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Diverse Hedge Funds

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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 who 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. (*JEL* G20, G23, J15, J16, J24, M14)

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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

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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 (Budra and Wilson 2023). 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 (Burton and Parmar 2020). 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.[2]

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 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 (Parmar and Massa 2020). 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.[3]

[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 (Cohen, Malloy, and Foreman 2015).

[2] See Bär, Niessen, and Ruenzi 2009, Gompers and Wang 2021, and Evans et al. 2022, all of whom we will discuss further.

[3] 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.

Theoretically, whether diversity should create value in asset management is not clear. 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.

In this paper, we study diversity based on educational institution, academic specialization, work experience, gender, and race.[4] 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 (Chuprinin and Sosyura 2018), including a female in an all-male team should elevate performance as the female manager would likely be of higher quality than the men.

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 et al. (2007) manipulation-proof performance measures, and Berk and van Binsbergen (2015) value-added skill. Diverse hedge funds also demonstrate savvy stock

4 In an earlier draft of the paper, we studied diversity based on fund manager nationality and obtained qualitatively similar results.

selection skills. The stocks they hold earn greater raw returns, Daniel et al. (1997) DGTW alphas, and Carhart (1997) four-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 after adding back the constant term. The portfolio sorts indicate that diverse teams outperform homogeneous teams by 4.44% to 6.00% per annum after adjusting for covariation 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) 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 controls after adding back the constant term. 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 (a) vary the length of the event window, (b) match treatment to control funds based on propensity score, (c) match treatment to control funds based on team characteristics in addition to fund performance, (d) study manager additions that diminish diversity, or (e) 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, as reported in 1980 U.S. Census data, of the respective cities 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 not driven by differences in founders' access to resources or education quality during childhood directly affecting fund performance, or by a 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 who 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 lockup 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 2007; 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 et al. (2021), who show that relative to solo-managed mutual funds, team-managed mutual funds are less susceptible to capacity constraints.[5]

Do investors value team diversity? We show that investors allocate more capital to diverse funds even after controlling for past fund performance. Moreover, they place greater value on functional diversity than on nonfunctional diversity, which is in line with our findings that functional diversity contributes more to investment performance than does nonfunctional diversity. 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 experience tend to be more homogeneous.

Our work complements the nascent literature on team diversity in asset management.[6] 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.

5 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.

6 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 et al. (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), Munro and Slear (2020), and Mirabella (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.

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.[7]

1. Data and Methodology

1.1 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.

Following Agarwal, Daniel, and Naik (2009), we classify funds into four broad investment styles: Security Selection, Multiprocess, Directional Trader,

[7] 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, namely, prominent stock anomalies, and the implications of such investment behavior, namely, lower capacity constraints and greater performance persistence.

and Relative Value. Security Selection funds take long and short positions in undervalued and overvalued securities, respectively. They typically take positions in equity markets. Multiprocess 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 nonbackfilled 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.

1.2 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.[8] 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;

[8] 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).

Kalmijn 1998), gender (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 affected 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 one and diversity equals zero. 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 along 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, that is, funds with two or more managers, although we also analyze solo-managed funds in some of our tests.[9] There are 16,307 team-managed funds, composing a substantial 58.76% of the funds in our combined hedge fund database. We obtain undergraduate and post-graduate educational institution information for 3,385 managers operating 5,250 funds, college major information for 3,092 managers running 4,514 funds, and prior employment information for 3,315 managers operating 5,019 funds by manually searching LinkedIn pages and matching based on manager and fund management company names.

To determine the gender and race of managers, 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 information on gender and race 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 its inclusion of the dates for which fund managers joined and/or exited 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

9 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.

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 on 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%).

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.[10]

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 some evidence indicates 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 feature 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

[10] 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.

Table 1
Summary statistics

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
1: 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
2: 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
3: 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
4: Gender			
1	Male	11829	94.12
2	Female	739	5.88
5: Race			
1	White	7319	64.83
2	Asian	1845	16.34
3	Black	1299	11.51
4	Hispanic	827	7.33

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	1.426	1.000	1.500	2.000	0.588
PERFFEE	17.390	20.000	20.000	20.000	6.516
HWM	0.729	0.000	1.000	1.000	0.445
LOCKUP	0.256	0.000	0.000	0.250	0.517
LEVERAGE	0.592	0.000	1.000	1.000	0.492
AGE	6.468	2.583	5.083	8.917	5.244
REDEMPTION	2.063	1.000	1.000	3.000	2.656
FUNDSIZE	441.380	18.900	68.540	249.960	2732.220

(*Continued*)

Table 1
(Continued)

