts. The results show that inferences do not change when we value-weight the portfolios nor do they change when we exclude small funds with AUM below US$50 million. Inferences also remain qualitatively unchanged when we estimate the monthly alphas dynamically using factor loadings estimated over the prior 24 months and current month factor realizations. The spread alphas are also robust when we allow for two structural breaks in the estimation of the factor loadings: March 2000 (the height of the technology bubble) and September 2008 (the collapse of Lehman Brothers). We obtain similar results when we separately augment the Fung and Hsieh (2004) model with (i) the Fama and French (1993) HML value factor and the Carhart (1997) UMD momentum factor, (ii) the Fama and French (2015) RMW profitability and CMA investment factors, (iii) the Pástor and Stambaugh (2003) PS traded liquidity factor, (iv) the Frazzini and Pedersen (2014) BAB betting-against-beta factor, (v) the Bali, Brown, and Caglayan (2014) $MACRO$ macroeconomic uncertainty factor, (vi) the Agarwal and Naik (2004) $CALL$ out-of-the-money call option and PUT out-of-the-money put option factors, and (vii) the EM emerging markets factor derived from the MSCI Emerging Markets index.

3.2. Endogeneity

To address identification, we evaluate difference-in-differences estimates from an event study, estimate instrumental variable regressions, and analyze fund managers that simultaneously operate both solo- and team-managed funds.

3.2.1 Event study

To cater for endogeneity concerns that relate to *time-invariant* differences between homogeneous and diverse teams, we conduct an event study to investigate fund performance when a fund management team increases diversity by including a new team member from a different background. For example, in the event study for educational institution-based diversity, the treatment group consists of funds that hired new managers who attended a different university (or universities) relative to the existing managers in the respective teams. The control group consists of funds, with the same starting diversity levels as the treatment funds, that hired non-diversity enhancing managers during the event month.

The event window is the period that starts 36 months prior to and ends 36 months after the inclusion of the new manager. To be included in the sample, a fund must have monthly return information during the event window. This leaves 132, 161, 278, 513, and 467 funds for the educational institution-, college major-, work experience-, gender-, and race-based diversity analyses, respectively.

To account for endogeneity concerns stemming from *observable time-varying* differences in fund characteristics, we match treatment funds to control funds based on fund performance and conduct a difference-in-differences analysis. For example, in the fund alpha analysis, treatment funds are matched to control funds by minimizing the sum of the absolute differences in monthly fund alpha in the 36-month pre-event period.

[Insert Table 4 and Figure 2 here]

Columns 1 to 4 of Table 4 indicate that relative to comparable funds and to the prior 36-month period, funds that enhance diversity improve their risk-adjusted returns by 5.29% to 6.35% per annum in the 36-month period following the diversity change. These difference-in-differences estimates are statistically significant at the 1% or 5% level. Figure 2 illustrates the cumulative abnormal returns of the treatment and control groups over the event window and suggests that the parallel trends assumption is not violated.

To better understand the causal link between diversity and fund performance controlling for fund and team characteristics, we conduct an analogous difference-in-differences analysis on the residuals from the regressions of fund performance on the fund and team covariates in Eq. (1). Columns 5 to 8 of Table 4 reveal that relative to comparable funds and to the prior 36-month period, funds that enhance educational institution-, college major-, work experience-, gender- and race-based diversity improve their risk- and fund characteristics-adjusted returns by 3.19%, 5.69%. 3.67%, 3.50%, and 3.20% per annum, respectively, in the 36-month period following the diversity change.[18] These results echo the findings from the baseline performance regressions and broadly suggest that functional diversity adds more value than does non-functional diversity.

Table IA7 of the Internet Appendix indicates that inferences remain unchanged when we (i) change the event window to 24 or 48 months before and after the event, (ii) match control funds to treatment funds based on propensity score, where the covariates are the fund and team controls from the baseline performance regressions, (iii) study diversity-diminishing manager additions, and (iv) match control funds to treatment funds based on team characteristics, such as team SAT score or team size, and then fund performance. In results available upon request, to address concerns that the factor loadings of treatment funds may change after the event, we reestimate the post-event alphas using factor loadings generated from post-event returns only and obtain similar findings.

Given that only 34.3% of the new managers at treatment funds have school SAT scores

[18]We note that the average increase in diversity among the treatment funds in the event study is 0.223.

that are greater than those of the existing team, it is unlikely that our results are driven by the quality of the incoming managers. Moreover, we obtain similar results when we confine the sample of treatment funds to those that hire lower quality fund managers, i.e., those with school SAT scores that fall below the average SAT scores of the current team.

3.2.2 Instrumental variable analysis

Next, to complement the event study and address *unobservable time-varying* differences between diverse and homogeneous funds, we conduct an instrumental variable analysis. The instrument that we use is the racial diversity of the inhabitants in the hedge fund founder's hometown. We argue that diversity imprinting during childhood (Marquis and Tilcsik, 2013; Simsek, Fox, and Heavey, 2015) induces founders who grew up in demographically diverse cities to set up funds that feature diverse teams. Founders who grew up in demographically diverse localities are likely to be more comfortable or have more experience interacting with people who differ from them in multiple salient ways. We note that children from different racial groups are likely to differ in several dimensions, including family wealth and income, parental education, occupation and health, childhood experiences, and housing quality (Rosenbaum, 1996; Williams, Priest, and Anderson, 2016; Nelson and Vallas, 2021).

We compute the diversity of the residents at a founder's hometown as the racial diversity of the city in which the hedge fund founder grew up. To proxy for founders' experiences during childhood, racial distributions are derived from 1980 US Census data.[19] We obtain hometown information for 240 hedge fund founding partners who manage 897 funds by searching for founder wikipedia pages, online media reports, and online articles that mention the founder's hometown, high school, etc.

The first-stage results in columns 1 to 5 of Table 5 confirm this prediction. The diversity of the residents in a hedge fund founder's hometown is a positive and significant predictor of a

[19] Racial diversity is one minus the Herfindahl-Hirschman concentration measure for race divided by 10,000. The Herfindahl-Hirschman measure is based on city-level racial distributions obtained from Tables 69, 69a, 70, and 70a of the 1980 US Census of Population. See https://www2.census.gov/prod2/decennial/documents/1980/1980censusofpopu8011u_bw.pdf. Our results are robust to using as an alternative instrument the average racial and income diversity of founder hometowns, where hometown racial and income diversity are derived from 2014 U.S. Census data.

fund's team diversity, regardless of whether team diversity is based on manager educational institution, college major, work experience, gender, or race, with F-statistics that either exceed or are close to the threshold of ten prescribed by Stock, Wright, and Yogo (2002).

Next, we test the conceptual underpinnings of our instrumental variable approach. If the racial composition of a founder's hometown influences the racial composition of hedge fund teams via imprinting during childhood, we should observe a strong positive relation between the percentage of residents from a specific racial group in the founder's hometown and the percentage of team members from the same racial group. Table IA8 of the Internet Appendix confirms that this is indeed the case. Since the vast majority of fund founders with hometown information are white (91.67%), the Table IA8 results capture the greater propensity of white founders who grew up in racially diverse localities to hire non-whites.[20]

The exclusion restriction is that conditional on covariates, the demographic diversity of the founder's hometown affects investment performance only through its impact on team diversity. As in Acemoglu, Johnson, and Robinson (2001) and Glaeser, Kerr, and Kerr (2015), we rely on the separation of time to motivate the exclusion requirement. One concern is that founders who grew up in demographically diverse hometowns may be more affluent and have access to greater resources or better schools during childhood. This may explain why these founders outperform later in life. However, the correlation between founder hometown demographic diversity and average hometown income is economically modest at 0.087 and statistically insignificant, suggesting that founders who grew up in demographically diverse hometowns did not enjoy substantially better access to resources during childhood. Moreover, the correlation between founders' high school quality and hometown demographic diversity while positive at 0.133 is also statistically insignificant, indicating that demographic diversity does not consistently relate to the quality of the education that founders received in childhood.[21] Another concern is that demographically diverse hometowns may be larger and funds based in larger cities outperform due to knowledge spillovers (Christoffersen and

[20] In results available upon request, we find that our instrumental variable findings are qualitatively unchanged when we focus on hedge funds run by white founders.

[21] High school information is available for 67 of the 240 founders for whom we have hometown information. To infer high school quality, we use the U.S. News Best High School ranking. See https://www.usnews.com/education/best-high-schools/national-rankings.

Sarkissian, 2009). However, the vast majority of the founders (i.e., 90%) do not set up hedge funds in their hometowns, thereby casting doubt on this view.

Columns 6 to 10 of Table 5 report the second-stage results for the fund alpha equation. After instrumenting for team diversity, funds managed by diverse teams continue to outperform those managed by homogeneous teams. A comparison with the equivalent naïve OLS estimates in columns 11 to 15 of Table 5 shows that the coefficient estimates are larger after instrumenting for team diversity. In results that are available upon request, we find that our findings are qualitatively unchanged when we limit the sample to hedge funds set up outside of their founder hometowns or to hedge funds based in New York City.

[Insert Table 5 here]

3.2.3 Managers that simultaneously operate solo- and team-managed funds

To further address endogeneity concerns, especially those stemming from time-varying differences in manager quality at diverse versus homogeneous teams, we focus on the subset of managers that simultaneously operate both solo-managed and team-managed hedge funds. For our analysis, we study teams that comprise only managers that also operate solo-managed hedge funds, thereby reducing our sample to 1,493 managers operating 995 team-managed funds. Next, to explicitly control for manager quality, we analyze the relation between team diversity and the performance of team-managed hedge funds *relative to* the average performance of the solo-managed funds concurrently operated by the individual members of the respective teams while adjusting for the explanatory power of the fund covariates from the baseline Eq. (1) regressions.

This identification strategy echoes Barahona, Casella, and Jansen (2023) who also analyze within-subject performance differences albeit for mutual funds. A key difference is that we do not simply analyze the difference in performance between team-managed and the corresponding solo-managed funds but we relate those differences to the diversity of the teams themselves. Our difference-in-differences set up allows us to abstract from observed and unobserved differences in characteristics between diverse and homogeneous funds.

The OLS coefficient estimates reported in Table 6 indicate that diverse teams still outperform homogeneous teams after controlling for fund manager quality this way. Relative to the performance of solo-managed hedge funds operated by the individual members of the respective teams and after adjusting for risk as well as a host of team fund covariates, diverse teams outpace homogeneous teams by 0.59% to 2.80% per annum. These findings likely understate the performance benefits from diversity since managers face strong incentives to import any best practices that they learn from teams to the solo-managed funds that they operate. Note that we obtain qualitatively similar results when we employ Fama and MacBeth (1973) regressions or when we control for the difference in fund characteristics between team- and solo-managed funds. These results, together with those from the event study and instrumental variable analysis, provide strong and compelling evidence that endogeneity explanations do not drive our findings.

[Insert Table 6 here]

3.3. Underlying mechanisms

If the superior performance of diverse teams is driven by diversity, we postulate that diverse teams should exploit a wider range of investment opportunities in financial markets by leveraging the heterogeneous experiences and expertise of their team members. In particular, they should arbitrage more of the 11 prominent stock market anomalies identified by Stambaugh, Yu, and Yuan (2015).

To test, for each fund and over each non-overlapping 24-month period, we estimate regressions analogous to those in Eq. (1) on the number of stock anomalies with positive and statistically significant (at the 5% level) loadings. Panel A of Table 7 reveals that diverse funds load on more stock market anomaly factors than do homogeneous funds. For example, the coefficient estimate on $DIVERSITY\_EDU$ indicates that a one-unit increase in educational institution-based diversity is associated with a 0.209 increase in the number of stock anomalies with positive and significant loadings, which is economically significant given that the unconditional number of anomalies with positive and significant loadings per fund is

1.66. Panel B of Table 7 shows that we obtain qualitatively similar results for equity-focused funds. In results available upon request, we show that hedge funds that load positively and significantly on more stock anomalies also outperform. These findings suggest that diverse teams earn superior returns by exploiting a wider array of investment opportunities.

[Insert Table 7 here]

According to Rock and Grant (2016), a more diverse workplace serves to keep team members' biases in check and make them question their assumptions. Therefore, diverse teams should be less susceptible to behavioral biases. To test, we construct quarterly hedge fund trading behavior metrics, using Thomson Financial 13-F data on long-only stock holdings of hedge fund firms, that proxy for the disposition effect, overconfidence-induced excessive trading, and the preference for lottery-like stocks: *DISPOSITION*, *OVERCONFIDENCE*, and *LOTTERY*. *DISPOSITION* is the percentage of gains realized minus the percentage of losses realized as in Odean (1998). *OVERCONFIDENCE* is the difference between the return that quarter of the portfolio of stocks held by the fund at the end of the prior year and the return that same quarter of the actual portfolio of stocks held by the fund as per Barber and Odean (2000, 2001). *LOTTERY* is the maximum daily stock return over the past one month averaged across stocks held by the fund as in Bali, Cakici, and Whitelaw (2011). According to Odean (1998), Barber and Odean (2000, 2001), and Bali, Cakici, and Whitelaw (2011), such biases are detrimental to investment performance. Next, we estimate multivariate regressions on these trading behavior metrics with the team diversity measures as the main independent variables of interest. The regressions are estimated for the full sample of hedge funds and for equity-focused hedge funds. The results reported in Panels C to H of Table 7 reveal that hedge funds operated by diverse teams are indeed less susceptible to behavioral biases. In results available upon request, we find that funds that are more vulnerable to behavioral biases also deliver poorer investment performance.

If diversity drives the superior performance of diverse teams, we should find that the positive relation between team diversity and fund performance is stronger for funds with access to long-term capital. Following Stein (2005), we argue that funds with long redemption periods, lengthy redemption notice periods, and extended lock-ups arbitrage more long-horizon investment opportunities as they attract more patient capital. By attacking long-horizon mispricings, they should have time to overcome the operational problems associated with motivating, coordinating, and communicating with a diverse group of team members.

To test, we first sort hedge funds into three groups based on (i) redemption period, (ii) notice period, and (iii) lock-up period.[22] Next, we reestimate the Eq. (1) regressions on fund alpha for each of the three groups without fund redemption period and lock-up period as control variables. The coefficient estimates reported in Table 8 indicate that consistent with the notion that diversity is more helpful when arbitraging long-horizon opportunities and managing patient capital, diverse teams outperform homogeneous teams most when they impose lengthy redemption periods, notice periods, and lock-up periods.

[Insert Table 8 here]

3.4. Fund investment and operational risk

Due to the absence of group think, hedge fund partners working in more diverse teams could better serve as checks and balances for each other when it comes to risk taking. Therefore, we postulate that diverse teams are more prudent when taking on investment risk. In particular, since bearers of idiosyncratic risk forgo risk premia and bearers of tail risks could face significant drawdowns and sudden fund closure (Duarte, Longstaff, and Yu, 2007), diversity should negatively relate to idiosyncratic and downside risk.

To test, we estimate multivariate regressions on fund investment risk metrics such as idiosyncratic risk ($IDIORISK$), downside beta ($DOWNSIDEBETA$), maximum loss ($MAXLOSS$), and maximum drawdown ($MAXDRAWDOWN$) with the independent

[22] The three groups are not equal in size due to the granular nature of the shareholder restrictions data. The low, middle, and high redemption period groups comprise funds with redemption periods that do not exceed 15 days, with redemption periods that exceed 15 days but do not exceed one month, and with redemption periods that exceed one month, respectively. The low, middle, and high notice period groups are defined analogously. The low, middle, and high lock-up period groups comprise funds with no lock-ups, with lock-up periods that are less than or equal to a year, and with lock-up periods that exceed a year, respectively. The discrete nature of the redemption period, notice period, and lock-up period data prevents us from sorting funds into equal terciles based on their share restrictions.

variables from Eq. (1). $IDIORISK$ is the standard deviation of fund monthly residuals from the Fung and Hsieh (2004) model. $DOWNSIDEBETA$ is downside beta relative to the S&P 500. $MAXLOSS$ is maximum monthly loss. $MAXDRAWDOWN$ is maximum cumulative loss. The investment risk measures are estimated over each nonoverlapping 24-month period post fund inception. To maximize the number of observations, we compute the downside betas over non-contiguous periods. Panel A in Table 9 indicates that diverse funds bear lower idiosyncratic risk than do homogeneous funds. Diverse funds also deliver returns that exhibit lower downside betas, smaller maximum monthly losses, and shallower maximum drawdowns, suggesting that they are more successful at avoiding tail risks.

