Diversity Investing

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March 18, 2016

Abstract

Using a new dataset on more than 50,000 top executives in US firms from 2002 to 2014, we show that top management team diversity – a new text-based measure of how diverse managers are in terms of personal characteristics and prior experiences – matters for stock returns. Firms with diverse management teams have significantly higher risk-adjusted returns than firms with homogenous management teams. A long-short strategy on the diversity characteristic yields higher risk-adjusted returns, and higher Sharpe ratios, than most leading asset pricing anomalies over our sample period. Diversity returns are driven by large-cap stocks and the long leg of the strategy, so diversity investing seems feasible for investors. Additional results suggest the large returns to diversity investing are due to (i) diversity being a new dimension of "quality" stocks and (ii) mispricing.

Keywords: Behavioral Finance, Top Management Teams, Anomalies, Diversity

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1. Introduction

A large management literature analyzes how *diversity* of a top management team affects corporate decision making. Broadly defined, diversity refers to within top management team variation in functional backgrounds, industry and firm tenures, educational credentials, and other characteristics that define an executive's "cognitive frame" (Hambrick (2007)). Compared with literally hundreds of papers on the subject in other fields, there is very little work on team diversity in the finance literature.

Our paper aims to close this gap by studying the impact of top management team diversity on stock returns. We exploit a new source of data, managerial biographies firms are required to disclose to the Securities and Exchange Commission (SEC), and use them to develop a novel text-based measure of team diversity. Our final dataset covers more than 50,000 executives in about 5,400 unique firms in the U.S. over the period from 2002 to 2014.

Our central result is that firms with diverse top management teams ("diverse firms") have higher risk-adjusted stock returns than firms with non-diverse top management teams ("homogenous firms"). Over the period we study, the magnitude of the risk-adjusted return difference is on par with, or even exceeding, the leading return anomalies in the literature. A "diversity investing" strategy – buying diverse firms and selling homogenous firms – is easily implementable, because its returns are concentrated in large-cap stocks and the long leg.

A key challenge our paper addresses is measuring diversity of the top management team for a large set of firms. To that end, we propose using textual analysis on a new source of managerial background data available for almost all U.S. executives. Specifically, we exploit the fact that the SEC requires listed firms to disclose biographies of top executives, containing information about, for example, their educational background and prior work experience. We retrieve those biographies for all top management team members, and we then measure diversity of a team from the similarity of the underlying texts, using textual analysis tools as in Hanley and Hoberg (2010) and Hoberg and Phillips (2010). An advantage of this approach is that we can build a dataset on diverse management teams that is, to the best of our knowledge, among the largest ever assembled.

A second advantage of our approach is conceptual. While diversity is a broad, multi-faceted aspect of management teams (e.g, Jackson, Joshi, and Erhardt (2003)), most existing work on diversity focuses on individual, easy-to-measure, managerial attributes such as tenure, ethnicity, gender, or pay. Such studies may capture some relevant dimensions of diversity, but miss many others. By contrast, our text-based measure allows us to capture many dimensions of diversity simultaneously, and therefore to bring fundamentally new evidence to the table.

Using our new measure, we show that firms with diverse top management teams outperform firms with homogenous top management teams. For raw returns, the strategy of going long diverse firms and shorting homogenous firms provides a 55bps average monthly outperformance over our sample period, with an annualized Sharpe ratio of 0.79. This significant outperformance is robust to the standard risk-adjustments for size and book-to-market, as well as three-factor, four-factor, and other factor models. Independent of risk-adjustments, we find that returns from diversity investing are in most cases higher than those from prominent investment strategies like momentum, asset growth, accruals, net stock issuance, and profitability.

Figure 1 presents cumulative size and book-to-market adjusted returns from various investment strategies over our 13-year sample period. The diversity strategy delivers a cumulative risk-adjusted return of 90%, which dominates all of the prominent alternative strategies we consider. A remarkable feature of diversity investing, visible from Figure 1, is that it combines higher returns with lower volatility.