C: Distribution of diversity measures by investment strategy

Investment strategy	No. of funds	Mean	25%	Median	75%	Std dev
1: Diversity in educational institution						
Directional Trader	587	0.804	1.000	1.000	1.000	0.382
Relative Value	468	0.713	0.000	1.000	1.000	0.445
Security Selection	2152	0.790	1.000	1.000	1.000	0.394
Multiprocess	600	0.822	1.000	1.000	1.000	0.362
2: 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
3: Diversity in work experience						
Directional Trader	649	0.597	0.000	1.000	1.000	0.486
Relative Value	426	0.472	0.000	0.125	1.000	0.490
Security Selection	2101	0.567	0.000	1.000	1.000	0.491
Multiprocess	631	0.554	0.000	1.000	1.000	0.488
4: Diversity in gender						
Directional Trader	2770	0.410	0.000	0.000	0.667	0.476
Relative Value	1151	0.293	0.000	0.000	0.667	0.432
Security Selection	6013	0.397	0.000	0.000	0.500	0.472
Multiprocess	1702	0.543	0.000	0.000	0.500	0.480
5: Diversity in race						
Directional Trader	2761	0.556	0.000	1.000	1.000	0.474
Relative Value	1149	0.508	0.000	0.553	1.000	0.454
Security Selection	5171	0.566	0.000	0.697	1.000	0.460
Multiprocess	1697	0.706	0.303	1.000	1.000	0.427

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

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 lockup 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.

of fund performance, we will carefully control for the explanatory power of these fund characteristics in a multivariate regression setting.

2. Empirical Results

2.1 Fund investment performance

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

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

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 lockup 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.[11] 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 diverse team) is synonymous with a 5.59% per annum increase in fund alpha. Similarly, the coefficient

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

Table 2
Multivariate regressions on hedge fund performance

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	.028	.008	.028	.008	.028	.008	.000	.002	.000	.002
N	116,587	92,417	119,849	95,009	116,587	92,417	214,906	161,059	198,320	149,271

(*Continued*)

Table 2
(Continued)

B: Fama-MacBeth 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	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	.126	.079	.122	.076	.130	.079	.052	.038	.053	.037
N	116,587	92,417	119,730	94,935	116,587	92,417	214,906	161,059	198,320	149,271

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*), lockup period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and logarithm 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 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. $^*p<.1$; $^{**}p<.05$.

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.[12] These results suggest that functional diversity (based on educational institution, college major, and work experience) more positively relates to investment performance than does nonfunctional diversity (based on gender and race).

The signs of the coefficient estimates on the fund control variables broadly agree with the extant literature. Following Aggarwal and Jorion (2010), fund age is negatively associated with 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). 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, that is, 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 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 affecting inferences, we reestimate the regressions on unsmoothed fund returns and alphas, which are constructed 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 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.

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

[12] 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. It also shows diminishing marginal returns to diversity, as evidenced by the negative coefficient estimates on the square of aggregate diversity.

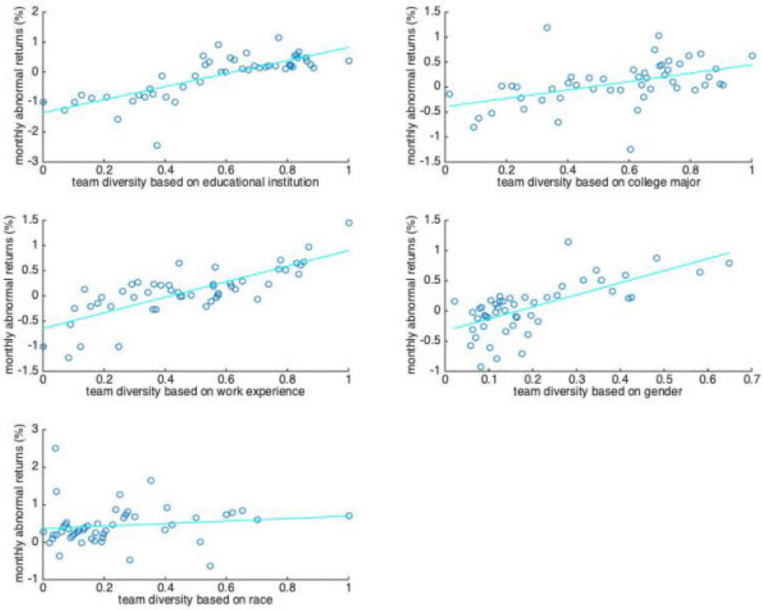

Figure 1
Binned scatter plots of fund monthly abnormal return against team diversity.
Fund monthly abnormal return is estimated relative to the Fung and Hsieh (2004) model, where the factor loadings are estimated over the prior 24 months. Team diversity is defined as one minus the number of shared connections 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.

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) four-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 controls in Equation (1) after adding back the constant term. 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.[13] Next, we link the equal-weighted post-formation residuals

[13] 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,

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) 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 covariation 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.