[Insert Table 9 here]

Team diversity could also lead to lower operational risk as team members from different backgrounds are better able to call attention to the fraudulent actions of specific individuals in the team. To check, we estimate multivariate regressions on fund operational risk variables such as the fund termination indicator ($TERMINATION$), the Form ADV violation indicator ($VIOLATION$), and ω-Score ($OMEGA$). $TERMINATION$ takes a value of one after a hedge fund stops reporting returns to the database and states that it has liquidated that month. $VIOLATION$ takes a value of one when the hedge fund manager reports on Item 11 of Form ADV that the manager has been associated with a regulatory, civil, or criminal violation. $OMEGA$ is an operational risk instrument derived from various fund characteristics as per Brown, Goetzmann, Liang, and Schwarz (2009).

We analyze fund termination, since Brown et al. (2009) find that operational risk is more important than financial risk for explaining fund failure. Our analysis of fund termination is limited to TASS and HFR funds since only TASS and HFR provide the reason for why a fund stopped reporting returns. In addition to the controls from Eq. (1), the regression on fund termination includes past 24-month fund returns to control for past fund performance. Item 11 disclosures on Form ADV provide insights into unethical behavior that precipitate regulatory action and lawsuits, as well as civil and even criminal violations. The ω-Score is based on a canonical correlation analysis that relates a vector of responses from Form

ADV to a vector of fund characteristics in the TASS database, across all hedge funds that registered as advisors in the first quarter of 2006. Since only TASS provides data on manager personal capital – one of the characteristics used to compute the ω-Score – we only compute the ω-Score for TASS funds, as per Brown et al. (2009).

The results in Panel B of Table 9 show that diverse teams are less likely to terminate their funds, report fewer violations to the SEC, and exhibit lower ω-Scores. The marginal effects reveal that relative to hedge funds operated by homogeneous teams, hedge funds operated by diverse teams have a 2.37% to 6.97% lower probability of terminating in any given year.[23] Similarly, compared to hedge fund firms run by homogeneous teams, hedge fund firms run by diverse teams have a 5.8% to 38.0% lower likelihood of reporting a violation to the SEC in any given year. Given that the unconditional probability of fund termination in any given year is 7.31% and the unconditional probability that a firm reports a violation to the SEC in any given year is 3.43%, these results are economically meaningful.

To further test the view that diverse teams exhibit lower operational risk, we estimate analogous probit regressions on the probability that hedge funds trigger the four performance flags that are most often linked to funds with reporting violations as per Panel B of Table 5 in Bollen and Pool (2012): %Negative, Kink, Maxrsq, and %Repeat. %Negative is triggered by a low number of negative returns. Kink is triggered by a discontinuity at zero in the hedge fund return distribution. Maxrsq is triggered by an adjusted R^2 that is not significantly different from zero. %Repeat is triggered by a high number of repeated returns. The results in Panel C of Table 9 show that diverse teams are less likely to trigger these performance flags, which Bollen and Pool (2009; 2012) argue may be indicative of fraud.[24]

[23] Specifically, the marginal effect reported in column 1 in Panel B of Table 9 indicates that the difference in probability of fund termination between funds managed by educationally diverse versus educationally homogeneous teams equals $100 * (1 - (1 - 0.006)^{12}) = 6.97\%$.

[24] One caveat is that, as Jorion and Schwarz (2014) note, a return discontinuity around zero may instead reflect the imputation of incentive fees.

3.5. *Fund capacity constraints and performance persistence*

Several studies show that hedge funds are affected by fund-level capacity constraints (Getmansky, 2012; Ramadorai, 2013). We postulate that by harnessing the heterogeneous experiences of their team members, diverse teams exploit a wider range of investment opportunities and are, therefore, less susceptible to fund-level capacity constraints.

To test, for each team diversity measure, we sort hedge funds every January 1 into three groups based on team diversity.[25] Next, for each diversity group, we estimate regressions on fund performance with the log of last month's fund size as the independent variable of interest. We include as independent variables the other fund controls from Eq. (1).

The results reported in Panel A of Table 10 suggest that the fund-level capacity constraints are largely confined to hedge funds managed by homogeneous teams. Regardless of the diversity measure that we consider, the coefficient estimates on the logarithm of fund size in the performance regressions are negative and statistically significant at the 1% or 5% level only for funds in the low-diversity group. Conversely, for funds in the high-diversity group, the coefficient estimates on the logarithm of fund size in the performance regressions are positive and statistically significant at the 1% or 5% level. These results suggest that team diversity allows funds to circumvent capacity constraints.

[Insert Table 10 here]

Capacity constraints make it difficult for skilled fund managers to maintain outperformance as they grapple with capital inflows from return-chasing fund investors (Berk and Green, 2004). Therefore, fund performance persistence (Agarwal and Naik, 2000; Kosowski, Naik, and Teo, 2007; Jagannathan, Malakhov, and Novikov, 2010) should be concentrated in hedge funds managed by diverse teams given their ability to sidestep capacity constraints.

[25] For all diversity dimensions except gender, funds managed by teams with diversity equals to one or zero are placed in the high- or low-diversity groups, respectively. The other funds are placed in the medium-diversity group. For the sort on gender diversity, funds managed by teams with gender diversity equals to zero are placed in the low-diversity group. Since there are no teams with gender diversity equals to one, the other funds are sorted equally into the other two groups based on gender diversity.

To test, we first sort hedge funds every January 1 into three groups based on team diversity. Next, within each diversity group, we sort hedge funds into quintiles based on past two-year Fung and Hsieh (2004) fund alpha and string the post-formation returns over the next 12 months across years to form a single return series for each quintile portfolio. As per the baseline portfolio sorts, we evaluate performance relative to the Fung and Hsieh (2004) model and base statistical inferences on White (1980) standard errors.

The alphas of the winner-minus-loser spread portfolios reported in Subpanel A of Panel B in Table 10 reveal that performance persistence is mostly concentrated in funds managed by diverse teams. Among funds operated by teams with high diversity scores, the spreads between the past winner and past loser quintiles are economically meaningful, i.e., between 6.00% and 7.54% per annum, and statistically significant at the 1% level. In contrast, among funds managed by teams with low diversity scores, the spreads between the past winner and past loser quintiles are smaller and statistically indistinguishable from zero at the 10% level.

By using the same asset pricing model to sort funds and estimate performance, we could pick up any model bias that appears between ranking and formation periods. Therefore, we also perform a double sort on team diversity and past 24-month fund returns, and then evaluate the post-formation fund alpha of the resultant portfolios. Subpanel B of Panel B in Table 10 indicates that our conclusions remain unchanged with this adjustment.

3.6. Discussion

Do investors value diversity in fund management? To investigate, we estimate multivariate regressions on fund annual flow controlling for past fund performance rank and the fund and team covariates from Eq. (1). Table IA9 of the Internet Appendix reveals that a one-unit increase in team diversity is associated with a 1.62% to 10.46% increase in annual fund flow after controlling for past fund Fung and Hsieh (2004) alpha rank. The positive relation with fund flow is strongest for educational institution diversity and weakest for racial diversity. In general, flows tend to respond more positively to functional diversity than to non-functional diversity, suggesting that investors value functional diversity more.

In light of the benefits of team diversity, why do hedge fund firm founders not set up teams that are more diverse? One view is that search frictions prevent firm founders from forming teams that are more diverse. Founders who set up funds opportunistically to take advantage of hot investment strategies may encounter greater search frictions. Similarly, founders with limited working experience are likely to face greater search frictions when launching funds. To test the search frictions view, we investigate the relation between team diversity at fund inception and these proxies for search frictions. Consistent with the notion that search frictions constrain team diversity, Table IA10 of the Internet Appendix reveals that diverse teams are less likely to engage in hot investment strategies (as defined in Cao, Farnsworth, and Zhang (2021)) and are more likely to be established by seasoned founders.[26]

4. Robustness tests

To test whether our results are sensitive to the way we measure diversity, we redo the baseline performance regressions in Eq. (1) with alternative diversity measures based on one minus the Herfindahl-Hirschman index (scaled by 10,000), as well as the Teachman (1980) entropy metric used by Jehn, Northcraft, and Neale (1999) and Pelled, Eisenhardt, and Xin (1999).[27] To evaluate the strength of the findings over the sample period, we split the sample period into two (January 1994 to December 2004 and January 2005 to June 2016) and reestimate the baseline performance regressions. To mitigate concerns that fixed effects based on the Agarwal, Daniel, and Naik (2009) broad investment strategy classification do not adequately capture differences in performance across strategies, we adopt a more granular classification comprising the following 12 investment strategies: CTA, Emerging Markets, Event-Driven, Global Macro, Equity Long/Short, Equity Long Only, Market-Neutral, Multi-Strategy, Relative Value, Short Bias, Sector, and Others, and redo the baseline performance regressions. To check that our results apply to teams with at least three members, we reestimate the

[26] In results available upon request, we find that our baseline performance regression results continue to hold after controlling for hot investment strategies and founder work experience at fund inception.

[27] Since these alternative diversity measures do not allow for multiple institutions to be assigned to each manager, to compute these measures, we focus on the undergraduate institution of the manager (for educational institution based diversity) and on the most recent former employer of the manager (for work experience based diversity).

baseline regressions after limiting the sample to hedge funds managed by such teams. To ensure that our results are not driven by shareholder activists, we redo the baseline regressions after excluding shareholder activists, which we identify using information in 13D filings. Multi-collinearity concerns notwithstanding, we also estimate performance regressions that include all five diversity measures as independent variables. In addition, we reestimate the baseline regressions with family team diversity. Next, we redo the performance regressions after including solo-managed funds, which we classify as fully homogeneous funds, in the sample. To check that cross-country differences are not driving our results, we redo the baseline analysis on U.S.-based hedge funds. Finally, following the logic of Chuprinin and Sosyura (2018), we control for the presence of underrepresented groups who could outperform as they may need to overcome significant barriers of entry to join the industry. The underrepresented groups that we consider include women, racial minorities (asians, blacks, and hispanics), and graduates of non-Ivy League schools. Table 11 shows that our findings are robust to these adjustments.

[Insert Table 11 here]

5. Conclusion

In this study, we investigate the implications of team diversity for hedge funds. Hedge funds are uniquely positioned to harness the value of diversity given the complex and unconstrained strategies that they employ. Yet, they are often managed by teams with homogeneous educational backgrounds, academic specializations, work experiences, genders, and races.

We establish three main results. First, we show that hedge funds managed by diverse teams outpace those managed by homogeneous teams after adjusting for risk. The outperformance cannot be attributed to hedge fund database-induced biases, hedge fund characteristics, or omitted risk factors. Our findings are not a by-product of unobserved factors that simultaneously affect both team diversity and fund performance. Relative to comparable funds and to the previous 36-month period, funds that subsequently hire diversity-enhancing managers deliver greater fund alphas in the following 36-month period. After instrumenting for team diversity, using as the instrument the demographic diversity at the fund founder's hometown, we find that diverse teams still outperform homogeneous teams. Moreover, after controlling for the performance of solo-managed hedge funds operated by members of the respective teams, diverse teams continue to outpace homogeneous teams.

Second, we provide insights into the mechanisms by which diversity leads to superior investment performance. Diverse teams outpace homogeneous teams by arbitraging a greater variety of prominent stock anomalies, by capitalizing on long-horizon investment opportunities, and by avoiding behavioral biases such as the disposition effect, overconfidence, and the preference for lotteries. Diversity is also associated with prudent risk management. Diverse funds eschew tail risk, exhibit lower operational risk, and report fewer suspicious returns.

Third, we find that diversity moderates the widely studied capacity constraints and performance persistence effects in hedge funds. Diverse teams, by harnessing a wider range of investment opportunities, circumvent fund-level capacity constraints. Consequently, the performance of diverse teams persists more than that of homogeneous teams.

These findings showcase the value of diversity. Not only do diverse teams outperform homogeneous teams, they are also more resilient to tail risks, and less susceptible to capacity constraints. Our results are especially important for fund management firms that are reevaluating the diversity of their leadership and for investors who are keen to sidestep the capacity constraints that limit the returns from allocating capital to skilled fund managers.

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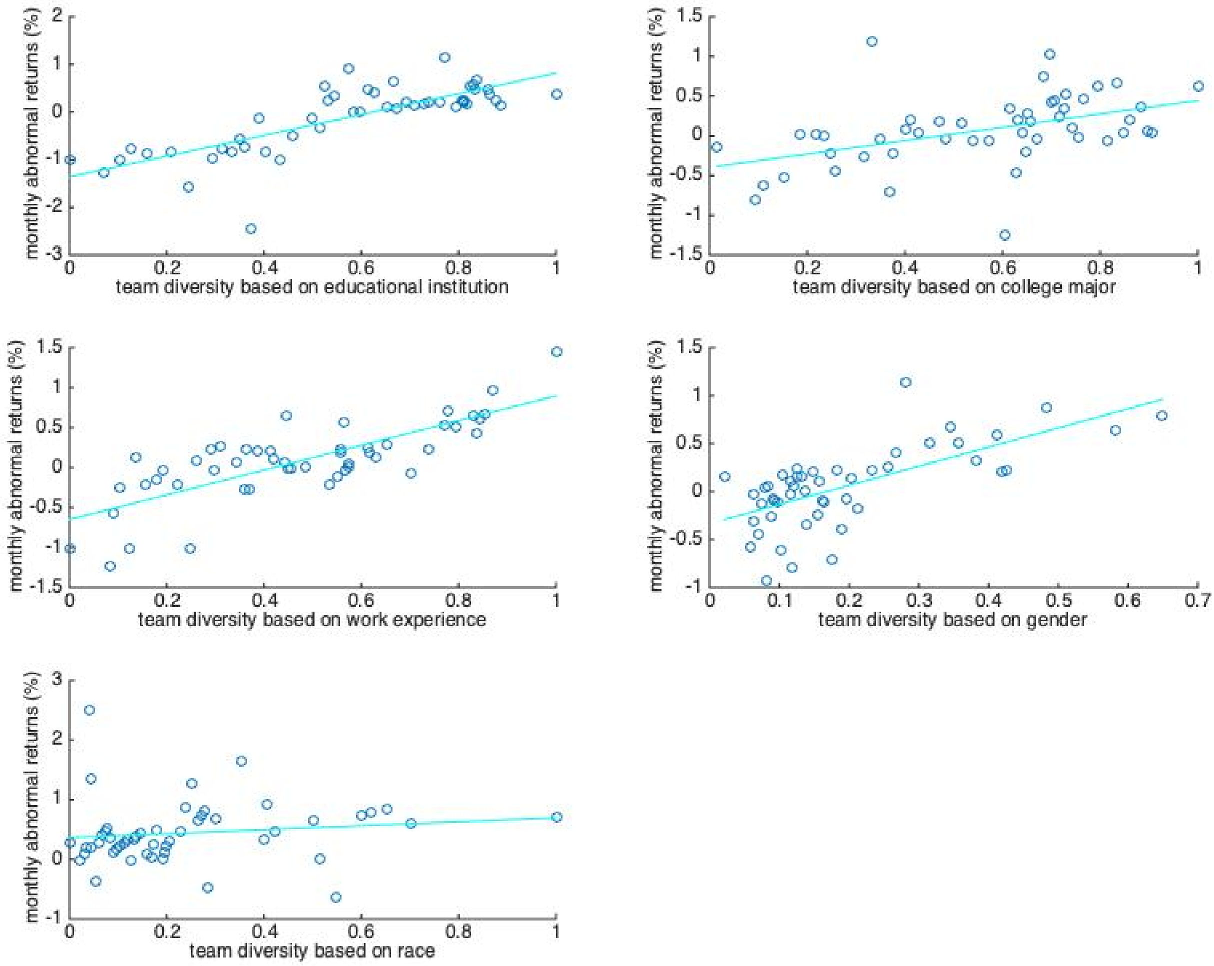

Figure 1: Binned scatter plots of fund monthly abnormal return against team diversity. Fund monthly abnormal return is estimated relative to the Fung and Hsieh (2004) model, where the factor loadings are estimated over the prior 24 months. Team diversity is defined as one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. Fund monthly abnormal return observations are sorted into 50 groups based on fund team diversity. The scatter plots graph the average monthly abnormal return for each group against its average team diversity. The lines represent the lines of best fit through the scatter plots. The sample period is from January 1994 to June 2016.