Another remarkable feature of the diversity strategy is that it is a large-cap phenomenon: it works only on a value-weighted basis, and it works best when we focus on stocks in the S&P500. This is interesting because a common concern about anomalies is that most of them produce alphas for tiny stocks, which are costly to trade (e.g., Novy-Marx and Velikov (2015)). Hence most reported anomalies are relevant only for a small portion of market wealth. The diversity strategy is different, because it generates alpha precisely for the largest stocks, which are most relevant on a dollar-weighted basis. Because diversity itself is quite stable over time, diversity investing does not require high portfolio turnover. Combined, the focus on large stocks and the low turnover imply that diversity investing seems feasible for investors because transaction costs are very low.

Additional results show that diversity investing is a robust new feature of the data that investors should care about. First, the diversity returns are not subsumed by a combination of other anomaly strategies. For example, sorting stocks on diversity *within* momentum groups still leads to significant outperformance of diverse firms. Second, within-firm changes in diversity lead to predictable changes in returns: firms whose top management team becomes less diverse experience an abnormal negative drift in returns in the 12 subsequent months, while there is a strong upward drift in returns for stocks that become more diverse. By construction of our tests, those results cannot be due to risk captured by the standard Fama-French-Carhart factors; they are also not driven by takeovers or sell-offs. These tests argue against the concern that diversity is a proxy for underlying fundamentals.

While the main contribution of our paper is documenting the diversity anomaly as a strong empirical fact, we also provide some suggestive evidence on potential mechanisms. One possibility is that diverse firms may be more risky, and therefore require higher returns to induce investors to hold their stocks in equilibrium. To the extent that the standard set of risk-adjustments captures the relevant risk factors, this is not the case.

An alternative, suggested by our results, is that the substantial returns to diversity investing may be driven by a combination of two things. First, diversity of the top management team may be a previously underemphasized dimension of "quality" stocks which is important *over and above* the quality variables used in the literature (e.g., Asness, Frazzini, and Pedersen (2013), Fama and French (2014), Novy-Marx (2014)). Quality, as currently measured in the literature, explains at best up to 25% of the observed diversity alphas. Second, diversity returns may be driven by mispricing. Consistent with this view, diversity returns are concentrated, all else equal, in firms with lower analyst coverage and higher idiosyncratic volatility, i.e. in firms which are harder to value, harder to arbitrage, and firms in which analysts provide less information for investors.

In sum, our paper suggests that diversity of top management teams is a powerful predictor of stock returns. The idea that top management team diversity matters for corporate outcomes is firmly rooted in a vast literature in other fields of business studies. Using diversity as a sorting variable for stock returns is therefore a natural subject of study. Hence, data mining concerns should be minimal. In addition, there is both anecdotal and scientific evidence suggesting investors and analysts often pay close attention to the quality of the management team (e.g., Du Pont Capital (2014), Brown, Call, Clement, and Sharp (2015)). Hence, understanding whether and how investors' views on top management teams affect stock returns is important. Our paper contributes by suggesting diversity is a specific characteristic of top management teams which investors care about, and which, therefore, affects stock returns.

The finance literature on diversity is sparse, and we are not aware of any study on how top management team diversity affects stock returns which uses a dataset of comparable size and a diversity measure that can capture multiple dimensions of diversity. The papers most closely related to ours include studies on the effects of women on boards (e.g., Adams and Ferreira (2009), Ahern and Dittmar (2012), Adams (2015)), and studies on CEO power and founder CEOs (e.g., Adams, Almeida, and Ferreira (2005), Fahlenbrach (2009), Bebchuk, Cremers, and Peyer (2011)).

While we share with these papers the general notion that characteristics of a firm's leadership matter, our paper is different on several important dimensions. First, while the mentioned studies focus on a specific dimension of diversity (i.e., gender, power, founder status), our text-based approach captures many facets of diversity simultaneously. We can therefore contribute fundamentally new results to the literature. Second, by analyzing texts we are able to work with an unusually large sample of firms. Third, the work on gender diversity focuses on boards, while we focus on executives. Fourth, studies on founder CEOs and CEO power focus on *Diversity as Disparity*, i.e. differences in hierarchy within teams. By contrast, we look at *Diversity as Variety*, which refers to "differences in kind, source, or category of relevant knowledge or experience among unit members." Harrison and Klein (2007) argue that these different types of diversity may have different bearing on firm performance. Finally, our approach focuses on what Jackson, Joshi, and Erhardt (2003) call *Task-Related Diversity*, i.e. diversity in function, prior experience, and education which, according to those authors, are more likely to be related to "knowledge, skills and abilities needed in the workplace," than demographic variables like age, gender, or race.