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 (a) the Fama and French (1993) HML value factor and the Carhart (1997) UMD momentum factor, (b) the Fama and French (2015) RMW profitability and CMA investment factors, (c) the Pástor and Stambaugh (2003) PS traded liquidity factor, (d) the Frazzini and Pedersen (2014) BAB betting-against-beta factor, (e) the Bali, Brown, and Caglayan (2014) $MACRO$ macroeconomic uncertainty factor, (f) the Agarwal and Naik (2004) $CALL$ out-of-the-money call option and PUT out-of-the-money put option factors, and (g) the EM emerging markets factor derived from the MSCI Emerging Markets index.

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.

Table 3
Portfolio sorts on hedge fund team 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
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
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
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
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
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

The table reports portfolio sorts that analyze the residuals from the regression of fund returns on the fund and team controls from Equation (1) after adding back the constant term. 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. $^{*}p<.1$; $^{**}p<.05$.

2.2 Endogeneity

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

2.2.1 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 nondiversity 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.

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 controls in Equation (1) after adding back the constant term. 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

Table 4
Event study with difference-in-differences analysis

	Fund performance				Fund residuals			
Fund performance attribute	Before (1)	After (2)	After - before (3)	*t*-statistic (4)	Before (5)	After (6)	After - before (7)	*t*-statistic (8)
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
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
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
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
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

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 Equation (1) after adding back the constant term. 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. *$p < .1$; **$p < .05$.

following the diversity change.[14] These results echo the findings from the baseline performance regressions and broadly suggest that functional diversity adds more value than does nonfunctional diversity.

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

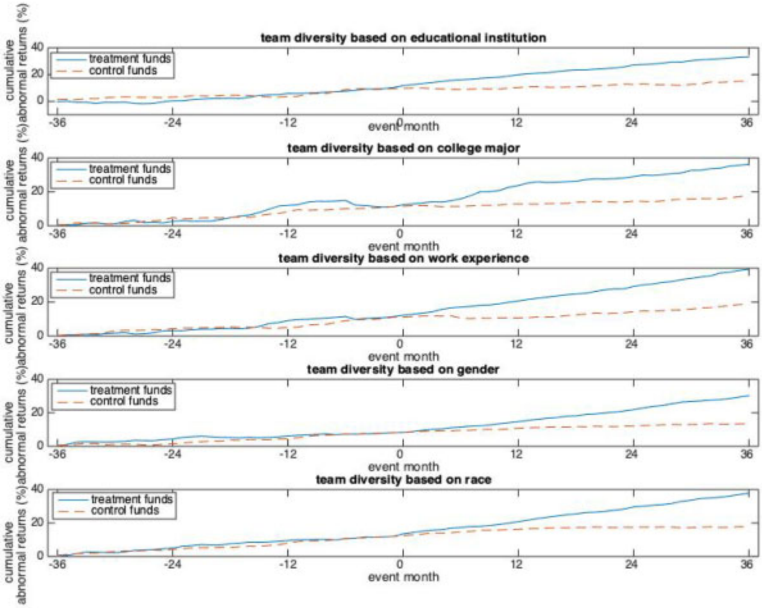

Figure 2
Event study analysis of diversity-enhancing manager additions to hedge fund teams.
Fund abnormal return is Fung and Hsieh (2004) seven-factor monthly alpha with factor loadings estimated over the last 24 months. Event month is the month that a fund management team increases its educational institution-, 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 represent the performance of the treatment funds. The dashed lines represent the performance of the control funds. The sample period is from January 1994 to June 2016.

Table IA7 of the Internet Appendix indicates that inferences remain unchanged when we (a) change the event window to 24 or 48 months before and after the event, (b) match control funds to treatment funds based on propensity score, where the covariates are the fund and team controls from the baseline performance regressions, (c) study diversity-diminishing manager additions, and (d) 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 on 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 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, that is, those with school SAT scores that fall below the average SAT scores of the current team.

2.2.2 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 U.S. Census data.[15] We obtain hometown information for 240 hedge fund founding partners who manage 897 funds by searching for founders' 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 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 10 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 most of the fund founders with hometown information are white (91.67%), the Table IA8 results capture the

[15] 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.