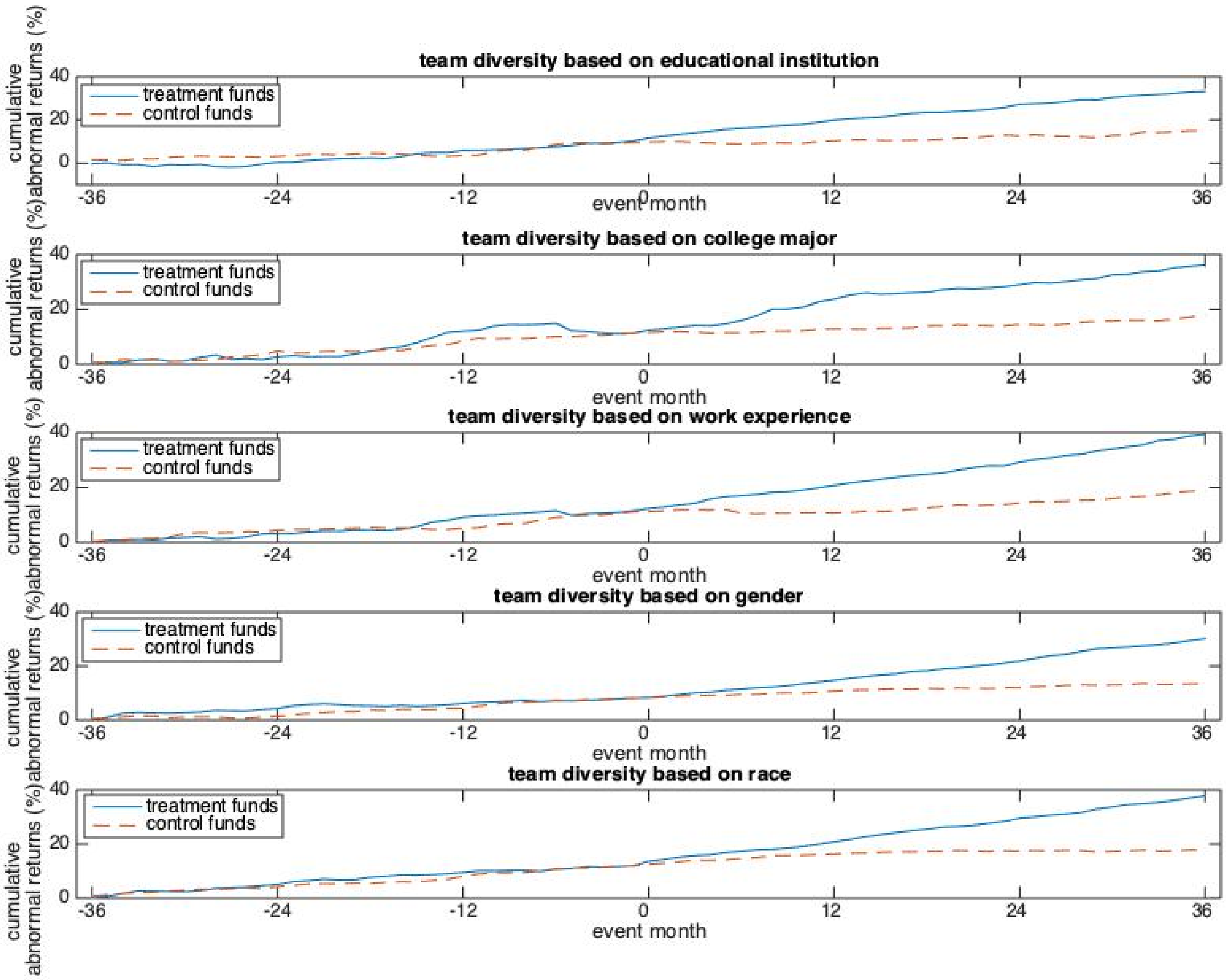

Figure 2: Event study analysis of diversity-enhancing manager additions to hedge fund teams. Fund abnormal return is Fung and Hsieh (2004) seven-factor monthly alpha with factor loadings estimated over the last 24 months. Event month is the month that a fund management team increases its educational institution-, college major-, work experience-, gender-, or race-based diversity score with the inclusion of a new team member from a different background. To be included in the analysis, a hedge fund must survive at least 36 months before and after the event month. Funds in the control group are matched to funds in the treatment group based on team diversity and by minimizing the sum of the absolute differences in monthly fund alpha in the 36-month pre-event period. The solid lines denote the performance of the treatment funds. The dashed lines denote the performance of the control funds. The sample period is from January 1994 to June 2016.

Table 1: **Summary statistics**

This table reports summary statistics of the team diversity measures and key variables used in the study. Team diversity is defined as one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. $DIVERSITY\_EDU$, $DIVERSITY\_MAJOR$, $DIVERSITY\_EXP$, $DIVERSITY\_GENDER$, and $DIVERSITY\_RACE$ are team diversity measures based on manager educational institution, college major, work experience, gender, and race. $RETURN$ is the monthly hedge fund net-of-fee return. $MGTFEE$ is management fee in percentage. $PERFFEE$ is performance fee in percentage, HWM is high-water mark indicator. $LOCKUP$ is lock-up period in years. $LEVERAGE$ is leverage indicator. AGE is fund age in years, $REDEMPTION$ is redemption period in months, $FUNDSIZE$ is fund size in US$m, $TEAMSIZE$ is the number of members in the team, and SAT is team SAT score or the median SAT score of the managers' undergraduate institutions averaged across managers in the team. Panel A reports the top universities, top college majors, top former workplaces, genders, and races of hedge fund managers. Panel B reports the distribution of the diversity measures and key variables. Panel C reports the distribution of the diversity measures by investment strategy. Panel D reports the correlation between the diversity measures and the key variables. The sample period is from January 1994 to June 2016.

Panel A: Universities, college majors, former workplaces, genders, and races of hedge fund managers

No.	University/Major/Workplace/Gender/Race	Number of managers	Percentage of managers
Subpanel A: Top ten universities			
1	Harvard University	270	7.98%
2	University of Pennsylvania	212	6.26%
3	Columbia University	186	5.49%
4	New York University	182	5.38%
5	University of Chicago	115	3.40%
6	Yale University	95	2.81%
7	Cornell University	87	2.57%
8	University of Virginia	78	2.30%
9	Massachusetts Institute of Technology	73	2.16%
10	Stanford University	71	2.10%
Subpanel B: Top ten college majors			
1	Finance	921	29.79%
2	Economics	500	16.17%
3	Accounting	204	6.60%
4	Computer Science	172	5.56%
5	Mathematics	168	5.43%
6	History	97	3.14%
7	Management	83	2.68%
8	Physics	55	1.78%
9	Commerce	43	1.39%
10	Politics	35	1.13%
Subpanel B: Top ten former workplaces			
1	Goldman Sachs	153	4.52%
2	Morgan Stanley	142	4.19%
3	Merrill Lynch	129	3.81%
4	JP Morgan	124	3.66%
5	UBS	90	2.66%
6	Credit Suisse	72	2.13%
7	Deutsche Bank	68	2.01%
8	Bear Stearns	61	1.80%
9	Lehman Brothers	56	1.65%
10	Citigroup	55	1.62%
Subpanel D: Gender			
1	Male	11829	94.12%
2	Female	739	5.88%
Subpanel E: Race			
1	White	7319	64.83%
2	Asian	1845	16.34%
3	Black	1299	11.51%
4	Hispanic	827	7.33%

Panel B: Distribution of diversity measures and key variables

Diversity measure/variable	Mean	25%	Median	75%	Std dev
DIVERSITY_EDU	0.789	0.100	1.000	1.000	0.393
DIVERSITY_MAJOR	0.742	0.476	1.000	1.000	0.416
DIVERSITY_EXP	0.560	0.000	1.000	1.000	0.490
DIVERSITY_GENDER	0.112	0.000	0.000	0.000	0.272
DIVERSITY_RACE	0.584	0.000	1.000	1.000	0.462
SAT	1434.680	1400.000	1475.000	1505.000	108.600
RETURN	0.449	-1.080	0.450	2.040	5.179
MGTFEE	1.436	1.000	1.500	2.000	0.628
PERFFEE	17.228	20.000	20.000	20.000	6.626
HWM	0.733	0.000	1.000	1.000	0.442
LOCKUP	0.589	0.000	1.000	1.000	0.492
LEVERAGE	78.287	32.000	62.000	108.000	62.921
AGE	6.524	2.667	5.167	9.000	5.243
REDEMPTION	2.063	1.000	1.000	3.000	2.656
FUNDSIZE	489.230	21.710	77.771	278.000	3102.390

Panel C: Distribution of diversity measures by investment strategy

Investment strategy	No. of funds	Mean	25%	Median	75%	Std dev
Subpanel A: Diversity in educational institution						
Directional Trader	775	0.804	1.000	1.000	1.000	0.382
Relative Value	618	0.713	0.000	1.000	1.000	0.445
Security Selection	2841	0.790	1.000	1.000	1.000	0.394
Multiprocess	780	0.822	1.000	1.000	1.000	0.362
Subpanel B: Diversity in college major						
Directional Trader	787	0.726	0.333	1.000	1.000	0.431
Relative Value	534	0.636	0.000	1.000	1.000	0.445
Security Selection	2457	0.759	0.533	1.000	1.000	0.407
Multiprocess	736	0.775	0.700	1.000	1.000	0.399
Subpanel C: Diversity in work experience						
Directional Trader	850	0.597	0.000	1.000	1.000	0.486
Relative Value	558	0.472	0.000	0.125	1.000	0.490
Security Selection	2752	0.567	0.000	1.000	1.000	0.491
Multiprocess	827	0.554	0.000	1.000	1.000	0.488
Subpanel D: Diversity in gender						
Directional Trader	3102	0.410	0.000	0.000	0.667	0.476
Relative Value	1289	0.293	0.000	0.000	0.667	0.432
Security Selection	6734	0.397	0.000	0.000	0.500	0.472
Multiprocess	1906	0.543	0.000	0.000	0.500	0.480
Subpanel E: Diversity in race						
Directional Trader	3313	0.556	0.000	1.000	1.000	0.474
Relative Value	1378	0.508	0.000	0.553	1.000	0.454
Security Selection	6205	0.566	0.000	0.697	1.000	0.460
Multiprocess	2036	0.706	0.303	1.000	1.000	0.427

Panel D: Correlations between diversity measures and key variables

Key variable	*DIVERSITY_EDU*	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*
DIVERSITY_EDU	1.000				
DIVERSITY_MAJOR	0.412	1.000			
DIVERSITY_EXP	0.547	0.692	1.000		
DIVERSITY_GENDER	0.066	0.066	0.050	1.000	
DIVERSITY_RACE	-0.061	0.021	0.016	0.199	1.000
SAT	0.649	0.264	0.472	0.243	0.183
RETURN	0.023	0.033	0.039	0.009	0.008
MGTFEE	0.038	0.022	0.000	0.056	-0.010
PERFFEE	-0.035	0.123	0.041	0.065	0.041
HWM	-0.076	0.000	-0.042	-0.024	0.050
LOCKUP	0.008	-0.056	-0.049	-0.055	-0.086
LEVERAGE	0.001	0.047	0.040	-0.036	-0.030
AGE	0.083	0.072	0.104	0.022	0.004
REDEMPTION	0.064	0.041	0.040	0.033	-0.033
FUNDSIZE	-0.078	0.016	-0.018	-0.028	0.022
TEAMSIZE	-0.406	-0.159	-0.380	-0.013	0.057

Table 2: **Multivariate regressions on hedge fund performance**

This table reports results from multivariate OLS and Fama-MacBeth regressions on hedge fund return (*RETURN*) and alpha (*ALPHA*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The other independent variables include fund management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for fund investment strategy and team size. The OLS regressions also include dummy variables for year-month. The t-statistics, in parentheses, are derived from robust standard errors clustered by fund and month for the OLS regressions and from Newey and West (1987) standard errors with lag length as per Greene (2018) for the Fama and MacBeth (1973) regressions. Panels A and B present the OLS and Fama-MacBeth regression estimates, respectively. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

Panel A: OLS regressions

	Dependent variable									
Independent variable	*RETURN* (1)	*ALPHA* (2)	*RETURN* (3)	*ALPHA* (4)	*RETURN* (5)	*ALPHA* (6)	*RETURN* (7)	*ALPHA* (8)	*RETURN* (9)	*ALPHA* (10)
DIVERSITY_EDU	0.387**	0.466**								
	(7.65)	(5.73)								
DIVERSITY_MAJOR			0.187**	0.252**						
			(4.19)	(5.47)						
DIVERSITY_EXP					0.296**	0.300**				
					(6.73)	(6.74)				
DIVERSITY_GENDER							0.324**	0.250**		
							(3.03)	(4.86)		
DIVERSITY_RACE									0.317**	0.163**
									(3.88)	(7.37)
SAT/100	0.000**	0.000*	0.005**	0.005**	0.001	0.001*	0.000**	0.000	0.000**	0.000
	(5.05)	(2.43)	(4.94)	(5.57)	(1.29)	(2.45)	(4.98)	(1.35)	(3.88)	(0.82)
MGTFEE	0.002	0.010	0.014	0.016	0.011	0.021	0.243	-0.017	0.240	-0.017
	(0.04)	(0.20)	(0.37)	(0.32)	(0.25)	(0.39)	(1.08)	(-0.80)	(1.07)	(-0.82)
PERFFEE	0.003	0.010*	0.002	0.008*	0.001	0.008	-0.025	0.002	-0.025	0.002
	(0.70)	(2.32)	(0.45)	(2.14)	(0.39)	(1.95)	(-0.91)	(0.52)	(-0.90)	(0.58)
HWM	-0.025	-0.088	-0.029	-0.093	-0.027	-0.091	-0.131	-0.067*	-0.139	-0.070*
	(-0.53)	(-1.00)	(-0.65)	(-1.06)	(-0.58)	(-1.04)	(-1.30)	(-2.43)	(-1.31)	(-2.54)
LOCKUP	0.024	0.118	0.039	0.129	0.050	0.146	0.133	0.126	0.136	0.126
	(0.43)	(0.95)	(0.76)	(1.04)	(0.91)	(1.15)	(1.86)	(1.16)	(1.89)	(1.15)
LEVERAGE	-0.000	0.027	0.006	0.030	-0.003	0.029	-0.188	0.053	-0.184	0.050
	(-0.00)	(0.71)	(0.21)	(0.76)	(-0.10)	(0.75)	(-0.79)	(1.82)	(-0.78)	(1.75)
AGE	-0.003	-0.003	-0.004	-0.004	-0.004	-0.004	-0.043**	-0.018**	-0.044**	-0.018**
	(-0.80)	(-0.59)	(-1.06)	(-0.81)	(-0.98)	(-0.73)	(-2.62)	(-6.18)	(-2.62)	(-6.44)
REDEMPTION	0.011	0.015*	0.011	0.015*	0.012*	0.016*	0.012	0.001	0.012	0.001
	(1.96)	(2.06)	(1.89)	(2.00)	(2.14)	(2.28)	(1.16)	(0.23)	(1.13)	(0.26)
log(*FUNDSIZE*)	-0.001	0.019	0.000	0.020	-0.001	0.019	-0.002	-0.003	-0.002	-0.003
	(-0.11)	(1.65)	(0.03)	(1.79)	(-0.05)	(1.62)	(-0.05)	(-0.32)	(-0.05)	(-0.38)
Year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.028	0.008	0.028	0.008	0.028	0.008	0.000	0.002	0.000	0.002
N	116587	92417	119849	95009	116587	92417	214906	161059	198320	149271

Panel B: Fama-MacBeth regressions

	Dependent variable									
	RETURN	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*	*RETURN*	*ALPHA*
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DIVERSITY_EDU	1.071	0.657**								
	(1.25)	(3.54)								
DIVERSITY_MAJOR			0.326**	0.363**						
			(2.65)	(3.41)						
DIVERSITY_EXP					0.345**	0.302**				
					(4.34)	(4.45)				
DIVERSITY_GENDER							0.567*	0.328**		
							(2.41)	(8.54)		
DIVERSITY_RACE									0.553**	0.225**
									(3.31)	(6.61)
SAT/100	0.001	0.000**	0.010*	0.003	-0.001	0.001*	0.000**	0.000	0.000**	-0.000
	(1.34)	(2.73)	(2.26)	(1.57)	(-0.61)	(2.54)	(4.12)	(0.23)	(3.37)	(-0.41)
MGTFEE	0.005	0.005	0.009	0.019	0.014	0.021	0.339	0.022	0.337	0.023
	(0.13)	(0.10)	(0.21)	(0.42)	(0.34)	(0.45)	(1.17)	(0.60)	(1.16)	(0.63)
PERFFEE	-0.002	0.012	0.000	0.009	-0.003	0.010	-0.044	0.001	-0.044	0.001
	(-0.23)	(1.95)	(0.01)	(1.75)	(-0.45)	(1.67)	(-0.89)	(0.23)	(-0.88)	(0.26)
HWM	0.065	-0.119	0.022	-0.104	0.093	-0.112	-0.210	-0.044	-0.232	-0.047
	(1.07)	(-1.23)	(0.43)	(-1.13)	(1.38)	(-1.25)	(-1.03)	(-1.18)	(-1.07)	(-1.27)
LOCKUP	74.068	0.473	52.266	0.527	74.930	0.490	0.155*	0.183	0.150*	0.179
	(1.55)	(1.46)	(1.41)	(1.51)	(1.57)	(1.50)	(2.18)	(0.98)	(2.33)	(0.96)
LEVERAGE	-0.016	0.031	0.074	0.020	-0.022	0.041	-0.247	0.043	-0.248	0.042
	(-0.16)	(0.53)	(0.92)	(0.36)	(-0.23)	(0.66)	(-1.04)	(1.23)	(-1.05)	(1.20)
AGE	0.002	-0.014	-0.000	-0.013	0.001	-0.013	-0.069	-0.024**	-0.069	-0.024**
	(0.27)	(-1.18)	(-0.02)	(-1.04)	(0.16)	(-1.11)	(-1.94)	(-4.32)	(-1.94)	(-4.26)
REDEMPTION	-0.022	0.016*	-0.031	0.016*	-0.015	0.016*	0.022	0.007	0.025	0.007
	(-0.35)	(2.36)	(-0.48)	(2.47)	(-0.21)	(2.34)	(1.62)	(1.23)	(1.60)	(1.35)
log(*FUNDSIZE*)	-0.029	0.005	-0.010	-0.001	-0.028	0.003	-0.005	-0.022	-0.011	-0.023
	(-1.39)	(0.37)	(-0.58)	(-0.06)	(-1.35)	(0.17)	(-0.09)	(-1.27)	(-0.21)	(-1.38)
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.126	0.079	0.122	0.076	0.130	0.079	0.052	0.038	0.053	0.037
N	116587	92417	119730	94935	116587	92417	214906	161059	198320	149271