2. Background and Data

2.1 Background on Top Management Team Diversity

The idea that top management teams matter for firm outcomes has a long tradition in the management literature. In their seminal paper, Hambrick and Mason (1984) argue that key to understanding why organizations act or perform the way they do is the analysis of the biases and disposition of their "upper echelon", i.e., their top executives. A central conjecture in Hambrick and Mason (1984) is that an executive's cognitive frame, which determines her values and beliefs, and therefore, ultimately, her corporate decisions, can be proxied for by observable characteristics. In a review article on the vast upper echelons literature, Hambrick (2007) writes:

> "Given the great difficulty obtaining conventional psychometric data on top executives (especially those who head major firms), researchers can reliably use information on executives' functional backgrounds, industry and firm tenures, educational credentials, and affiliations to develop predictions of strategic actions... researchers have generated substantial evidence that demographic profiles of executives (both individual executives and top management teams) are highly related to strategy and performance outcomes."

The empirical approach we use in this paper, to analyze biographical texts on corporate executives with respect to how similar they are, is consistent with the upper echelon paradigm.

A branch of research heavily influenced by the upper echelons idea analyzes how top management team diversity affects corporate decisions (Jackson, Joshi, and Erhardt (2003), Harrison and Klein (2007), Nielsen (2010)). While the literature on diversity in top management teams has not yet reached a consensus on just how much diversity matters for firm outcomes, the sheer volume of papers written on the subject over several decades suggests that it is a first-order economic issue. Perhaps surprisingly, given the attention diversity has received in other fields, our paper is among the first attempts to analyze its impact in the finance literature.

Contributing to the debate about whether diverse management teams help firms make better decisions is not our central goal, even though some of our results speak to this issue. Our central goal is to investigate whether top management team diversity matters for stock returns. This is interesting, because, with rational investors, better managerial decisions should be reflected in higher *prices*, but not, in general, in higher *returns*. So whether teams make better decisions, and whether stock returns are higher when diversity is high, are separate questions.

As we detail below, there are three reasons why diversity could matter for stock returns. First, diversity may be related to risk factors, and therefore discount rates. Second, diversity may be a dimension of "quality" investing, and therefore command higher returns *holding market-to-book constant*. Third, diversity may be a characteristic investors systematically misprice.

2.2 Measuring Diversity from Biographical Texts

A main innovation of our study is to propose a new way of measuring top management team diversity, which builds on recent advances in textual analysis in the finance literature.

The core of our data are biographical texts which all listed U.S. firms need to file with the SEC under Regulation S-K for each top executive and year. Regulation S-K falls under the U.S. Securities Act of 1933. Among its reporting requirements, item 401(e) requires firms to report for each individual director or executive "the business experience during the past five years [...] including: each person's principal occupations and employment during the past five years, [...] the specific experience, qualifications, attributes or skills that led to the conclusion that the person should serve as a director for the registrant at the time that the disclosure is made, in light of the registrant's business and structure, [...] the person's particular areas of expertise or other relevant qualifications [...] the nature of the responsibility undertaken by the individual in prior positions."

For each firm, and each of its top management team members, filings are available in electronic form from the SEC on its EDGAR website. We use a web crawler to retrieve these data, going back until 2002 (coverage issues and changes in layout requirements dictate our starting year).

Diversity in our study is the degree of dissimilarity in the backgrounds of a firms' executive officers, as represented in the biographies reported in the firms' filings. To measure Diversity, we rely on the cosine similarity method, widely used in a recent strand of the finance literature (e.g., Hanley and Hoberg (2010), Hoberg and Phillips (2010)).