Table 5
Instrumental variable analysis

	Dependent variable														
	IV first stage					IV second stage					OLS regressions				
Independent variable	*DIVERSITY_ EDU* (1)	*DIVERSITY_ MAJOR* (2)	*DIVERSITY_ EXP* (3)	*DIVERSITY_ GENDER* (4)	*DIVERSITY_ RACE* (5)	*ALPHA* (6)	*ALPHA* (7)	*ALPHA* (8)	*ALPHA* (9)	*ALPHA* (10)	*ALPHA* (11)	*ALPHA* (12)	*ALPHA* (13)	*ALPHA* (14)	*ALPHA* (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	.657	.258	.046	.346	.209	.044	.040	.013	.014	.011	.056	.056	.056	.032	.031
N	31,250	31,412	31,250	60,223	59,998	24,715	24,770	24,715	43,944	43,788	24,715	24,770	24,715	43,944	43,788

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 the management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lockup period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and logarithm 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. $^{*}p<.1$; $^{**}p<.05$.

greater propensity of white founders who grew up in racially diverse localities to hire nonwhites.[16]

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.[17] Another concern is that demographically diverse hometowns may be larger and funds based in larger cities outperform due to knowledge spillovers (Christoffersen and 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 available on request, we find that our findings are qualitatively unchanged when we limit the sample to hedge funds set up outside of their founders' hometowns or to hedge funds based in New York City.

2.2.3 Managers who 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 who simultaneously operate both solo-managed and team-managed hedge funds. For our analysis, we study teams that comprise only managers who 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

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

17 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.

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 Equation (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.

2.3 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 nonoverlapping 24-month period, we estimate regressions analogous to those in Equation (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

Table 6
Managers who simultaneously operate both solo- and team-managed hedge funds

Independent variable	Dependent variable									
	RET_DIFF (1)	*ALPHA_DIFF* (2)	*RET_DIFF* (3)	*ALPHA_DIFF* (4)	*RET_DIFF* (5)	*ALPHA_DIFF* (6)	*RET_DIFF* (7)	*ALPHA_DIFF* (8)	*RET_DIFF* (9)	*ALPHA_DIFF* (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	.040	.051	.046	.053	.048	.047	.084	.064	.076	.053
N	31,115	24,422	23,938	19,567	31,115	24,422	44,987	31,438	32,193	23,083

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*), lockup period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and logarithm 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. $^{*}p < .1$; $^{**}p < .05$.

Table 7
Diversity, stock market anomalies, and behavioral biases

Independent variable				
DIVERSITY_EDU (1)	*DIVERSITY_MAJOR* (2)	*DIVERSITY_EXP* (3)	*DIVERSITY_GENDER* (4)	*DIVERSITY_RACE* (5)
A: Regressions on ANOMALY for all hedge funds				
0.209**	0.155**	0.171**	0.101**	0.123**
(3.66)	(5.15)	(6.94)	(3.00)	(3.58)
B: Regressions on ANOMALY for equity-focused hedge funds				
0.312**	0.173**	0.179**	0.192**	0.120*
(4.83)	(4.05)	(4.15)	(3.35)	(2.31)
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)
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)
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)
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)
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)
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)

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 nonoverlapping 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 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*), lockup period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and logarithm 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. $*p<.1$; $**p<.05$.

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 on 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.

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 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 on 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 lockups 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 (a) redemption period, (b) notice period, and (c) lockup period.[18] Next, we reestimate the Equation (1) regressions on fund alpha for each of the three groups without fund redemption period and lockup period as control variables. The coefficient

[18] The three groups are not equal in size because of 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 lockup period groups comprise funds with no lockups, with lockup periods that are less than or equal to a year, and with lockup periods that exceed a year, respectively. The discrete nature of the redemption period, notice period, and lockup period data prevents us from sorting funds into equal terciles based on their share restrictions.

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 lockup periods.

2.4 Fund investment and operational risk

Because of 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 premiums 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 variables from Equation (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 noncontiguous 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.

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 per Brown et al. (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

Table 8
Diversity and fund shareholder restrictions

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)
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)
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)
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)

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 the management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), and logarithm 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 lockup period groups in panel C comprise funds with no lockups, with lockup periods that are less than or equal to a year, and with lockup periods that exceed a year, respectively. The sample period is from January 1994 to June 2016. *$p<.1$; **$p<.05$.

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

A: Regressions on fund investment risk

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

B: Regressions on fund operational risk

		Independent variable		
DIVERSITY_EDU	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*
(1)	(2)	(3)	(4)	(5)
1: 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]
2: Cox regressions on TERMINATION				
−0.526**	−0.139*	−0.223**	−0.206**	−0.265**
(−5.47)	(−2.26)	(−3.77)	(−3.90)	(−5.92)
3: 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]
4: OLS regressions on OMEGA				
−0.177**	−0.264*	−0.170**	−0.125**	−0.142**
(−2.65)	(−2.04)	(−2.64)	(−3.29)	(−2.70)

(*Continued*)

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 Equation (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, 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

Table 9
(Continued)

C: Regressions on fund performance flags

Independent variable				
DIVERSITY_EDU	*DIVERSITY_MAJOR*	*DIVERSITY_EXP*	*DIVERSITY_GENDER*	*DIVERSITY_RACE*
(1)	(2)	(3)	(4)	(5)
1: 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]
2: 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]
3: 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]
4: 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]

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 per Brown et al. (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 the management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lockup period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and logarithm 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 regressions) 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. $*p<.1$; $**p<.05$.

homogeneous teams, hedge funds operated by diverse teams have a 2.37% to 6.97% lower probability of terminating in any given year.[19] Similarly,

19 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 $100*(1-(1-0.006)^{12})=6.97\%$.