Table 3: **Portfolio sorts on hedge fund team diversity**

The table reports portfolio sorts that analyze the residuals of the regression of fund returns on the fund and team covariates from Eq. (1). Every January 1st, hedge funds are sorted into five portfolios based on team diversity, which is defined as one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. Portfolio performance is estimated relative to the Fung and Hsieh (2004) factors, which are S&P 500 return minus risk free rate (SNPMRF), Russell 2000 return minus S&P 500 return (SCMLC), change in the constant maturity yield of the U.S. 10-year Treasury bond appropriately adjusted for the duration (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodity PTFS (PTFSCOM), where PTFS is primitive trend following strategy. Panels A, B, C, D, and E report results for team diversity based on educational institution, college major, work experience, gender, and race, respectively. The t-statistics are derived from White (1980) standard errors. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

Hedge fund portfolio	Number of funds	Residuals (annualized)	t-statistic of residuals	Alpha from residuals (annualized)	t-statistic of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Panel A: Diversity in educational institution													
Portfolio 1 (high diversity)	2,562	5.04*	2.40	2.64*	2.08	0.29**	0.18**	-0.31	-2.39**	-0.00	0.02**	0.00	0.564
Portfolio 2	256	2.64	0.91	-0.36	-1.31	0.23**	0.11	0.46	-1.97	0.00	-0.00	0.04	0.638
Portfolio 3	301	3.36	2.84	-1.08	-1.08	0.17**	0.13**	-1.34**	-2.61**	-0.00	0.01	-0.00	0.481
Portfolio 4	268	0.96	0.77	-1.44*	-2.17	0.13**	0.10**	-1.11*	-3.14**	-0.01	0.00	0.00	0.374
Portfolio 5 (low diversity)	339	-0.36	-0.23	-2.52**	-3.20	0.24**	0.20**	-0.03	-1.41*	-0.01	0.00	-0.01	0.525
Spread (1-5)		5.40*	2.04	5.16**	4.91	0.05**	-0.02	-0.28**	-0.98*	0.01	0.02*	0.01	0.098
Panel B: Diversity in college major													
Portfolio 1 (high diversity)	1,711	7.08**	3.42	4.20**	2.82	0.27**	0.18**	0.08	-2.40**	-0.01	0.02	-0.00	0.458
Portfolio 2	334	2.88	1.93	3.96**	3.72	0.54	-0.61	6.65	-5.65	-0.07	0.08	0.07	0.541
Portfolio 3	360	4.08**	4.15	1.56*	2.12	0.25**	0.14**	-1.11**	-2.90**	-0.01**	0.01*	-0.00	0.742
Portfolio 4	365	0.00	0.45	0.84	0.61	0.27**	0.12**	-1.39*	-3.79**	-0.03*	0.00	-0.00	0.551
Portfolio 5 (low diversity)	331	-2.04	0.21	-1.80	-0.28	0.28**	0.17**	-0.34	-2.10**	-0.00	0.02**	0.00	0.566
Spread (1-5)		6.12*	2.41	6.00*	2.44	-0.01	0.01	0.42	-0.30	-0.01	0.00	0.00	0.041
Panel C: Diversity in work experience													
Portfolio 1 (high diversity)	1,761	6.96**	2.91	2.16	1.64	0.28**	0.19**	-0.25	-2.24**	-0.00	0.02**	0.00	0.549
Portfolio 2	366	2.88	1.19	0.76	1.17	0.20**	0.10	-2.08	-6.54*	-0.00	-0.00	-0.02	0.441
Portfolio 3	442	4.20	0.98	1.44*	1.97	0.52**	0.20*	1.49	-5.58	-0.05*	0.02	0.02	0.323
Portfolio 4	399	-0.72	-0.10	-0.75	-0.90	0.56**	-0.20	-2.13	-10.42**	0.04	-0.04	-0.01	0.525
Portfolio 5 (low diversity)	765	0.84	0.69	-2.28**	-2.86	0.23**	0.19**	-0.64	-1.73**	-0.01	0.01	-0.00	0.631
Spread (1-5)		6.12*	2.22	4.44**	3.85	0.05*	0.00	-0.39	-0.51	0.01	0.01**	0.00	0.162
Panel D: Diversity in gender													
Portfolio 1 (high diversity)	672	6.72**	4.43	5.88**	7.05	0.37**	0.27**	-0.70	-2.31*	0.00	0.01*	0.02*	0.593
Portfolio 2	723	5.64	1.92	6.24*	2.20	0.21**	0.22	-1.56	-2.46**	-0.02	0.02*	0.02	0.564
Portfolio 3	815	6.96**	3.01	3.60*	2.10	0.54**	0.55**	-2.14	-12.97**	0.01	0.02	0.02	0.623
Portfolio 4	832	4.92*	2.42	1.44	1.74	0.31**	0.17**	-0.85*	-2.00**	-0.01	0.01	-0.00	0.664
Portfolio 5 (low diversity)	9123	1.56	1.23	0.96	1.02	0.26**	0.15**	-0.97**	-2.05**	-0.00	0.01**	0.00	0.664
Spread (1-5)		5.16**	4.03	4.92**	7.59	0.11**	0.12**	0.27	-0.26	0.00	0.00	0.02	0.345
Panel E: Diversity in race													
Portfolio 1 (high diversity)	5,872	5.88**	7.87	5.52**	4.17	0.27**	0.21**	-1.13*	-1.95**	-0.00	0.02**	0.01	0.204
Portfolio 2	655	4.92**	7.22	3.24**	3.14	0.31**	0.15**	-0.98**	-2.67**	-0.01	0.01	-0.00	0.630
Portfolio 3	783	4.32**	6.72	2.04*	2.53	0.31**	0.13**	-1.02**	-2.87**	-0.01*	0.01	-0.01	0.716
Portfolio 4	803	5.04**	3.62	0.96	1.00	0.25**	0.11**	-0.98**	-2.61**	-0.01	0.02**	0.00	0.628
Portfolio 5 (low diversity)	3,654	1.56*	2.49	0.55	0.65	0.27**	0.16**	-1.00**	-1.93**	-0.00	0.01**	0.01	0.643
Spread (1-5)		4.32**	4.57	4.97**	3.38	0.00	0.05	-0.13	-0.02	0.00	0.01	0.00	0.066

Table 4: **Event study with difference-in-differences analysis**

This table reports results from an event study analysis of hedge fund performance around an increase in the diversity of the fund management team. Alpha is Fung and Hsieh (2004) seven-factor monthly alpha with factor loadings estimated over the last 24 months. Event month is the month that a fund management team increases its educational institution, college major, work experience, gender, or race-based diversity score with the inclusion of a new team member from a different background. Control funds are fund that hired a new manager during the event month who did not increase the diversity of the fund management team. The period "before" is the 36-month period before the event month and the period "after" is the 36-month period after the event month. To be included in the analysis, a hedge fund must survive at least 36 months before and after the event month. Columns 1 to 4 report results where funds in the control group are matched to funds in the treatment group based first on team diversity and then by minimizing the sum of the absolute differences in monthly fund return or alpha in the 36-month pre-event period. Columns 5 to 8 report an event study on the residuals from regressions of fund returns or alphas on the fund and team controls from Eq. (1). Funds in the control group are matched to funds in the treatment group based first on team diversity and then by minimizing the sum of the absolute differences in monthly fund residuals in the 36-month pre-event period. Panels A, B, C, D, and E report results for team diversity based on educational institution, college major, work experience, gender, and race, respectively. The sample period is from January 1994 to June 2016. *, ** denote difference-in-differences estimates that are significant at the 5% and 1% levels, respectively.

	Fund performance				Fund residuals			
	Before	After	After - before	*t*-statistic	Before	After	After - before	*t*-statistic
Fund performance attribute	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Diversity in educational institution								
Fund return (percent/month), treatment group	0.547	0.890	0.343	2.00	0.447	0.657	0.210	1.76
Fund return (percent/month), control group	0.532	0.324	-0.208	-1.64	0.456	0.345	-0.111	-1.56
Difference in return (percent/month)			0.551*	2.58			0.321*	2.31
Fund alpha (percent/month), treatment group	0.288	0.694	0.406	1.71	0.203	0.435	0.232	1.98
Fund alpha (percent/month), control group	0.268	0.145	-0.123	-1.11	0.199	0.165	-0.034	-0.98
Difference in alpha (percent/month)			0.529*	2.02			0.266*	2.18
Panel B: Diversity in college major								
Fund return (percent/month), treatment group	0.447	0.647	0.200	1.65	0.457	0.639	0.182	1.54
Fund return (percent/month), control group	0.445	0.237	-0.208	-2.21	0.489	0.378	-0.111	-1.67
Difference in return (percent/month)			0.408**	2.66			0.293*	2.16
Fund alpha (percent/month), treatment group	0.316	0.671	0.355	3.1	0.279	0.536	0.257	2.99
Fund alpha (percent/month), control group	0.318	0.172	-0.146	-1.98	0.251	0.034	-0.217	-1.45
Difference in alpha (percent/month)			0.501**	3.68			0.474**	2.75
Panel C: Diversity in work experience								
Fund return (percent/month), treatment group	0.539	0.788	0.249	1.83	0.489	0.623	0.134	1.56
Fund return (percent/month), control group	0.532	0.245	-0.287	-2.11	0.452	0.273	-0.179	-1.56
Difference in return (percent/month)			0.536**	2.79			0.313*	2.18
Fund alpha (percent/month), treatment group	0.319	0.752	0.433	2.76	0.235	0.467	0.232	2.21
Fund alpha (percent/month), control group	0.309	0.213	-0.096	-0.91	0.278	0.204	-0.074	-1.99
Difference in alpha (percent/month)			0.529**	2.80			0.306**	2.75
Panel D: Diversity in gender								
Fund return (percent/month), treatment group	0.439	0.656	0.267	1.61	0.476	0.698	0.222	1.98
Fund return (percent/month), control group	0.443	0.225	-0.218	-2.22	0.478	0.274	-0.204	-2.27
Difference in return (percent/month)			0.485*	2.52			0.426**	2.96
Fund alpha (percent/month), treatment group	0.226	0.607	0.381	3.11	0.223	0.439	0.216	2.11
Fund alpha (percent/month), control group	0.228	0.145	-0.083	-0.99	0.201	0.125	-0.076	-1.94
Difference in alpha (percent/month)			0.464**	3.13			0.292**	2.66
Panel E: Diversity in race								
Fund return (percent/month), treatment group	0.497	0.657	0.160	1.68	0.467	0.595	0.128	1.87
Fund return (percent/month), control group	0.501	0.325	-0.176	-1.88	0.437	0.318	-0.119	-2.28
Difference in return (percent/month)			0.336*	2.52			0.247**	2.87
Fund alpha (percent/month), treatment group	0.332	0.587	0.255	1.69	0.267	0.438	0.171	1.99
Fund alpha (percent/month), control group	0.331	0.145	-0.186	-2.01	0.261	0.165	-0.096	-0.98
Difference in alpha (percent/month)			0.441*	2.49			0.267*	2.05

Table 5: **Instrumental variable analysis**

This table reports results from using an instrumental variable (IV) approach to examine whether the observed differences in fund performance between hedge funds with different team diversity values reflect unobserved differences that endogenously determine team diversity. Our instrument for team diversity exploits the propensity of hedge fund founding partners who grew up in more diverse cities to set up hedge funds with more diverse teams. *DIVERSITY_HOMETOWN* is the racial diversity of the hedge fund founder's US hometown where diversity is one minus the respective Herfindahl concentration measure scaled by 10,000. The independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Columns 1 to 5 show the first stage regression of team diversity on *DIVERSITY_HOMETOWN* and the group of control variables used in Table 2. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)), as well as team SAT score scaled by 100 (*SAT/100*), and dummy variables for year-month, fund investment strategy, and team size. Columns 6 to 10 show the second stage results where the dependent variable is hedge fund alpha. Alpha is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. For comparison, columns 11 to 15 report results from regressions analogous to those reported in columns 6 to 10 but without instrumenting for hedge fund team diversity. The t-statistics, in parentheses, are derived from robust standard errors that are clustered by fund and month. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

	Dependent variable														
	IV first stage					IV second stage					OLS regressions				
	DIVERSITY_EDU	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*	*ALPHA*	*ALPHA*	*ALPHA*	*ALPHA*	*ALPHA*	*ALPHA*	*ALPHA*	*ALPHA*	*ALPHA*	*ALPHA*
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
DIVERSITY_EDU						2.216*					0.859**				
						(2.42)					(3.01)				
DIVERSITY_MAJOR							2.608*					0.356**			
							(2.22)					(3.40)			
DIVERSITY_EXP								1.417*					0.739**		
								(2.31)					(3.95)		
DIVERSITY_GENDER									1.023**					0.269*	
									(6.68)					(2.12)	
DIVERSITY_RACE										1.660**					0.264**
										(3.02)					(2.80)
SAT/100	0.008**	0.003**	0.002**	0.019**	0.011*	-0.000	-0.003	0.005*	0.021**	0.015	0.001**	0.035	-0.001	0.015*	0.193*
	(3.00)	(3.89)	(7.70)	(3.34)	(1.97)	(-0.18)	(-0.62)	(2.02)	(2.81)	(1.84)	(2.83)	(1.31)	(-0.93)	(2.36)	(2.38)
MGTFEE	-0.048*	-0.031	-0.077*	-0.003	-0.006	-0.133	-0.073	-0.045	-0.057	-0.023	-0.053	-0.027	-0.016	-0.044	-0.049
	(-2.37)	(-1.46)	(-2.15)	(-0.22)	(-0.54)	(-1.23)	(-0.78)	(-0.44)	(-1.72)	(-0.46)	(-0.63)	(-0.36)	(-0.21)	(-1.18)	(-1.01)
PERFFEE	0.003	0.006	0.010**	-0.006*	-0.002	0.010	0.006	0.007	0.003	0.008	-0.003	-0.003	-0.006	-0.000	0.004
	(1.14)	(1.74)	(2.94)	(-2.12)	(-0.93)	(1.16)	(0.64)	(0.83)	(0.65)	(1.82)	(-0.41)	(-0.44)	(-0.83)	(-0.00)	(0.92)
HWM	-0.115**	-0.159**	-0.034	-0.111*	-0.032	-0.070	-0.311	0.290	0.133	0.190	0.405*	0.377*	0.436**	0.176	0.143
	(-2.79)	(-2.94)	(-0.53)	(-2.44)	(-0.77)	(-0.44)	(-1.62)	(1.82)	(1.21)	(1.94)	(2.56)	(2.40)	(2.59)	(1.75)	(1.47)
LOCKUP	0.091	-0.127	-0.119	0.160*	0.024	-0.021	0.229	0.233	0.024	0.124	0.308	0.229	0.343	0.111	0.078
	(1.58)	(-1.25)	(-1.29)	(2.49)	(0.89)	(-0.05)	(0.76)	(0.71)	(0.17)	(0.89)	(0.99)	(0.70)	(1.01)	(0.86)	(0.58)
LEVERAGE	-0.041	0.097*	0.104*	0.049	0.069*	0.163	0.345	0.157	0.248**	0.170*	0.141	0.157	0.080	0.144	0.131*
	(-1.51)	(2.07)	(2.40)	(1.25)	(2.26)	(1.14)	(1.92)	(1.17)	(2.78)	(2.26)	(1.14)	(1.19)	(0.65)	(1.86)	(2.06)
AGE	0.003	0.007	0.004	0.002	0.002	0.018	0.043*	0.018	-0.008	-0.007	0.023	0.023	0.024	-0.009	-0.013
	(1.24)	(1.34)	(0.85)	(0.56)	(0.50)	(1.00)	(2.01)	(1.14)	(-0.96)	(-0.81)	(1.67)	(1.76)	(1.81)	(-1.20)	(-1.59)
REDEMPTION	0.015*	-0.005	-0.040**	0.027**	0.015	-0.104*	-0.057	-0.118	-0.037*	-0.017	-0.087*	-0.062	-0.070*	-0.012	-0.012
	(2.21)	(-0.41)	(-3.70)	(2.77)	(1.79)	(-2.50)	(-1.09)	(-1.80)	(-2.55)	(-1.17)	(-2.28)	(-1.75)	(-2.06)	(-0.81)	(-0.86)
log(*FUNDSIZE*)	0.015	-0.006	-0.006	-0.014	-0.004	0.017	-0.060	-0.057	-0.074*	-0.050	-0.082	-0.057	-0.063	-0.033	-0.046
	(1.75)	(-0.41)	(-0.43)	(-1.36)	(-0.58)	(0.30)	(-1.04)	(-1.17)	(-2.21)	(-1.43)	(-1.78)	(-1.31)	(-1.48)	(-1.08)	(-1.36)
DIVERSITY_HOMETOWN	2.497**	1.595*	3.490**	3.727**	1.303**										
	(6.77)	(2.38)	(5.42)	(5.09)	(2.80)										
F-test: *DIVERSITY_HOMETOWN* = 0	45.83	5.66	29.38	25.91	7.84										
Year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.657	0.258	0.046	0.346	0.209	0.044	0.040	0.013	0.014	0.011	0.056	0.056	0.056	0.032	0.031
N	31250	31412	31250	60223	59998	24715	24770	24715	43944	43788	24715	24770	24715	43944	43788