First, using all executive biographies in all companies in a given year t, we define a word dictionary for year t. The word dictionary is a vector containing all N_t unique words used in all biographies. Only word roots are considered: for example, "sell", "selling" and "sold" all enter the dictionary as "sell". Next, for each biographical text associated with executive i, company k, and year t, we create a vector T_{ikt}. T_{ikt} describes the biography's word usage, taking value x in the n-th position if word n of the dictionary appears in the biography x times. For each pair of executives i, j of company k, in year t, we then define the similarity of two biographical texts as:

$$CS_{ijkt} = \frac{T'_{ikt} T_{jkt}}{\parallel T_{ikt} \parallel \times \parallel T_{jkt} \parallel} = \frac{\sum_{n=1}^{N} T_{nikt} \times T_{njkt}}{\sqrt{\sum_{n=1}^{N_t} T_{nikt}^2} \times \sqrt{\sum_{n=1}^{N_t} T_{njkt}^2}}. \tag{1}$$

CS is the cosine of the angle between T_{ikt} and T_{jkt} in Euclidean space, and is thus bounded between 0 and 1. We then define diversity for a given firm-year as:

$$D_{kt} = 1 - \overline{CS}_{kt}, \tag{2}$$

where $\overline{CS}_{kt}$ is the average of CS_{ijkt} over all executive pairs in firm k in year t. If a firm has only one listed top executive, which happens in about 7% of firm-years in our final dataset, we set D to zero, because a single-manager team is maximally homogenous. We leave those single-manager firms in our dataset to be conservative, but we show later that our main results become stronger when we exclude single-manager firms.

To get an intuition for our measure, consider a simple example with only two executives and a word dictionary of only two words "Ball" and "Red". If executive i's biography reads "Ball", her vector T_{ikt} is (1 0). If executive j's biography is also "Ball", then $T_{jkt} = (1\ 0)$ and, using the definition above, $CS_{ijkt} = (1 \times 1 + 0 \times 0)/\left(\sqrt{1} \times \sqrt{1}\right) = 1$. Hence, if executives have identical biographies, $CS = 1$ and, therefore, $D = 0$. Diversity for this top management team is consequently zero. Suppose now that executive j's biography reads "Red". Then, $T_{jkt} = (0\ 1)$ and $CS_{ijkt} = (1 \times 0 + 0 \times 1)/\left(\sqrt{1} \times \sqrt{1}\right) = 0$. Hence, $D = 1$, which means this team of top executives is maximally diverse.

To get an impression of how well the procedure works, we provide selected examples of firms with low diversity scores, according to equation (2), in Appendix B. For brevity, we only show two executives for each team. The first two examples suggest we capture similarities in education (Anaren Inc.'s executives both got an MBA from Syracuse University) and prior work experience (Enbridge Energy LLC's executives both worked for Shell Gas Transmission). In the final example, Giant Motorsports, the two executives share the same last name (they are, in fact, brothers), and they both had previously been "founder, President and sole shareholder" of companies in the motorcycle business. These three examples show how the text-based approach helps us measure a number of diversity dimensions simultaneously. Because the approach is automated, we can overcome the problem that reading the biographies of more than 50,000 executives is practically impossible.

A potential concern is that the executives may not write the biographies themselves. However, since the underlying biographical information (e.g. where the executive obtained her MBA or whether she has worked for Shell Gas Transmission in the past) does not depend on who writes the biography, we believe this should not be a major issue. Moreover, the SEC requires certain items to be part of the bio, so the ability to "cherry-pick" entries is limited. If someone else writes the bio, or if there is some cherry-picking, we expect this to lower the signal-to-noise ratio, which would work against us finding any results. Most importantly, we show later that diversity is related to stock returns. It is simply not obvious how the fact that someone else writes an executive's biographical text could be systematically related to stock returns.