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 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.[20]

2.5 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.[21] Next, for each diversity group, we estimate regressions on fund performance with the logarithm of last month's fund size as the independent variable of interest. We include as independent variables the other fund controls from Equation (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

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

[21] Along 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 equal to one, the other funds are sorted equally into the other two groups based on gender diversity.

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

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

	Diversity in educational inst.			Diversity in college major			Diversity in work experience			Diversity in gender			Diversity in race		
Independent variable	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)	High (7)	Medium (8)	Low (9)	High (10)	Medium (11)	Low (12)	High (13)	Medium (14)	Low (15)
1: 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)
2: 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)

B: Double sorts on team diversity and past fund performance

	Diversity in educational inst.			Diversity in college major			Diversity in work experience			Diversity in gender			Diversity in race		
Hedge fund portfolio	High (1)	Medium (2)	Low (3)	High (4)	Medium (5)	Low (6)	High (7)	Medium (8)	Low (9)	High (10)	Medium (11)	Low (12)	High (13)	Medium (14)	Low (15)
1: 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
2: 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

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 logarithm of fund size (log(*FUNDSIZE*)). The other independent variables include fund characteristics, such as the management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lockup 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. Panels A1 and A2 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 (panel B1) or on past 24-month fund return (panel B2). The t-statistics are derived from White (1980) standard errors. The sample period is from January 1994 to June 2016. $^{*}p<.1$; $^{**}p<.05$.

5% level. These results suggest that team diversity allows funds to circumvent capacity constraints.

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) should be concentrated in hedge funds managed by diverse teams given their ability to sidestep capacity constraints.

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. 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 panel B1 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, that is, 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. Panel B2 in Table 10 indicates that our conclusions remain unchanged with this adjustment.

2.6 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 Equation (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-based diversity and weakest for race-based diversity. In general, flows tend to respond more positively to functional diversity than to nonfunctional diversity, suggesting that investors value functional diversity more. These results echo those of Chidambaran, Liu, and Prabhala (2022), who find that boards tend to value skill diversity more than they do age or ethnic diversity.

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.[22]

3. Robustness Tests

To test whether our results are sensitive to the way we measure diversity, we redo the baseline performance regressions in Equation (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).[23] 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, Multistrategy, 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 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. Multicollinearity 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

22 In results available on 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.

23 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).

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 plausibly 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.

4. 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.

Table 11
Robustness tests

Regressions on *RETURN*					Regressions on *ALPHA*				
Independent variable									
DIVERSITY_EDU (1)	*DIVERSITY_MAJOR* (2)	*DIVERSITY_EXP* (3)	*DIVERSITY_GENDER* (4)	*DIVERSITY_RACE* (5)	*DIVERSITY_EDU* (6)	*DIVERSITY_MAJOR* (7)	*DIVERSITY_EXP* (8)	*DIVERSITY_GENDER* (9)	*DIVERSITY_RACE* (10)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)

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 the management fee (*MGTFEE*), performance fee (*PERFFEE*), high-water mark indicator (*HWM*), lockup period in years (*LOCKUP*), leverage indicator (*LEVERAGE*), fund age in years (*AGE*), redemption period in months (*REDEMPTION*), and logarithm 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. $^{*}p<.1$; $^{**}p<.05$.

These findings showcase the value of diversity. Diverse teams not only outperform homogeneous teams but 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.

References

Acemoglu, D., S. Johnson, and J. Robinson. 2001. The colonial origins of comparative development: An empirical investigation. *American Economic Review* 91:1369–01.

Adams, R. B., and D. Ferreira. 2009. Women in the boardroom and their impact on governance and performance. *Journal of Financial Economics* 94:291–309.

Agarwal, V., N. Daniel, and N. Y. Naik. 2009. Role of managerial incentives and discretion in hedge fund performance. *Journal of Finance* 64:2221–56.

Agarwal, V., and N. Y. Naik. 2000. Multi-period performance persistence analysis of hedge funds. *Journal of Financial and Quantitative Analysis* 35:327–42.

———. 2004. Risk and portfolio decisions involving hedge funds. *Review of Financial Studies* 17:63–98.

Aggarwal, R. K., and N. Boyson. 2016. The performance of female hedge fund managers. *Review of Financial Economics* 29:23–36.