Table 6: **Managers that simultaneously operate both solo- and team-managed hedge funds**

This table reports results from multivariate OLS regressions on the difference between the performance of team-managed hedge funds and the average performance of the solo-managed hedge funds concurrently operated by members of the respective teams. The dependent variables include *RET_DIFF* and *ALPHA_DIFF*. *RET_DIFF* is the difference in monthly hedge fund net-of-fee return. *ALPHA_DIFF* is the difference in Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The other independent variables include fund management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for fund investment strategy, team size, and year-month. The t-statistics, in parentheses, are derived from robust standard errors clustered by fund and month. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

	Dependent variable									
	RET_DIFF	*ALPHA_DIFF*	*RET_DIFF*	*ALPHA_DIFF*	*RET_DIFF*	*ALPHA_DIFF*	*RET_DIFF*	*ALPHA_DIFF*	*RET_DIFF*	*ALPHA_DIFF*
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DIVERSITY_EDU	0.174**	0.049*								
	(3.60)	(2.09)								
DIVERSITY_MAJOR			0.185**	0.105**						
			(5.66)	(8.49)						
DIVERSITY_EXP					0.162**	0.085**				
					(4.56)	(5.77)				
DIVERSITY_GENDER							0.341*	0.220**		
							(2.27)	(2.83)		
DIVERSITY_RACE									0.483**	0.233**
									(5.11)	(4.11)
SAT/100	-0.000	-0.000*	-0.002	-0.000	0.000	0.000	0.001	-0.003	-0.001	-0.005
	(-0.43)	(-2.48)	(-1.13)	(-0.58)	(0.88)	(1.56)	(0.15)	(-1.01)	(-0.16)	(-1.16)
MGTFEE	0.025	0.010	0.022	0.004	0.015	0.007	0.040	0.024	0.002	0.010
	(0.88)	(0.73)	(0.85)	(0.40)	(0.55)	(0.59)	(0.95)	(1.04)	(0.04)	(0.39)
PERFFEE	-0.005	-0.001	-0.005	-0.001	-0.006	-0.002	0.001	0.000	0.001	0.003
	(-1.63)	(-1.00)	(-1.53)	(-0.59)	(-1.78)	(-1.66)	(0.26)	(0.15)	(0.12)	(1.17)
HWM	-0.059	-0.027	-0.070	-0.030	-0.048	-0.011	-0.060	-0.018	-0.137*	-0.058
	(-1.24)	(-1.42)	(-1.57)	(-1.76)	(-1.03)	(-0.60)	(-0.92)	(-0.54)	(-1.96)	(-1.53)
LOCKUP	-0.049	-0.020	-0.065*	-0.022*	-0.040	-0.017	-0.118**	-0.063**	-0.107**	-0.074**
	(-1.58)	(-1.35)	(-2.24)	(-2.01)	(-1.13)	(-1.07)	(-3.81)	(-3.31)	(-3.02)	(-3.89)
LEVERAGE	-0.047	-0.015	-0.045	-0.020	-0.063*	-0.021	0.010	0.006	0.006	-0.002
	(-1.51)	(-1.27)	(-1.58)	(-1.81)	(-2.07)	(-1.67)	(0.20)	(0.25)	(0.14)	(-0.07)
AGE	-0.001	0.001	-0.000	-0.000	-0.001	0.000	0.003	0.000	0.003	-0.000
	(-0.21)	(0.45)	(-0.12)	(-0.50)	(-0.32)	(0.40)	(0.58)	(0.03)	(0.57)	(-0.07)
REDEMPTION	-0.009	-0.002	-0.012**	-0.002	-0.012**	-0.004*	-0.010	0.001	-0.014	-0.003
	(-1.95)	(-0.95)	(-2.87)	(-0.79)	(-3.36)	(-2.16)	(-1.09)	(0.33)	(-1.90)	(-0.73)
log(*FUNDSIZE*)	-0.019	-0.006	-0.020*	-0.008**	-0.016	-0.006	-0.059**	-0.029**	-0.052**	-0.031**
	(-1.91)	(-1.65)	(-2.38)	(-2.82)	(-1.74)	(-1.64)	(-5.86)	(-5.08)	(-4.76)	(-5.09)
Year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.040	0.051	0.046	0.053	0.048	0.047	0.084	0.064	0.076	0.053
N	31115	24422	23938	19567	31115	24422	44987	31438	32193	23083

Table 7: **Diversity, stock market anomalies, and behavioral biases**

This table reports multivariate OLS regressions on the number of significant loadings on prominent stock market anomalies for hedge funds and on quarterly hedge fund trading behavior measures that proxy for behavioral biases. The dependent variables include *ANOMALY*, *DISPOSITION*, *OVERCONFIDENCE*, and *LOTTERY*. *ANOMALY* is the number of the 11 prominent stock anomalies identified by Stambaugh, Yu, and Yuan (2015) with positive and statistically significant loadings at the 5% level for each fund over each non-overlapping 24-month period post fund inception. *DISPOSITION* is percentage of gains realized (PGR) minus percentage of losses realized (PLR) as in Odean (1998). *OVERCONFIDENCE* is the difference between the return that quarter of the portfolio of stocks held by the fund at the end of the prior year and the return that same quarter of the actual portfolio of stocks held by the fund as per Barber and Odean (2000, 2001). *LOTTERY* is the maximum daily stock return over the past one month averaged across stocks held by the fund as in Bali, Cakici, and Whitelaw (2011). The independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The other independent variables include fund management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for fund investment strategy, team size, and year (for the regressions on *ANOMALY*) or year-quarter (for the regressions on behavioral bias measures). The t-statistics, in parentheses, are derived from robust standard errors clustered by fund and year (for the regressions on *ANOMALY*) or year-quarter (for the regressions on the behavioral bias measures). Panels A, C, E, and G report regressions for all hedge funds. Panels B, D, F, and H report regressions for equity-focused hedge funds. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

		Independent variable		
DIVERSITY_EDU	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*
(1)	(2)	(3)	(4)	(5)
Panel A: Regressions on *ANOMALY*, all hedge funds				
0.209**	0.155**	0.171**	0.101**	0.123**
(3.66)	(5.15)	(6.94)	(3.00)	(3.58)
Panel B: Regressions on *ANOMALY*, equity-focused hedge funds				
0.312**	0.173**	0.179**	0.192**	0.120*
(4.83)	(4.05)	(4.15)	(3.35)	(2.31)
Panel C: Regressions on *DISPOSITION* for all hedge funds				
-0.180**	-0.295**	-0.221**	-0.192**	-0.034**
(-3.25)	(-3.09)	(-6.35)	(-4.38)	(-2.73)
Panel D: Regressions on *DISPOSITION* for equity-focused hedge funds				
-0.182**	-0.421**	-0.225**	-0.192**	-0.054**
(-3.34)	(-3.20)	(-6.34)	(-4.38)	(-3.60)
Panel E: Regressions on *OVERCONFIDENCE* for all hedge funds				
-0.152**	-0.205**	-0.028**	-0.194*	-0.303*
(-4.56)	(-3.95)	(-2.63)	(-2.46)	(-2.49)
Panel F: Regressions on *OVERCONFIDENCE* for equity-focused hedge funds				
-0.236**	-0.206**	-0.029**	-0.157**	-0.331**
(-3.51)	(-5.82)	(-3.19)	(-3.70)	(-3.29)
Panel G: Regressions on *LOTTERY* for all hedge funds				
-0.013**	-0.008**	-0.011**	-0.007**	-0.008**
(-4.53)	(-3.43)	(-6.05)	(-4.52)	(-4.65)
Panel H: Regressions on *LOTTERY* for equity-focused hedge funds				
-0.013**	-0.014**	-0.011**	-0.006**	-0.009**
(-3.13)	(-4.86)	(-4.93)	(-3.26)	(-4.04)

Table 8: **Diversity and fund shareholder restrictions**

This table reports results from multivariate OLS regressions on fund alpha for funds that are first sorted on their shareholder restrictions. The dependent variable is Fung and Hsieh (2004) seven-factor monthly fund alpha where factor loadings are estimated over the last 24 months (*ALPHA*). The independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), and log of fund size (log(*FUNDSIZE*)) as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for year-month, fund investment strategy, and team size. The coefficient estimates on the fund and team control variables are omitted for brevity. The t-statistics, in parentheses, are derived from robust standard errors clustered by fund and month. The low, middle, and high redemption period groups in Panel A comprise funds with redemption periods that do not exceed 15 days, that exceed 15 days but do not exceed one month, and that exceed one month, respectively. The low, middle, and high notice period groups in Panel B are defined analogously. The low, middle, and high lock-up period groups in Panel C comprise funds with no lock-ups, with lock-up periods that are less than or equal to a year, and with lock-up periods that exceed a year, respectively. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

Regressions on *ALPHA*														
Independent variable														
DIVERSITY_EDU			*DIVERSITY_MAJOR*			*DIVERSITY_EXP*			*DIVERSITY_GENDER*			*DIVERSITY_RACE*		
Shareholder restrictions group														
Low	Middle	High	Low	Middle	High	Low	Middle	High	Low	Middle	High	Low	Middle	High
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: Funds sorted on redemption period														
0.057	0.323*	0.467**	-0.007	0.162*	0.352**	0.183*	0.278**	0.371**	0.178	0.268**	0.403**	0.153*	0.203**	0.299**
(0.41)	(2.02)	(4.35)	(-0.11)	(2.26)	(4.45)	(2.50)	(3.35)	(4.22)	(1.83)	(3.84)	(6.75)	(2.44)	(5.38)	(4.53)
Panel B: Funds sorted on notice period														
0.188	0.441**	0.549**	-0.254	-0.171	0.257**	-0.160	0.265**	0.475**	0.218**	0.279**	0.334**	0.346**	0.231**	0.207**
(1.49)	(3.04)	(4.28)	(-1.52)	(-1.81)	(3.80)	(-1.48)	(3.02)	(6.96)	(2.63)	(2.95)	(6.13)	(3.66)	(5.40)	(4.61)
Panel C: Funds sorted on lockup period														
0.321**	0.583**	0.746**	-0.089	0.491	0.572**	0.206**	0.450**	0.711**	0.236**	0.115	0.516**	0.211**	0.215	0.276**
(2.65)	(2.91)	(3.22)	(-1.79)	(1.62)	(6.00)	(3.16)	(4.06)	(7.58)	(4.89)	(0.54)	(6.50)	(6.61)	(1.64)	(3.65)

Table 9: **Multivariate regressions on hedge fund investment risk, operational risk, and performance flags**

This table reports results from multivariate regressions on hedge fund investment risk, operational risk, and performance flags. The dependent variables include investment risk metrics, such as idiosyncratic risk (*IDIORISK*), downside beta (*DOWNSIDEBETA*), maximum monthly loss (*MAXLOSS*), and maximum drawdown (*MAXDRAWDOWN*), operational risk metrics, such as fund termination indicator (*TERMINATION*), Form ADV violation indicator (*VIOLATION*), and ω-Score (*OMEGA*), and performance flags, such as *%NEGATIVE*, *KINK*, *MAXRSQ*, and *%REPEAT*. *IDIORISK* is the standard deviation of monthly hedge fund residuals from the Fung and Hsieh (2004) model. *DOWNSIDEBETA* is the downside beta relative to the S&P 500. *MAXLOSS* is the maximum monthly loss. *MAXDRAWDOWN* is the maximum cumulative loss. *TERMINATION* takes a value of one after a hedge fund stops reporting returns to the database and states that it has liquidated that month. *VIOLATION* takes a value of one when the hedge fund manager reports on Item 11 of Form ADV that the manager has been associated with a regulatory, civil, or criminal violation. *OMEGA* is an operational risk instrument as per Brown, Goetzmann, Liang, and Schwarz (2009). *KINK* takes a value of one when any of the funds managed by a firm exhibits a discontinuity at zero in its return distribution. *%NEGATIVE* takes a value of one when any of the funds managed by a firm reports a low number of negative returns. *MAXRSQ* takes a value of one when any of the funds managed by a firm features an adjusted R^2 that is not significantly different from zero. *%REPEAT* takes a value of one when any of the funds managed by a firm reports a high number of repeated returns. The independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for year, fund investment strategy, and team size. The regressions on *TERMINATION* also control for past 24-month fund return (*PRIOR_RETURN*). The coefficient estimates for these fund and team control variables are omitted for brevity. For the investment risk and performance flag regressions, the t-statistics, in parentheses, are derived from robust standard errors that are clustered by fund and year. For the operational risk regressions, the t-statistics or z-statistics (in the case of the Cox regression) in parentheses are derived from robust standard errors that are clustered by fund. The marginal effects are in brackets. Panels A, B, and C report regressions on fund investment risk, operational risk, and performance flags, respectively. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

Panel A: Regressions on fund investment risk

		Independent variable		
DIVERSITY_EDU	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*
(1)	(2)	(3)	(4)	(5)
Subpanel A: Regressions on *IDIORISK*				
-2.590**	-0.828**	-1.567**	-0.656**	-0.351**
(-3.93)	(-4.55)	(-6.04)	(-4.65)	(-4.03)
Subpanel B: Regressions on *DOWNSIDEBETA*				
-0.192*	-0.184**	-0.211**	-0.181**	-0.113**
(-2.23)	(-3.09)	(-5.10)	(-3.59)	(-3.01)
Subpanel C: Regressions on *MAXLOSS*				
-1.965*	-1.588**	-1.040**	-1.372**	-0.830**
(-2.25)	(-4.09)	(-3.59)	(-4.13)	(-3.72)
Subpanel D: Regressions on *MAXDRAWDOWN*				
-3.967**	-4.213**	-1.467**	-2.016**	-0.914**
(-2.96)	(-6.86)	(-2.95)	(-3.61)	(-2.78)

Panel B: Regressions on fund operational risk

Independent variable				
DIVERSITY_EDU	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*
(1)	(2)	(3)	(4)	(5)
Subpanel A: Logit regressions on *TERMINATION*				
-0.563**	-0.146*	-0.230**	-0.231**	-0.359**
(-5.93)	(-2.25)	(-3.77)	(-4.16)	(-8.28)
[-0.006]	[-0.002]	[-0.002]	[-0.002]	[-0.002]
Subpanel B: Cox regressions on *TERMINATION*				
-0.526**	-0.139*	-0.223**	-0.206**	-0.265**
(-5.47)	(-2.26)	(-3.77)	(-3.90)	(-5.92)
Subpanel C: Logit regressions on *VIOLATION*				
-1.610**	-1.066**	-0.561**	-0.679*	-0.283*
(-4.86)	(-6.09)	(-3.93)	(-2.17)	(-2.22)
[-0.380]	[-0.171]	[-0.132]	[-0.151]	[-0.058]
Subpanel D: OLS regressions on *OMEGA*				
-0.177**	-0.264*	-0.170**	-0.125**	-0.142**
(-2.65)	(-2.04)	(-2.64)	(-3.29)	(-2.70)