2.3 Data

Our main source of biographical texts is the company's annual report, form 10–K in the EDGAR database. If no executive biography is found in the 10–K, we search form 10–KSB.[1] If we cannot find biographical information in forms 10–K or 10–KSB, we search form DEF 14A, the definitive proxy statement. If we do not obtain a biography from any of these forms, we code the executive-firm-year observation as missing. We extract this information with a web-crawler, written using a combination of Python and SAS, and complement it with manual intervention when the structure of the document is non-standard. Finally, we use equation (2) to construct the distraction measure D for each firm-year. If D is missing in year t, but available in years $t-1$ and $t+1$, we replace the missing year t value with $t-1$ value (but those cases are rare).

We are able to retrieve full biography information for 11,440 unique companies and 81,076 individual executives, providing us with 244,572 executive-firm-year observations. We then merge with the CRSP-Compustat Merged database, drop all firms with missing or negative book value, drop all firms with less than 12 months of previous stock returns, and keep all firms with common stock traded on the NYSE, AMEX, and Nasdaq (CRSP share code 10–12). The final dataset comprises 53,743 executives, in 5,391 unique firms, and has 34,271 useable firm-years.

Table 1 presents summary statistics. The key feature of that table is the strong relation between value-weighted returns and diversity. The value-weighted raw returns, computed as the time-series average of the value-weighted average of all stocks in a diversity quintile in a given month, are substantially higher in firms with diverse top management teams ("diverse firms"). The top quintile of diverse firms outperform the bottom quintile ("homogenous firms") by 55bps per month, which is significant both economically as well as statistically (t-statistic = 2.84). By contrast, equal-weighted returns are not different across diversity groups, which suggests that

[1]Form 10–KSB is an abbreviated version of the 10–K, also known as Annual Report for Small Businesses, and was available as an option to smaller companies until March 16, 2009.

the differences are coming from large firms in the sample.

Table 1 also shows that diverse firms are smaller than homogenous firms, but, at $3 billion of average market capitalization, they are not small in absolute terms. Diverse firms are similar to homogenous firms in the book-to-market ratio, and have higher idiosyncratic volatility, gross profitability, and lower analyst coverage.

3. Baseline Results

3.1 The Diversity Strategy

We start by analyzing raw returns. Table 2 compares a "diversity strategy" of going long a value-weighted portfolio of stocks in the top diversity quintile and short stocks in the bottom quintile, with a set of leading anomalies suggested by Fama and French (2008) and Novy-Marx (2013). We follow Novy-Marx (2013) in constructing gross profitability, and Fama and French (2008) for momentum, net stock issuance, accruals, asset growth, and value. Over our sample period, the average return of the diversity strategy is higher than that of any other strategy except for value. Diversity investing returns are therefore economically first-order. A remarkable fact about diversity returns is that they come with low volatility. As a result, the annualized Sharpe Ratio of the diversity strategy is 0.79, which is higher than the Sharpe Ratio of all alternatives, including value.

Table 3 shows the outperformance of diverse firms is robust to risk-adjustments. Panel A matches stocks by size and book-to-market, Panel B presents results for the Fama and French (1993) three factor model, and Panel C adds the Carhart (1997) momentum factor. In all cases the diversity strategy delivers significant abnormal returns on a value-weighted basis between 42bps (three-factor model) and 57bps (size and book-to-market adjustment).

A striking feature of the diversity strategy, shown in Table 3, is that its returns obtain only for value-weighted portfolios, and therefore pertain to the economically most important set of stocks. Value-weighted returns from diversity investing become even more pronounced when we restrict attention to stocks in the S&P500 index. The fact that diversity returns come from the largest stocks is informative about potential drivers of the pattern, as we argue in greater detail below.

In Figure 2, we decompose the performance of the diversity strategy shown in Figure 1 into the long and short legs. While there is some action in the short leg (homogenous firms underperform), most of the action is in the long leg (diverse firms outperform). That diversity returns are concentrated in large stocks, and that most of the returns can be reaped without going short, means diversity investing may be profitable for investors even after transaction costs. Further supporting the view that transaction costs from diversity investing are comparatively low, we find portfolio turnover for diversity is only slightly higher than turnover for size and value strategies, but substantially lower for momentum (results not shown).