Aggarwal, R. K., and P. Jorion. 2010. The performance of emerging hedge funds and managers. *Journal of Financial Economics* 96:238–56.

Ahern, K. R., and A. K. Dittmar. 2012. The changing of the boards: The impact on firm valuation of mandated female board representation. *Quarterly Journal of Economics* 127:137–97.

Alesina, A., and E. La Ferrara. 2005. Ethnic diversity and economic performance. *Journal of Economic Literature* 43:762–800.

Aragon, G. 2007. Share restrictions and asset pricing: Evidence from the hedge fund industry. *Journal of Financial Economics* 83:33–58.

Bali, T., S. Brown, and O. Caglayan. 2014. Macroeconomic risk and hedge fund returns. *Journal of Financial Economics* 114:1–19.

Bali, T., N. Cakici, and R. Whitelaw. 2011. Maxing out: Stocks as lotteries and the cross-section of stock returns. *Journal of Financial Economics* 99:427–46.

Bär, M., A. Niessen, and S. Ruenzi. 2009. The impact of team diversity on mutual fund performance. Working Paper, University of Mannheim.

Barahona, R., S. Casella, and K. A. E. Jansen. 2023. Do teams alleviate or exacerbate biased beliefs? Evidence from extrapolation bias in mutual funds. Working Paper, Tilburg University.

Barber, B., and T. Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55:773–806.

———. 2001. Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics* 116:261–92.

Barclays Capital. 2011. Affirmative investing: Women and minority owned hedge funds. June. http://www.managedfunds.org/wp-content/uploads/2011/08/HF-Pulse-Affirmative-Investing-June-2011-Letter.pdf

Berger, A. N., T. Kick, M. Koetter, and K. Schaeck. 2013. Does it pay to have friends? Social ties and executive appointments in banking. *Journal of Banking and Finance* 37:2087–105.

Berk, J., and R. Green. 2004. Mutual fund flows and performance in rational markets. *Journal of Political Economy* 112:1269–95.

Berk, J., and J. H. van Binsbergen. 2015. Measuring skill in the mutual fund industry. *Journal of Financial Economics* 118:1–20.

Bhardwaj, G., G. Gorton, and K. G. Rouwenhorst. 2014. Fooling some of the people all of the time: The inefficient performance and persistence of commodity trading advisors. *Review of Financial Studies* 27:3099–132.

Bollen, N., and V. Pool. 2009. Do hedge fund managers misreport returns? Evidence from the pooled distribution. *Journal of Finance* 64:2257–88.

———. 2012. Suspicious patterns in hedge fund returns and the risk of fraud. *Review of Financial Studies* 25:2673–702.

Brown, S., W. Goetzmann, B. Liang, and C. Schwarz. 2009. Estimating operational risk for hedge funds: The ω-score. *Financial Analysts Journal* 65:43–53.

Brunnermeier, M. K., and S. Nagel. 2004. Hedge funds and the technology bubble. *Journal of Finance* 59:2013–40.

Budra, M., and D. Wilson. 2023. The alternatives: A practical guide to how hedge fund firms large and small can improve diversity and inclusion. Report, AIMA. https://www.aima.org/sound-practices/guides-to-sound-practices/the-alternatives.html

Burton, K., and H. Parmar. 2020. Hedge funds face mounting pressure with diversity questionnaire. *Bloomberg*, November 10. https://www.bloomberg.com/news/articles/2020-11-10/hedge-funds-face-mounting-pressure-with-diversity-questionnaire

Cao, C., G. Farnsworth, and H. Zhang. 2021. The economics of hedge fund startups: Theory and empirical evidence. *Journal of Finance* 76:1427–69.

Carhart, M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52:57–82.

Catsambis, S. 1994. The path to math: Gender and racial-ethnic differences in mathematics participation from middle school to high school. *Sociology of Education* 67:199–215.

Chevalier, J., and G. Ellison. 1999. Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance. *Journal of Finance* 54:875–99.

Chidambaran, N. K., Y. Liu, and N. Prabhala. 2022. Director diversity and inclusion: At the table but in the game? *Financial Management* 51:193–225.

Christoffersen, S. E. K., and S. Sarkissian. 2009. City size and fund performance. *Journal of Financial Economics* 92:252–75.

Chuprinin, O., and D. Sosyura. 2018. Family descent as a signal of managerial quality: Evidence from mutual funds. *Review of Financial Studies* 31:3756–820.

Cohen, L., A. Frazzini, and C. Malloy. 2008. The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy* 116:951–79.

Cohen, L., C. Malloy, and M. Foreman. 2015. Domeyard: Starting a high-frequency trading (HFT) hedge fund. Case 9-215-036. Harvard Business School, Boston, MA.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance* 52:1035–58.