Panel C: Regressions on fund performance flags

Independent variable				
DIVERSITY_EDU	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*
(1)	(2)	(3)	(4)	(5)
Subpanel A: Regressions on *%NEGATIVE*				
-0.220	-0.914**	-0.214**	-0.104	-0.306**
(-1.66)	(-8.33)	(-2.78)	(-1.47)	(-5.90)
[-0.034]	[-0.160]	[-0.036]	[-0.016]	[-0.046]
Subpanel B: Regressions on *KINK*				
-0.474**	-0.351*	-0.525**	-0.369**	-0.112**
(-3.44)	(-4.07)	(-6.99)	(-5.97)	(-2.91)
[-0.108]	[-0.086]	[-0.102]	[-0.084]	[-0.031]
Subpanel C: Regressions on *MAXRSQ*				
-1.092**	-1.408**	-0.436**	-0.944**	-0.122*
(-6.97)	(-9.16)	(-5.60)	(-6.45)	(-2.52)
[-0.066]	[-0.084]	[-0.148]	[-0.446]	[-0.012]
Subpanel D: Regressions on *%REPEAT*				
-0.498**	-0.448**	-0.500**	-0.275**	-0.016
(-3.90)	(-5.30)	(-7.19)	(-4.56)	(-0.41)
[-0.135]	[-0.113]	[-0.115]	[-0.064]	[-0.005]

Table 10: **Diversity, fund capacity constraints, and fund performance persistence**

Panel A reports results from multivariate regressions on hedge fund performance for funds sorted by fund management team diversity. Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The dependent variables include hedge fund return (*RETURN*) and alpha (*ALPHA*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The independent variable of interest is the log of fund size (log(*FUNDSIZE*)). The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), and redemption period in months (*REDEMPTION*), as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for year-month, fund investment strategy, and team size. The coefficient estimates on these fund and team control variables are omitted for brevity. Subpanels A and B report results from regressions on *RETURN* and *ALPHA*, respectively. The t-statistics, in parentheses, are derived from robust standard errors that are clustered by fund and month. Panel B reports fund portfolio alphas from double sorts on fund diversity and past fund performance. Every January 1st, hedge funds are sorted into three groups based on team diversity in educational institution, college major, work experience, gender, or race. Thereafter, hedge funds in each group are sorted into five groups based on past 24-month fund Fung and Hsieh (2004) alpha (Subpanel A) or on past 24-month fund return (Subpanel B). The t-statistics are derived from White (1980) standard errors. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

Panel A: Regressions on fund performance for funds sorted by team diversity

	Diversity in educational institution			Diversity in college major			Diversity in work experience			Diversity in gender			Diversity in race		
	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Subpanel A: Regressions on *RETURN*															
log(*FUNDSIZE*)	0.069**	0.005	-0.056**	0.130**	0.083**	-0.026	0.061*	-0.026	-0.047**	0.046**	0.009	-0.064**	0.104**	0.002	-0.065**
	(3.21)	(0.30)	(-4.04)	(8.96)	(3.63)	(-1.09)	(2.48)	(-1.32)	(-2.59)	(3.28)	(0.84)	(-5.67)	(7.11)	(0.18)	(-4.41)
Subpanel B: Regressions on *ALPHA*															
log(*FUNDSIZE*)	0.047*	0.036*	-0.038*	0.089**	0.009	-0.070**	0.087**	-0.009	-0.027	0.068**	-0.018	-0.054**	0.072**	-0.016	-0.076**
	(2.18)	(2.22)	(-2.54)	(3.96)	(0.30)	(-4.50)	(3.48)	(-0.41)	(-1.64)	(5.22)	(-1.05)	(-5.83)	(6.28)	(-1.01)	(-3.61)

Panel B: Double sorts on team diversity and past fund performance

	Diversity in educational institution			Diversity in college major			Diversity in work experience			Diversity in gender			Diversity in race		
	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low
Hedge fund portfolio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Subpanel A: Double sort on team diversity and past 24-month fund alpha															
Portfolio 1 (high past 24m alpha)	6.77	0.99	-0.67	7.21	2.04	-1.44	7.34	1.76	1.44	5.78	0.89	1.66	6.11	5.47	3.22
Portfolio 2	2.20	1.78	0.14	1.67	-0.89	3.21	3.32	1.34	-0.45	4.21	3.88	3.32	4.23	3.99	2.99
Portfolio 3	1.34	0.56	-1.66	2.01	-0.67	1.56	2.22	0.56	-0.23	3.09	2.34	3.09	4.89	2.89	2.11
Portfolio 4	3.89	2.34	-2.45	3.87	0.38	-0.91	4.39	-2.21	-1.11	2.90	2.78	2.21	2.21	2.45	1.98
Portfolio 5 (low past 24m alpha)	0.56	-2.22	1.45	1.21	-0.81	0.34	1.12	0.56	1.34	-1.09	2.01	2.23	-1.43	1.90	1.80
Spread (1-5)	6.21**	3.21*	-2.12	6.00**	2.85*	-1.78	6.22**	1.20	0.10	6.87**	-1.12	-0.67	7.54**	3.57**	1.42
Subpanel B: Double sort on team diversity and past 24-month fund return															
Portfolio 1 (high past 24m return)	6.34	3.34	-0.34	8.72	3.44	4.21	6.78	5.12	1.09	5.78	5.04	2.88	7.32	4.32	3.21
Portfolio 2	3.45	2.78	1.66	5.43	4.12	1.56	5.34	3.42	2.21	3.39	5.99	7.22	6.13	6.22	4.89
Portfolio 3	2.89	1.56	-0.56	4.23	0.89	4.55	4.21	2.56	0.89	2.21	4.32	6.01	5.21	4.10	3.96
Portfolio 4	1.56	0.56	-2.56	3.23	0.78	-2.21	3.09	-1.01	-2.01	-1.89	3.12	3.45	3.12	2.98	2.87
Portfolio 5 (low past 24m return)	-0.44	1.12	0.26	2.36	2.21	3.99	1.44	2.01	2.21	1.04	2.19	0.45	2.88	1.96	1.99
Spread (1-5)	6.78**	2.22*	-0.60	6.36**	1.23	0.22	5.34**	3.11*	-1.12	4.74**	2.85*	2.43	4.44**	2.36*	1.22

Table 11: **Robustness tests**

This table reports results from multivariate OLS regressions on hedge fund return (*RETURN*) and alpha (*ALPHA*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as team SAT score scaled by 100 (*SAT/100*), and dummy variables for year-month, fund investment strategy, and team size. The coefficient estimates on the fund control variables are omitted for brevity. The t-statistics, in parentheses, are derived from robust standard errors clustered by fund and month. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

Regressions on *RETURN*					Regressions on *ALPHA*				
Independent variable									
DIVERSITY _EDU	*DIVERSITY _MAJOR*	*DIVERSITY _EXP*	*DIVERSITY _GENDER*	*DIVERSITY _RACE*	*DIVERSITY _EDU*	*DIVERSITY _MAJOR*	*DIVERSITY _EXP*	*DIVERSITY _GENDER*	*DIVERSITY _RACE*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Herfindahl Hirschman index-based diversity measures									
0.628	0.213*	0.524**	0.549**	0.375**	0.759	0.216*	0.377**	0.488**	0.350**
(1.85)	(2.37)	(4.90)	(7.02)	(8.38)	(1.48)	(2.52)	(3.18)	(6.70)	(6.60)
Panel B: Teachman (1980) entropy index-based diversity measures									
0.513*	0.190*	0.716**	0.371**	0.218**	0.822**	0.271*	0.719	0.333**	0.204**
(2.33)	(2.55)	(2.86)	(6.34)	(7.35)	(2.80)	(2.07)	(1.91)	(5.97)	(6.01)
Panel C: Subsample period (1994 - 2004)									
0.294*	0.199**	0.205**	0.277*	0.176**	0.318*	0.834**	0.295*	0.309**	0.482**
(2.17)	(3.06)	(3.56)	(2.54)	(3.43)	(2.22)	(3.42)	(2.33)	(3.39)	(4.36)
Panel D: Subsample period (2005 - 2016)									
0.563**	0.143*	0.211**	0.211**	0.070*	0.462*	0.355**	0.178**	0.246**	0.294**
(3.47)	(2.52)	(3.36)	(4.40)	(2.56)	(2.51)	(7.45)	(2.97)	(5.06)	(10.66)
Panel E: Alternative investment strategy classification									
0.285**	0.278**	0.169**	0.261**	0.160**	0.359**	0.341**	0.143*	0.245**	0.121**
(3.70)	(5.27)	(3.86)	(5.30)	(6.83)	(3.52)	(5.15)	(2.39)	(5.78)	(3.93)
Panel F: Fund management teams with at least three members									
0.317**	0.241**	0.133*	0.381**	0.102	0.381**	0.304**	0.301**	0.425**	0.189**
(3.76)	(3.91)	(2.30)	(3.10)	(1.72)	(3.61)	(5.32)	(4.41)	(3.85)	(3.96)
Panel G: Excluding shareholder activists									
0.271**	0.252**	0.142**	0.225**	0.095**	0.358**	0.327**	0.233**	0.238**	0.079*
(4.06)	(3.94)	(2.68)	(4.63)	(3.65)	(4.62)	(5.58)	(4.18)	(5.06)	(2.54)
Panel H: Including all diversity measures as independent variables in the regression									
0.358**	0.123*	0.272**	0.541**	0.175*	0.380**	0.357**	0.356**	0.159*	0.191**
(3.35)	(2.02)	(6.26)	(5.14)	(2.37)	(3.15)	(2.91)	(3.17)	(2.00)	(2.76)
Panel I: Family team diversity measures									
0.384**	0.202**	0.237**	0.362**	0.114**	0.461**	0.356**	0.316**	0.198*	0.142**
(6.13)	(3.43)	(5.15)	(2.78)	(4.32)	(5.31)	(4.28)	(4.24)	(2.01)	(4.36)
Panel J: Including solo-managed hedge funds									
0.406**	0.207**	0.316**	0.282**	0.232**	0.486**	0.272**	0.320**	0.208**	0.180**
(8.04)	(4.65)	(7.19)	(2.64)	(2.83)	(5.97)	(5.91)	(7.19)	(4.05)	(8.14)
Panel K: Hedge funds based in the U.S.									
0.329**	0.320**	0.184**	0.239**	0.154**	0.429**	0.365**	0.146*	0.230**	0.116**
(2.69)	(5.69)	(3.51)	(4.83)	(5.23)	(3.00)	(5.92)	(2.08)	(5.36)	(3.43)
Panel L: Controlling for the fraction of women managers									
0.323**	0.204**	0.269**	0.282**	0.232**	0.389**	0.259**	0.263**	0.208**	0.180**
(8.61)	(4.59)	(6.63)	(2.64)	(2.84)	(6.24)	(5.34)	(6.17)	(4.05)	(8.14)
Panel M: Controlling for the fraction of minority managers									
0.323**	0.206**	0.269**	0.282**	0.235**	0.389**	0.271**	0.265**	0.208**	0.181**
(8.52)	(4.51)	(6.59)	(2.64)	(2.80)	(6.18)	(5.06)	(6.04)	(4.05)	(8.20)
Panel N: Controlling for the fraction of non-Ivy League managers									
0.364**	0.205**	0.266**	0.282**	0.208**	0.457**	0.271**	0.270**	0.208**	0.180**
(7.05)	(4.67)	(6.05)	(2.64)	(4.05)	(5.26)	(5.06)	(6.05)	(4.05)	(8.25)

Internet Appendix: Diverse Hedge Funds

Table IA1: **Comparison of funds managed by teams of managers with and without LinkedIn information**

This table reports the fund characteristics of hedge funds managed by teams of managers with and without LinkedIn information. Teams comprise two or more fund managers. The fund characteristics include monthly return in percentage, monthly alpha in percentage, monthly flow in percentage, management fee in percentage, performance fee in percentage, high-water mark indicator, lockup period indicator, mean lockup period in days, redemption period in days, leverage indicator, and assets under management (AUM) in millions of US$. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

	Funds managed by teams of managers					
	with LinkedIn information		without LinkedIn information			
Fund characteristics	Mean	Std dev	Mean	Std dev	Spread	t-statistic
Monthly return (%)	0.49	1.61	0.47	1.58	0.02	1.21
Monthly alpha (%)	0.35	3.41	0.36	5.66	-0.01	-1.65
Monthly flow (%)	1.12	5.49	1.69	5.04	-0.57	-0.54
Management fee (%)	1.42	0.59	1.46	0.55	-0.04	-0.67
Incentive fee (%)	15.77	7.92	17.48	6.42	-1.71	-1.52
High-water mark indicator	0.70	0.46	0.75	0.44	-0.05	-1.12
Lockup indicator	0.27	0.44	0.18	0.38	0.09**	6.82
Lockup period (days)	188.49	221.15	157.44	193.87	31.05	1.22
Redemption period (days)	33.26	31.01	43.60	35.57	-10.34	-1.32
Leverage indicator	0.60	0.49	0.60	0.49	0.00	0.00
AUM (US$m)	614.58	5860.65	398.86	1395.51	215.72	1.07

Table IA2: **Aggregate diversity**

This table reports multivariate regressions on hedge fund performance with aggregate diversity and a portfolio sort on aggregate diversity. Panel A reports results from multivariate OLS regressions on hedge fund return (*RETURN*) and alpha (*ALPHA*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The independent variables of interest are aggregate diversity (*DIVERSITY_AGGREGATE*) and the square of aggregate diversity (*DIVERSITY_AGGREGATE_SQ*). The other independent variables include fund management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for fund investment strategy, team size, and year-month. The t-statistics, in parentheses, are derived from robust standard errors clustered by fund and month. Panel B reports results from the portfolio sort that analyzes the residuals of the regression of fund returns on the fund and team characteristics from Eq. (1). Every January 1st, hedge funds are sorted into five portfolios based on aggregate diversity, which is defined as the average of the educational institution-, college major-, work experience-, gender-, and race-based diversity measures of the fund management team. Portfolio performance is estimated relative to the Fung and Hsieh (2004) factors, which are S&P 500 return minus risk free rate (SNPMRF), Russell 2000 return minus S&P 500 return (SCMLC), change in the constant maturity yield of the U.S. 10-year Treasury bond appropriately adjusted for the duration (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodity PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The t-statistics are derived from White (1980) standard errors. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

Panel A: Multivariate regressions with aggregate diversity

Independent variable	*RETURN* (1)	*ALPHA* (2)	*RETURN* (3)	*ALPHA* (4)
DIVERSITY_AGGREGATE	0.353**	0.440**	1.182**	1.453**
	(4.98)	(2.82)	(4.46)	(3.38)
DIVERSITY_AGGREGATE_SQ			-0.591	-0.811*
			(-1.93)	(-1.99)
SAT/100	0.001	0.001*	0.001	0.001*
	(1.86)	(2.01)	(1.89)	(2.24)
MGTFEE	-0.007	0.026	-0.006	0.026
	(-0.16)	(0.47)	(-0.15)	(0.48)
PERFFEE	-0.005	-0.001	-0.005	-0.001
	(-1.27)	(-0.13)	(-1.23)	(-0.09)
HWM	0.049	0.067	0.044	0.058
	(0.94)	(1.09)	(0.84)	(0.96)
LOCKUP	0.017	0.132	0.028	0.145
	(0.29)	(0.79)	(0.48)	(0.86)
LEVERAGE	0.045	0.027	0.044	0.025
	(0.89)	(0.49)	(0.86)	(0.46)
AGE	-0.007	-0.017**	-0.007	-0.017**
	(-1.29)	(-3.57)	(-1.24)	(-3.49)
REDEMPTION	0.008	0.005	0.006	0.003
	(1.01)	(0.91)	(0.80)	(0.55)
log(*FUNDSIZE*)	-0.006	0.002	-0.010	-0.001
	(-0.44)	(0.21)	(-0.70)	(-0.15)
Year-month fixed effects	Yes	Yes	Yes	Yes
Strategy fixed effects	Yes	Yes	Yes	Yes
Team size fixed effects	Yes	Yes	Yes	Yes
R^2	0.022	0.007	0.023	0.008
N	89155	76747	89155	76747

Panel B: Portfolio sort on aggregate diversity

Hedge fund portfolio	Number of funds	Residuals (annualized)	t-statistic of residuals	Alpha from residuals (annualized)	t-statistic of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Portfolio 1 (high diversity)	521	6.12**	3.71	3.69**	3.06	0.29**	0.19**	-0.85	-2.76**	-0.03*	0.03**	0.01	0.336
Portfolio 2	522	4.68*	2.28	1.99	1.09	0.34**	0.25**	-1.13*	-1.59*	-0.00	0.00	0.01	0.550
Portfolio 3	518	4.32	1.59	2.89	0.18	0.25**	0.08*	-0.97	-1.93*	-0.00	0.00	-0.00	0.336
Portfolio 4	520	2.52	1.37	-0.12	-0.1	0.34**	0.12**	-1.48*	-2.60**	-0.01	0.02	-0.01	0.418
Portfolio 5 (low diversity)	520	-0.47	-0.20	-3.11	-1.53	0.26**	0.21**	-1.19*	-1.93*	-0.03**	0.01	0.00	0.593
Spread (1-5)		6.59*	2.33	6.80**	3.46	0.03	-0.02	0.36	-0.83	0.00	0.02	0.01	0.025

Table IA3: **Additional multivariate regressions on hedge fund performance**

This table reports results from additional multivariate OLS regressions on hedge fund return (*RETURN*) and alpha (*ALPHA*). *RETURN* is the monthly hedge fund net-of-fee return. *ALPHA* is the Fung and Hsieh (2004) seven-factor monthly alpha where factor loadings are estimated over the last 24 months. The independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)) as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for year-month, fund investment strategy, and team size. The coefficient estimates on the fund and team control variables are omitted for brevity. Panel A reports results from returns adjusted for incubation bias. Panel B reports results from returns adjusted for serial correlation. Panel C reports results from prefee returns. The *t*-statistics, in parentheses, are derived from robust standard errors clustered by fund and month. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

Independent variables									
Regressions on *RETURN*					Regressions on *ALPHA*				
DIVERSITY _EDU	*DIVERSITY _MAJOR*	*DIVERSITY _EXP*	*DIVERSITY _GENDER*	*DIVERSITY _RACE*	*DIVERSITY _EDU*	*DIVERSITY _MAJOR*	*DIVERSITY _EXP*	*DIVERSITY _GENDER*	*DIVERSITY _RACE*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Adjusted for incubation bias									
0.258*	0.262**	0.171**	0.223*	0.169*	0.344**	0.230**	0.146*	0.256**	0.185*
(2.46)	(4.70)	(2.90)	(2.17)	(2.56)	(3.18)	(3.75)	(2.29)	(3.19)	(2.56)
Panel B: Adjusted for serial correlation in fund returns									
0.373**	0.138**	0.087*	0.246**	0.266**	0.317*	0.146*	0.134	0.273**	0.283**
(5.52)	(2.99)	(2.52)	(3.17)	(3.89)	(2.53)	(2.40)	(1.92)	(3.54)	(3.50)
Panel C: Prefee returns									
0.463**	0.417**	0.315**	0.134*	0.145**	0.340*	0.446**	0.368**	0.117**	0.193**
(4.85)	(6.56)	(5.56)	(2.43)	(4.53)	(2.22)	(5.92)	(4.52)	(2.83)	(5.88)

Table IA4: **Multivariate regressions on hedge fund performance measures**

This table reports results from multivariate regressions on hedge fund annualized Sharpe ratio (*SHARPE*), annualized information ratio (*INFORMATION*), manipulation-proof performance measure (*MPPM*), and skill (*SKILL*). *SHARPE* is mean fund excess return divided by standard deviation of fund returns. *INFORMATION* is mean fund abnormal return divided by standard deviation of fund residuals from the Fung and Hsieh (2004) regression. *MPPM* is fund manipulation-proof performance measure with risk aversion parameter $\rho = 3$ (Goetzmann, Ingersoll, Spiegel, and Ross, 2007). *SKILL* is the monthly gross fund excess return multiplied by fund size (in millions of US$) as per Berk and van Binsbergen (2015). All performance measures, except *SKILL*, are measured over non-overlapping 24-month periods. The primary independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)), as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for year, fund investment strategy, and team size. The coefficient estimates on the fund and team control variables are omitted for brevity. The t-statistics, in parentheses, are derived from robust standard errors clustered by fund and month. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

		Independent variable		
DIVERSITY_EDU	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*
(1)	(2)	(3)	(4)	(5)
Panel A: Regressions on *SHARPE*				
0.234**	0.179*	0.134*	0.371**	0.222**
(3.36)	(2.41)	(2.56)	(4.46)	(4.60)
Panel B: Regressions on *INFORMATION*				
0.451**	0.467**	0.298**	0.251*	0.186**
(4.91)	(3.60)	(4.82)	(2.11)	(3.80)
Panel C: Regressions on *MPPM*				
0.442*	0.364**	0.370**	0.222*	0.180**
(2.06)	(3.39)	(3.21)	(2.36)	(3.05)
Panel D: Regressions on *SKILL*				
2.487**	1.386**	2.101**	1.630**	1.098**
(3.47)	(5.42)	(3.12)	(2.85)	(3.10)

Table IA5: **Stock performance of hedge funds sorted by diversity**

This table reports the performance of stocks held by hedge funds sorted on team diversity. Every January 1st, hedge funds are sorted into portfolios based on team diversity, which is defined as one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. Diverse hedge funds are hedge funds with diversity measures equal to one. Homogeneous hedge funds are hedge funds with diversity measures equal to zero. Stock holdings are derived from Thomson Reuters hedge fund firm 13-F filings. We compute monthly returns on diverse and homogeneous hedge fund holdings based on the assumptions that hedge fund firm holdings proxy for hedge fund holdings and that funds did not change their holdings between quarterly reports. Portfolios are rebalanced every calendar quarter and within a given fund portfolio, stocks are value weighted by the fund's dollar holdings. Finally, we compute value-weighted calendar time portfolios by averaging across funds, weighting individual fund portfolios by the fund's total net asset value at the end of the previous quarter. We report average returns, DGTW-adjusted returns, and 4-factor alphas. DGTW characteristic-adjusted returns are defined as raw returns minus the returns on a value-weighted portfolio of all CRSP firms in the same size, market-book, and one-year momentum quintile as per Daniel, Grinblatt, Titman, and Wermers (1997). 4-factor alpha is the intercept on a regression of monthly portfolio excess returns. The explanatory variables are the monthly returns from Fama and French (1993) factor mimicking portfolios and Carhart (1997) momentum factor. The t-statistics are derived from White (1980) standard errors. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

	Stock performance measure		
	Raw return	DGTW-adjusted return	4-factor alpha
Stock portfolio	(1)	(2)	(3)
Panel A: Diversity in educational institution			
Diverse hedge funds	11.94	4.99	4.94
Homogeneous hedge funds	9.92	2.28	2.01
Difference	2.02*	2.71**	2.93**
t-statistics	2.21	3.21	2.20
Panel B: Diversity in college major			
Diverse hedge funds	12.23	4.35	5.98
Homogeneous hedge funds	8.84	2.98	3.01
Difference	3.39**	1.37*	2.97**
t-statistics	4.79	2.56	3.11
Panel C: Diversity in work experience			
Diverse hedge funds	12.21	4.79	7.79
Homogeneous hedge funds	8.84	2.21	2.99
Difference	3.37**	2.58**	4.80*
t-statistics	4.99	3.22	1.99
Panel D: Diversity in gender			
Diverse hedge funds	12.67	4.96	8.81
Homogeneous hedge funds	6.89	2.01	4.43
Difference	5.78**	2.95**	4.38**
t-statistics	8.84	3.99	3.21
Panel E: Diversity in race			
Diverse hedge funds	10.94	3.99	4.48
Homogeneous hedge funds	7.99	1.93	2.02
Difference	2.95**	2.06*	2.46*
t-statistics	7.72	2.22	1.98

Table IA6: **Portfolio sorts on hedge fund team diversity, robustness tests**

This table reports the alphas and factor loadings for the high-minus-low diversity spread portfolio from the sort on fund diversity. The portfolio sort analyzes the residuals of the regression of fund returns on the fund and team covariates from Eq. (1). Every January 1st, hedge funds are sorted into five portfolios based on team diversity, which is defined as one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. Rows 1 to 4 in each panel report the performance of the spread portfolio estimated relative to the Fung and Hsieh (2004) model (FH). For row 3, the monthly alphas are estimated dynamically using factor loadings estimated over the prior 24 months and current month factor realizations. The adjusted R^2s reported in row 3 are the average adjusted R^2s of the 24-month rolling regressions used to estimate the factor loadings. For row 4, the estimation of the FH factor loadings allows for structural breaks in March 2000 (the height of the tech bubble) and Sept 2008 (the collapse of Lehman Brothers). The other rows report spread portfolio performance estimated relative to an augmented Fung and Hsieh (2004) model. HML is the Fama and French (1993) value factor. UMD is the Carhart (1997) momentum factor. RMW and CMA are the Fama and French (2015) profitability and investment factors, respectively. PS is the Pástor and Stambaugh (2003) traded liquidity factor. BAB is the Frazzini and Pedesen (2014) betting-against-beta factor. MACRO is the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor. CALL and PUT are the Agarwal and Naik (2004) out-of-the-money call and put option based factors. EM is the emerging markets factor derived from the MSCI Emerging Markets index. The loadings on the Fung and Hsieh factors are omitted for brevity. Panels A, B, C, D, and E report results for team diversity based on educational institution, college major, work experience, gender, and race, respectively. The t-statistics are derived from White (1980) standard errors. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

Risk model	Portfolio	Alpha from residuals	t-statistic of alpha	HML	UMD	RMW	CMA	PS	BAB	MACRO	CALL	PUT	EM	Adj R^2
Panel A: Diversity in educational institution														
FH (value-weighted)	Spread (1-5)	3.72**	2.74											0.070
FH (fund AUM>50M)	Spread (1-5)	4.80**	4.99											0.064
FH (24-month rolling betas)	Spread (1-5)	6.12**	4.41											0.267
FH (with structural breaks)	Spread (1-5)	3.24**	4.84											0.401
FH + HML +UMD	Spread (1-5)	3.48**	5.15	-0.024	-0.027*									0.228
FH + RMW + CMA	Spread (1-5)	2.88**	4.45			-0.000	-0.001**							0.317
FH + PS	Spread (1-5)	2.87**	4.47					0.012						0.209
FH + BAB	Spread (1-5)	3.24**	4.68						-0.019					0.210
FH + MACRO	Spread (1-5)	3.12**	4.70							-0.000				0.205
FH + CALL + PUT	Spread (1-5)	2.89**	3.60								0.072	0.320**		0.330
FH + EM	Spread (1-5)	3.72**	5.96										0.054**	0.337
Panel B: Diversity in college major														
FH (value-weighted)	Spread (1-5)	6.96**	3.09											0.096
FH (fund AUM>50M)	Spread (1-5)	6.24**	6.69											0.096
FH (24-month rolling betas)	Spread (1-5)	5.22**	4.23											0.087
FH (with structural breaks)	Spread (1-5)	3.12**	4.64											0.183
FH + HML + UMD	Spread (1-5)	7.80**	5.02	0.003	0.010									0.126
FH + RMW + CMA	Spread (1-5)	7.24**	5.18			-0.000	0.000							0.076
FH + PS	Spread (1-5)	6.84**	6.62					0.012						0.136
FH + BAB	Spread (1-5)	4.44**	6.17						0.005					0.123
FH + MACRO	Spread (1-5)	3.96**	4.48							0.015				0.124
FH + CALL + PUT	Spread (1-5)	5.88**	5.91								0.044	-0.027		0.125
FH + EM	Spread (1-5)	7.08**	5.54										-0.017	0.136

Risk model	Portfolio	Alpha from residuals	t-statistic of alpha	HML	UMD	RMW	CMA	PS	BAB	MACRO	CALL	PUT	EM	Adj R^2
Panel C: Diversity in work experience														
FH (value-weighted)	Spread (1-5)	5.52**	3.55											0.086
FH (fund AUM>50M)	Spread (1-5)	5.64**	6.67											0.078
FH (24-month rolling betas)	Spread (1-5)	5.10**	3.19											0.299
FH (with structural breaks)	Spread (1-5)	6.96**	5.86											0.334
FH + HML +UMD	Spread (1-5)	6.12**	6.70	-0.028	-0.013									0.217
FH + RMW + CMA	Spread (1-5)	6.95**	3.63			-0.001**	-0.000							0.186
FH + PS	Spread (1-5)	6.92**	5.36					0.008						0.199
FH + BAB	Spread (1-5)	3.84**	3.83						-0.038**					0.255
FH + MACRO	Spread (1-5)	4.92**	6.05							0.029				0.201
FH + CALL + PUT	Spread (1-5)	7.68**	3.19								0.012	0.016		0.248
FH + EM	Spread (1-5)	7.32**	8.13										0.034**	0.304
Panel D: Diversity in gender														
FH (value-weighted)	Spread (1-5)	6.72**	4.72											0.030
FH (fund AUM>50M)	Spread (1-5)	4.08**	6.31											0.040
FH (24-month rolling betas)	Spread (1-5)	4.20**	2.54											0.047
FH (with structural breaks)	Spread (1-5)	5.28**	3.93											0.020
FH + HML + UMD	Spread (1-5)	2.52**	2.56	0.017	0.035**									0.016
FH + RMW + CMA	Spread (1-5)	4.90**	3.45			-0.000	0.001							0.011
FH + PS	Spread (1-5)	4.92**	3.10					-0.020						0.011
FH + BAB	Spread (1-5)	5.04**	4.75						-0.013					0.007
FH + MACRO	Spread (1-5)	5.40**	3.20							-0.004				0.007
FH + CALL + PUT	Spread (1-5)	6.36**	5.56								0.190	0.210		0.012
FH + EM	Spread (1-5)	5.76**	3.66										-0.018**	0.010
Panel E: Diversity in race														
FH (value-weighted)	Spread (1-5)	4.68**	3.47											0.063
FH (fund AUM>50M)	Spread (1-5)	3.01**	3.52											0.055
FH (24-month rolling betas)	Spread (1-5)	3.38*	2.21											0.048
FH (with structural breaks)	Spread (1-5)	6.48**	2.88											0.022
FH + HML + UMD	Spread (1-5)	4.68**	2.79	-0.043**	-0.011									0.003
FH + RMW + CMA	Spread (1-5)	6.72**	2.93			0.000	-0.001							0.018
FH + PS	Spread (1-5)	6.60**	2.52					0.033						0.006
FH + BAB	Spread (1-5)	6.48**	3.87						0.021					0.002
FH + MACRO	Spread (1-5)	7.32**	2.65							-0.019				0.002
FH + CALL + PUT	Spread (1-5)	6.70**	3.69								0.261	0.231		0.004
FH + EM	Spread (1-5)	7.56**	2.89										0.080	0.011

Table IA7: **Event study with difference-in-differences analysis, robustness tests**

This table reports an event study analysis of hedge fund performance around a change in team diversity. Alpha is Fung and Hsieh (2004) seven-factor monthly alpha with factor loadings estimated over the last 24 months. For the baseline specification, the event month is the month in which a team increases its diversity with the inclusion of a new team member. Control funds are matched to treatment funds based first on team diversity and then on fund performance in the pre-event period. The event window is the period that spans 36 months before to 36 months after the event. Panel A presents results for when the event window is 24 months (columns 1 to 4) and 48 months (columns 5 to 8), and when funds are matched based on propensity score, where the covariates are the fund controls from the baseline performance regressions (columns 9 to 12). Panel B presents results for teams that experience diversity-diminishing manager additions (columns 1 to 4), and for when control funds are matched to treatment funds based on team SAT score and fund performance (columns 5 to 8), and based on team size and fund performance (columns 9 to 12). Subpanels A, B, C, D, and E report results for team diversity based on educational institution, college major, work experience, gender, and race, respectively. The sample period is from January 1994 to June 2016. *, ** denote difference-in-differences estimates that are significant at the 5% and 1% levels, respectively.