Duarte, J., F. Longstaff, and F. Yu. 2007. Risk and return in fixed income arbitrage: Nickels in front of a steamroller? *Review of Financial Studies* 20:769–811.

Evans, R. B., M. P. Prado, A. E. Rizzo, and R. Zambrana. 2022. Identity, diversity, and team performance: Evidence from U.S. mutual funds. Working Paper, University of Virginia.

Fama, E., and J. MacBeth. 1973. Risks, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81:607–36.

Fama, E., and K. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

———. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116:1–22.

Flap, H., and M. Kalmijn. 2001. Assortative meeting and mating: Unintended consequences of organized settings for partner choices. *Social Forces* 79:1289–312.

Frazzini, A., and L.H. Pedersen. 2014. Betting against beta. *Journal of Financial Economics* 111:1–25.

Fung, W., and D. Hsieh. 2004. Hedge fund benchmarks: A risk based approach. *Financial Analysts Journal* 60:65–80.

———. 2009. Measurement biases in hedge fund performance data: An update. *Financial Analysts Journal* 65:36–38.

Getmansky, M. 2012. The life cycle of hedge funds: Fund flows, size, competition, and performance. *Quarterly Journal of Finance* 2:1–53.

Getmansky, M., A. Lo, and I. Makarov. 2004. An econometric model of serial correlation and illiquidity of hedge fund returns. *Journal of Financial Economics* 74:529–610.

Glaeser, E., S. Kerr, and W. Kerr. 2015. Entrepreneurship and urban growth: An empirical assessment with historical mines. *Review of Economics and Statistics* 97:498–520.

Goetzmann, W., J. Ingersoll, M. Spiegel, and I. Welch. 2007. Portfolio performance manipulation and manipulation-proof performance measures. *Review of Financial Studies* 20:1503–46.

Gompers, P., and S. Wang. 2021. And the children shall lead: Gender diversity and performance in venture capital. *Journal of Financial Economics* 142:1–22.

Goodreau, S. M., J. A. Kitts, and M. Morris. 2009. Birds of a feather, or friend of a friend? Using exponential random graph models to investigate adolescent social networks. *Demography* 46:103–25.

Greene, W. H. 2018. *Econometric analysis*. New York: Pearson.

Harvey, C. R., Y. Liu, E. K. M. Tan, and M. Zhu. 2021. Crowding: Evidence from fund managerial structure. Working Paper, Duke University.

Hegde, D., and J. Tumlinson. 2014. Does social proximity enhance business partnerships? Theory and evidence from ethnicity's role in U.S. venture capital. *Management Science* 60:2355–80.

Hong, L., and S. E. Page. 2004. Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proceedings of the National Academy of Sciences* 101:16385–89.

Hwang, B. H., and S. Kim. 2009. It pays to have friends. *Journal of Financial Economics* 93:138–58.

Imai, K., and K. Khanna. 2016. Improving ecological inference by predicting individual ethnicity from voter registration records. *Political Analysis* 24:263–72.

Ingram, P., and P. W. Roberts. 2000. Friendships among competitors in the Sydney hotel industry. *American Journal of Sociology* 106:387–423.

Jehn, K. A., G. B. Northcraft, and M. A. Neale. 1999. Why differences make a difference: A field study of diversity, conflict, and performance in workgroups. *Administrative Science Quarterly* 44:741–63.

Jorion, P., and C. Schwarz. 2014. Are hedge fund managers misreporting? Or not? *Journal of Financial Economics* 111:311–27.

———. 2019. The fix is in: Properly backing out backfill bias. *Review of Financial Studies* 32:5048–99.

Kalmijn, M. 1998. Intermarriage and homogamy: Causes, patterns, trends. *Annual Review of Sociology* 24:395–421.

Kim, D., and L.T. Starks. 2016. Gender diversity on corporate boards: Do women contribute unique skills? *American Economic Review* 106:267–71.

Klocke, U. 2007. How to improve decision making in small groups: Effects of dissent and training interventions. *Small Group Research* 38:437–68.

Kosowski, R., N. Y. Naik, and M. Teo. 2007. Do hedge funds deliver alpha? A Bayesian and bootstrap approach. *Journal of Financial Economics* 84:229–64.

Laumann, E. O. 1973. *Bonds of pluralism: The form and substance of urban social networks*. New York: John Wiley and Sons.

Lazarsfeld, P. F., and R. K. Merton. 1954. Friendship as a social process: A substantive and methodological analysis. In *Freedom and control in modern society*, eds. M. Berger, T. Abel, and H. Charles, 18–66. New York: Van Nostrand.

Lerner, J., A. Leamon, R. Sessa, R. Dewan, and S. Holt. 2019. 2018 Diverse asset management firm assessment, Bella Research Group Report.