Panel A: Varying the event window and propensity score matching

	Event window = 24 months				Event window = 48 months				Propensity score matching			
	Before	After	After - before	t-statistic	Before	After	After - before	t-statistic	Before	After	After - before	t-statistic
Fund performance attribute	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Subpanel A: Diversity in educational institution												
Fund return (percent/month), treatment group	0.509	0.772	0.263	3.56	0.567	0.799	0.232	2.04	0.547	0.890	0.343	2
Fund return (percent/month), control group	0.504	0.234	-0.270	-6.65	0.524	0.257	-0.267	-3.19	0.643	0.481	-0.162	-1.35
Difference in return (percent/month)			0.533**	6.32			0.499**	3.53			0.505**	2.79
Fund alpha (percent/month), treatment group	0.289	0.489	0.200	3.24	0.298	0.614	0.316	4.12	0.288	0.694	0.406	1.71
Fund alpha (percent/month), control group	0.274	0.125	-0.149	-1.98	0.246	0.267	0.021	0.18	0.248	0.182	-0.066	-0.76
Difference in alpha (percent/month)			0.349**	3.59			0.295*	2.11			0.472**	2.78
Subpanel B: Diversity in college major												
Fund return (percent/month), treatment group	0.501	0.672	0.171	1.87	0.467	0.613	0.146	2.15	0.447	0.647	0.200	1.65
Fund return (percent/month), control group	0.498	0.202	-0.296	-3.32	0.401	0.205	-0.196	-2.96	0.504	0.107	-0.397	-2.09
Difference in return (percent/month)			0.467**	3.66			0.342**	3.61			0.597*	2.03
Fund alpha (percent/month), treatment group	0.278	0.503	0.225	1.12	0.203	0.455	0.252	2.09	0.316	0.671	0.355	3.1
Fund alpha (percent/month), control group	0.321	0.145	-0.176	-3.21	0.312	0.127	-0.185	-1.99	0.250	0.034	-0.216	-1.27
Difference in alpha (percent/month)			0.401	1.93			0.437**	2.87			0.571**	3.29
Subpanel C: Diversity in work experience												
Fund return (percent/month), treatment group	0.499	0.612	0.113	-2.01	0.421	0.698	0.277	2.28	0.539	0.788	0.249	1.83
Fund return (percent/month), control group	0.515	0.213	-0.302	-4.45	0.423	0.299	-0.124	-1.98	0.541	0.274	-0.267	-1.51
Difference in return (percent/month)			0.415**	4.71			0.401**	2.93			0.516*	2.09
Fund alpha (percent/month), treatment group	0.289	0.503	0.214	2.01	0.267	0.588	0.321	2.26	0.319	0.752	0.433	2.76
Fund alpha (percent/month), control group	0.398	0.125	-0.273	-2.34	0.297	0.216	-0.081	-1.65	0.382	0.154	-0.228	-3.37
Difference in alpha (percent/month)			0.487**	3.08			0.402**	2.68			0.661**	3.15
Panel D: Diversity in gender												
Fund return (percent/month), treatment group	0.567	0.649	0.082	1.11	0.556	0.798	0.242	3.02	0.439	0.706	0.267	1.61
Fund return (percent/month), control group	0.533	0.235	-0.298	3.89	0.498	0.356	-0.142	-1.98	0.410	0.192	-0.218	-3.26
Difference in return (percent/month)			0.380**	3.57			0.384**	3.57			0.485**	4.70
Fund alpha (percent/month), treatment group	0.346	0.514	0.168	1.16	0.312	0.601	0.289	3.05	0.226	0.607	0.381	3.11
Fund alpha (percent/month), control group	0.358	0.204	-0.154	-1.92	0.296	0.203	-0.093	-1.77	0.220	0.038	-0.182	-2.92
Difference in alpha (percent/month)			0.322	1.94			0.382**	3.53			0.563**	4.30
Subpanel E: Diversity in race												
Fund return (percent/month), treatment group	0.534	0.578	0.044	0.56	0.546	0.772	0.226	2.78	0.497	0.657	0.160	1.68
Fund return (percent/month), control group	0.521	0.109	-0.412	-3.39	0.523	0.298	-0.225	2.01	0.537	0.312	-0.225	-3.31
Difference in return (percent/month)			0.456**	3.15			0.451**	3.26			0.385**	3.54
Fund alpha (percent/month), treatment group	0.332	0.525	0.193	1.98	0.301	0.655	0.354	4.42	0.332	0.587	0.255	1.69
Fund alpha (percent/month), control group	0.378	0.279	-0.099	-1.45	0.295	0.201	-0.094	-1.45	0.262	-0.046	-0.308	-3.19
Difference in alpha (percent/month)			0.292*	2.45			0.448**	4.35			0.563*	2.34

Panel B: Diversity-diminishing manager additions and matching based on team characteristics

	Diversity-diminishing manager additions				Matching based on team SAT and fund performance				Matching based on team size and fund performance			
	Before	After	After - before	t-statistic	Before	After	After - before	t-statistic	Before	After	After - before	t-statistic
Fund performance attribute	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Subpanel A: Diversity in educational institution												
Fund return (percent/month), treatment group	0.465	0.123	-0.342	-6.54	0.547	0.890	0.343	2.00	0.547	0.890	0.343	2.00
Fund return (percent/month), control group	0.443	0.426	-0.017	-0.56	0.432	0.199	-0.233	-1.99	0.532	0.304	-0.228	-2.03
Difference in return (percent/month)			-0.325**	-5.37			0.576**	3.11			0.571**	3.10
Fund alpha (percent/month), treatment group	0.284	0.056	-0.228	-3.21	0.288	0.694	0.406	1.71	0.288	0.694	0.406	1.71
Fund alpha (percent/month), control group	0.286	0.390	0.104	3.14	0.243	0.143	-0.100	-1.12	0.204	0.107	-0.097	1.12
Difference in alpha (percent/month)			-0.332**	-4.24			0.506*	2.06			0.503*	2.05
Subpanel B: Diversity in college major												
Fund return (percent/month), treatment group	0.487	0.035	-0.452	-2.23	0.447	0.647	0.200	1.65	0.447	0.647	0.200	1.65
Fund return (percent/month), control group	0.478	0.512	0.034	0.34	0.456	0.237	-0.219	-1.78	0.445	0.245	-0.200	-1.45
Difference in return (percent/month)			-0.486*	-2.15			0.419**	3.07			0.400**	2.85
Fund alpha (percent/month), treatment group	0.143	-0.422	-0.565	-3.78	0.316	0.671	0.355	3.10	0.316	0.671	0.355	3.10
Fund alpha (percent/month), control group	0.178	0.234	0.056	0.89	0.345	0.132	-0.213	-2.68	0.318	0.145	-0.173	-2.22
Difference in alpha (percent/month)			-0.621**	-3.83			0.568**	4.70			0.528**	4.38
Subpanel C: Diversity in work experience												
Fund return (percent/month), treatment group	0.498	0.156	-0.342	-6.78	0.539	0.788	0.249	1.83	0.539	0.788	0.249	1.83
Fund return (percent/month), control group	0.489	0.386	-0.103	-2.21	0.524	0.233	-0.291	-2.22	0.533	0.256	-0.277	-2.11
Difference in return (percent/month)			-0.239**	-3.48			0.540**	3.52			0.526**	3.43
Fund alpha (percent/month), treatment group	0.364	0.176	-0.188	-1.99	0.319	0.752	0.433	2.76	0.319	0.752	0.433	2.76
Fund alpha (percent/month), control group	0.311	0.489	0.178	1.59	0.309	0.168	-0.141	-1.11	0.302	0.216	-0.086	-1.14
Difference in alpha (percent/month)			-0.366*	-2.50			0.574**	3.32			0.519**	3.19
Subpanel D: Diversity in gender												
Fund return (percent/month), treatment group	0.513	0.245	-0.268	-4.43	0.439	0.656	0.267	1.61	0.439	0.656	0.267	1.61
Fund return (percent/month), control group	0.502	0.712	0.21	2.21	0.446	0.309	-0.137	-1.99	0.457	0.343	-0.114	-1.87
Difference in return (percent/month)			-0.478**	-4.24			0.404*	2.37			0.381*	2.25
Fund alpha (percent/month), treatment group	0.331	0.156	-0.175	-2.12	0.226	0.607	0.381	3.11	0.226	0.607	0.381	3.11
Fund alpha (percent/month), control group	0.336	0.512	0.176	1.89	0.229	0.105	-0.124	-1.14	0.235	0.194	-0.041	-0.87
Difference in alpha (percent/month)			-0.351**	-2.82			0.505**	3.76			0.422**	3.38
Subpanel E: Diversity in race												
Fund return (percent/month), treatment group	0.489	0.190	-0.299	-4.43	0.497	0.657	0.16	1.68	0.497	0.657	0.16	1.68
Fund return (percent/month), control group	0.447	0.576	0.129	1.12	0.501	0.345	-0.156	-2.22	0.504	0.331	-0.173	-1.98
Difference in return (percent/month)			-0.428**	-3.21			0.316**	3.15			0.333**	3.24
Fund alpha (percent/month), treatment group	0.322	0.136	-0.411	-1.67	0.332	0.587	0.255	1.69	0.332	0.587	0.255	1.69
Fund alpha (percent/month), control group	0.356	0.401	0.045	0.94	0.321	0.206	-0.115	-1.02	0.321	0.204	-0.117	-1.17
Difference in alpha (percent/month)			-0.456	-1.82			0.370*	2.26			0.372*	2.31

Table IA8: **Racial composition of fund management teams**

This table reports results from multivariate regressions on the racial compositions of hedge fund management teams. The dependent variables are the percentages of white (*TEAM_WHITE*), black (*TEAM_BLACK*), asian (*TEAM_ASIAN*), and hispanic (*TEAM_HISPANIC*) members in the team at fund inception. The primary independent variables of interest are the percentages of white (*HOMETOWN_WHITE*), black (*HOMETOWN_BLACK*), asian (*HOMETOWN_ASIAN*), and hispanic (*HOMETOWN_HISPANIC*) residents in the hedge fund founder's hometown. The other independent variables include average team SAT score scaled by 100 (SAT/100) as well as dummy variables for team size. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

	Dependent variables							
	TEAM_WHITE	*TEAM_BLACK*	*TEAM_ASIAN*	*TEAM_HISPANIC*	*TEAM_WHITE*	*TEAM_BLACK*	*TEAM_ASIAN*	*TEAM_HISPANIC*
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Team racial percentages computed before excluding hedge fund founder								
HOMETOWN_WHITE	0.290**				0.306**			
	(3.29)				(3.25)			
HOMETOWN_BLACK		0.296				0.358*		
		(1.87)				(2.24)		
HOMETOWN_ASIAN			0.858**				0.920**	
			(3.11)				(3.23)	
HOMETOWN_HISPANIC				2.108**				2.312**
				(3.21)				(3.66)
Team controls and fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.225	0.074	0.082	0.167	0.290	0.155	0.132	0.253
N	1712	1712	1712	1712	1712	1712	1712	1712
Panel B: Team racial percentages computed after excluding hedge fund founder								
HOMETOWN_WHITE	0.508**				0.548**			
	(4.43)				(4.54)			
HOMETOWN_BLACK		0.322*				0.389*		
		(2.04)				(2.45)		
HOMETOWN_ASIAN			0.858**				0.920**	
			(3.11)				(3.23)	
HOMETOWN_HISPANIC				2.170**				2.314**
				(3.25)				(3.68)
Team controls and fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.225	0.074	0.082	0.167	0.234	0.308	0.132	0.253
N	1712	1712	1712	1712	1712	1712	1712	1712

Table IA9: **Multivariate regressions on hedge fund flow**

This table reports results from multivariate regressions on hedge fund annual flow in percentage (*FLOW*). The primary independent variables of interest are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and log of fund size (log(*FUNDSIZE*)), as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for year, fund investment strategy, and team size. The regressions also include controls for past-year fund return rank (*RETURN_RANK*), CAPM alpha rank (*CAPM_ALPHA_RANK*), or Fung and Hsieh (2004) alpha rank (*FH_ALPHA_RANK*). The coefficient estimates on the fund and team control variables are omitted for brevity. The t-statistics, in parentheses, are derived from robust standard errors clustered by fund and year. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

		Independent variable		
DIVERSITY_EDU	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*
(1)	(2)	(3)	(4)	(5)
Panel A: Regressions on *FLOW* controlling for *RETURN_RANK*				
6.616**	1.969**	5.864**	2.787**	1.576**
(3.35)	(2.78)	(3.97)	(5.43)	(6.29)
Panel B: Regressions on *FLOW* controlling for *CAPM_ALPHA_RANK*				
6.653**	2.749**	6.466**	2.716**	1.646**
(3.06)	(3.80)	(4.28)	(5.07)	(6.46)
Panel C: Regressions on *FLOW* controlling for *FH_ALPHA_RANK*				
10.455**	6.807**	9.295**	2.743**	1.619**
(5.15)	(8.62)	(5.51)	(5.23)	(6.42)

Table IA10: **Multivariate regressions on hedge fund team diversity at fund inception**

This table reports results from multivariate regressions on hedge fund team diversity at fund inception. The dependent variables are team diversity based on manager educational institution (*DIVERSITY_EDU*), college major (*DIVERSITY_MAJOR*), work experience (*DIVERSITY_EXP*), gender (*DIVERSITY_GENDER*), and race (*DIVERSITY_RACE*). Team diversity is one minus the number of shared connections in a team based on educational institution, college major, work experience, gender, and race scaled by the total number of possible shared connections. The independent variables of interest are an indicator variable for hot investment strategy at fund inception (*HOT_STRATEGY*) as well as founder industry experience (*FOUNDER_EXPERIENCE*). As per Cao, Farnsworth, and Zhang (2021), a hot strategy is an investment strategy with a high rank (eight of greater) based on 36-month prior flows and a high rank (eight of greater) based on 36-month prior returns among the set of ten investment strategies defined in Cao, Farnsworth, and Zhang (2021). Founder experience is the number of years of working experience that the founder has prior to starting the fund. The other independent variables include fund characteristics such as management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lock-up period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), redemption period in months (*REDEMPTION*), and log of fund size at fund inception (log(*FUNDSIZE*)), as well as team SAT score scaled by 100 (*SAT/100*) and dummy variables for year, fund investment strategy, and team size. The t-statistics, in parentheses, are derived from robust standard errors clustered by fund and year. The sample period is from January 1994 to June 2016. *, ** denote significance at the 5% and 1% levels, respectively.

	Dependent variable									
	DIVERSITY _EDU	*DIVERSITY _MAJOR*	*DIVERSITY _EXP*	*DIVERSITY _GENDER*	*DIVERSITY _RACE*	*DIVERSITY _EDU*	*DIVERSITY _MAJOR*	*DIVERSITY _EXP*	*DIVERSITY _GENDER*	*DIVERSITY _RACE*
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HOT_STRATEGY	-0.109**	-0.059	-0.123**	-0.114**	-0.081**					
	(-5.84)	(-1.93)	(-3.06)	(-2.79)	(-5.00)					
FOUNDER_EXPERIENCE						0.011**	0.007*	0.009**	0.002**	0.005**
						(6.94)	(2.09)	(3.13)	(2.93)	(3.44)
SAT/100	0.000	0.000**	0.004**	0.003**	0.001**	0.001*	0.000**	0.000**	0.000**	0.000**
	(0.98)	(4.74)	(4.20)	(7.74)	(2.88)	(2.15)	(5.79)	(4.43)	(4.19)	(4.18)
MGTFEE	-0.016	0.008	-0.012	0.012	-0.062*	-0.012	0.009	0.007	-0.003	-0.011
	(-1.58)	(0.69)	(-0.79)	(0.75)	(-2.48)	(-0.56)	(1.62)	(1.41)	(-0.38)	(-0.99)
PERFFEE	-0.003*	-0.005**	0.006**	0.003	0.006*	0.003	-0.000	0.002*	-0.001	-0.001
	(-2.31)	(-3.22)	(2.65)	(1.17)	(2.43)	(1.20)	(-0.14)	(2.34)	(-1.41)	(-0.76)
HWM	-0.056**	-0.080**	-0.054	-0.075*	-0.045	-0.112**	-0.006	-0.030	-0.011	0.021
	(-2.98)	(-3.19)	(-1.79)	(-2.25)	(-1.16)	(-2.84)	(-0.67)	(-1.49)	(-0.64)	(0.69)
LOCKUP	0.012	0.039	-0.138**	-0.084	-0.149**	-0.059	-0.021**	-0.036**	-0.023	-0.010
	(0.54)	(1.44)	(-2.80)	(-1.70)	(-2.75)	(-1.22)	(-2.97)	(-2.58)	(-1.38)	(-0.40)
LEVERAGE	0.024	0.000	0.042	0.061*	0.072*	0.055	-0.014	-0.024	-0.004	-0.013
	(1.42)	(0.00)	(1.75)	(2.44)	(2.50)	(1.96)	(-1.84)	(-1.91)	(-0.29)	(-0.60)
REDEMPTION	0.007	0.002	-0.001	-0.014	0.005	-0.006	0.000	-0.001	-0.006*	-0.008*
	(1.76)	(0.43)	(-0.21)	(-1.93)	(0.61)	(-0.80)	(0.12)	(-0.50)	(-2.11)	(-2.23)
log(*FUNDSIZE*)	-0.003	-0.003	-0.009	-0.007	-0.007	-0.007	-0.002	-0.004	0.001	-0.012*
	(-0.68)	(-0.52)	(-1.43)	(-1.03)	(-0.92)	(-0.90)	(-1.19)	(-1.42)	(0.28)	(-2.18)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.304	0.323	0.180	0.167	0.396	0.526	0.212	0.404	0.111	0.152
N	2251	2249	2251	6059	6059	2360	2358	2360	6096	6096