Li, H., X. Zhang, and R. Zhao. 2011. Investing in talents: Manager characteristics and hedge fund performances. *Journal of Financial and Quantitative Analysis* 46:59–32.

Liang, B. 2000. Hedge funds: The living and the dead. *Journal of Financial and Quantitative Analysis* 35:309–26.

Louch, H. 2000. Personal network integration: Transitivity and homophily in strong-tie relations. *Social Networks* 22:45–64.

Lowenstein, R. 2000. *When genius failed: The rise and fall of Long-Term Capital Management*. New York: Random House.

Marquis, C., and A. Tilcsik. 2013. Imprinting: Towards a multilevel theory. *Academy of Management Annals* 7:195–245.

Marsden, P. V. 1987. Core discussion networks of Americans. *American Sociological Review* 52:122–31.

McPherson, M., L. Smith-Lovin, and J. M. Cook. 2001. Birds of a feather: Homophily in social networks. *Annual Review of Sociology* 27:415–44.

Mirabella, A. 2021. Hedge funds run by women, minorities outperform market peers. *Bloomberg*, November 9. https://www.bloomberg.com/news/articles/2021-11-08/hedge-funds-run-by-women-minorities-outperform-market-peers#xj4y7vzkg

Munro, J., and C. Slear. 2020. These hedge funds are rare but they're starting to shine. *Bloomberg*, April 2. https://www.bloomberg.com/professional/blog/these-hedge-funds-are-rare-but-theyre-starting-to-shine/

Naik, N. Y., T. Ramadorai, and M. Strömqvist. 2007. Capacity constraints and hedge fund strategy returns. *European Financial Management* 13:239–56.

Nelson, J. L., and S. P. Vallas. 2021. Race and inequality at work: An occupational perspective. *Sociology Compass* 15, e12926.

Newey, W., and K. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–08.

Odean, T. 1998. Are investors reluctant to realize their losses? *Journal of Finance* 53:1775–98.

Parmar, H., and A. Massa. 2020. Hedge funds fall flat when it comes to diversifying their ranks. *Bloomberg*, October 7. https://www.bloomberg.com/news/articles/2020-10-07/hedge-funds-fall-flat-when-it-comes-to-diversifying-their-ranks

Pástor, L., and R. F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111:642–85.

Pelled, L. H., K. M. Eisenhardt, and K. R. Xin. 1999. Exploring the black box: An analysis of work group diversity, conflict, and performance. *Administrative Science Quarterly* 44:1–28.

Phillips, K. W., K. A. Liljenquist, and M. A. Neale. 2009. Is the pain worth the gain? The advantages and liabilities of agreeing with socially distinct newcomers. *Personality and Psychology Bulletin* 35:336–50.

Quillian, L., and M. E. Campbell. 2003. Beyond black and white: The present and future of multiracial friendship segregation. *American Sociological Review* 68:540–66.

Ramadorai, T. 2013. Capacity constraints, investor information, and hedge fund returns. *Journal of Financial Economics* 107:401–16.

Rock, D., and H. Grant. 2016. Why diverse teams are smarter. *Harvard Business Review*.

Rosenbaum, E. 1996. Racial/ethnic differences in home ownership and housing quality, 1991. *Social Problems* 43:403–26.

Shrum, W., N. H. Cheek, and S. M. Hunter. 1988. Friendship in school - gender and racial homophily. *Sociology of Education* 61:227–39.

Simsek, Z., B. C. Fox, and C. Heavey. 2015. “What’s past is prologue”: A framework, review, and future directions for organizational research on imprinting. *Journal of Management* 41:288–317.

Stambaugh, R. F., J. Yu, and Y. Yuan. 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance* 70:1903–48.

Stein, J. 2005. Why are most funds open-end? Competition and the limits of arbitrage. *Quarterly Journal of Economics* 120:247–72.

Stock, J. H., J. H. Wright, and M. Yogo. 2002. A survey of weak instruments and weak identification in Generalized Method of Moments. *Journal of Business and Economic Statistics* 20:518–29.

Stolper, O., and A. Walter. 2018. Birds of a feather: The impact of homophily on the propensity to follow financial advice. *Review of Financial Studies* 32:524–63.

Teachman, J. D. 1980. Analysis of population diversity. *Sociological Methods and Research* 8:341–62.

United States Department of the Army. 2014. *Insurgencies and countering insurgencies*. FM 3-24 MCWP 3-33.5.

White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48:817–38.

Williams, D. R., N. Priest, and N. B. Anderson. 2016. Understanding associations among race, socioeconomic status, and health: Patterns and prospects. *Health Psychology* 35:407–11.

Ye, J., S. Han, Y. Hu, B. Coskun, M. Liu, H. Qin, and S. Skiena. 2017. Nationality classification using name embeddings. Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, 1897–906.