As an alternative to the portfolio sorts we present results from Fama-MacBeth cross-sectional regressions in Table 4. Since, as we have shown above, the diversity strategy works only for value-weighted returns, we weigh each observation in those regressions by their market capitalization in June of year t. Table 4, specification (1), shows diversity investing yields 39bps in the average month when we control for the Fama-French-Carhart factors. When we add turnover, idiosyncratic volatility and previous-month returns as additional controls in specification (2), outperformance increases to 56bps. A notable fact is that diverse firms tend to have higher idiosyncratic volatility (Table 1). Since higher volatility is known to be associated with higher returns (Ang, Hodrick, Xing, and Zhang (2006)), controlling for volatility in specification (3) leads diversity returns to become even higher.

About 7% of our firm-years are from firms reporting a single manager. These are maximally homogenous teams, and one may wonder if they drive our results. Specifications (4) and (5) in Table 4 thus add a single-manager firm dummy. Our results become even more pronounced. Diversity investing yields 60bps in specification (5). In addition, statistical significance increases substantially, indicating that single-manager firms may add noise to the diversity measure which, in turn, leads to a downward bias in our diversity coefficients. We leave single-manager firms in our sample to be conservative, but specifications (4) and (5) in Table 4 show that this tends to work against us.

3.2 Comparing Diversity Investing to other Anomalies

Availability of usable text to create the diversity measure restricts our analysis to a relatively short sample period from 2002 to 2014. Hence, mechanically, coefficients may be estimated less precisely and t-values may be lower than those from other studies with more years of data. To gauge the strength of effects, comparing the diversity strategy results with a set to leading anomalies over the same period is therefore particularly informative.

As we show in Table 2, the raw long-short diversity investing returns exceed the returns on all other strategies except value, while the Sharpe ratio of diversity investing is higher than the ratio for any other strategy we consider including value. The statistical significance of those returns is also highest for the diversity strategy.

Figure 3 shows that this pattern also holds when we risk-adjust using size and book-to-market. The average monthly alpha of the diversity strategy is 57bps, and therefore higher than that of any of the competing strategies: momentum, net stock issues, accruals, asset growth, and profitability. Figure 3 highlights again the remarkable fact that diversity investing yields higher returns among the set of large stocks.

Returning once more to Figure 1, we observe that returns to diversity investing are not due to a specific year or event. The cumulative alphas steadily increase over our sample period, and seem more stable than those of any other strategy. Hence, while over the complete period, cumulative alphas from diversity investing exceed the alphas of all competitors, it delivers these returns with comparatively little volatility. This is consistent with the Sharpe Ratio in Table 2 being highest for diversity investing.

Based on this evidence, we conclude diversity investing yields economically large outperformance when compared with the leading anomalies in the literature.

3.3 Spanning Tests

In this section we show that diversity returns are not due to correlations with existing anomalies. We start by conditional sorts. We first sort the data into groups using another anomaly variable, and we then sort on diversity *within* these groups. Table 5 shows that the long-short strategy delivers large and significant returns also in conditional sorts.

Next, we use the time series of diversity strategy returns, and regress diversity returns on returns from other strategies. Table 6, specification (1) shows that diversity investing yields 43bps with a t-statistic of 2.34 when controlling for the standard four factors. The results also show that diversity returns are almost market neutral, load positively on size, negatively on value, and not at all on momentum.

In the next specifications, we add the anomaly strategy returns previously considered. The results in specifications (2) to (6) show that the alpha on diversity investing is not subsumed by other strategies. We estimate alphas between 33bps and 43bps per month, all highly economically significant.

An interesting finding is that diversity return seems to be correlated with gross profitability returns. Gross profitability has recently been suggested as a signature characteristic of "quality" stocks (Novy-Marx (2014)). Because diversity and profitability are correlated, controlling for profitability reduces diversity alphas by about 25% ($= (33-43)/43$). However, while profitability absorbs some of the diversity returns, the remaining 75% is not captured by it. As we explain below, these results are potentially useful for understanding the source of diversity returns: the diversity characteristic may be a dimension of quality providing information over and above proxies in the existing literature.

3.4 Changes in Diversity and Returns

The results so far suggest that investing based on top management team diversity is profitable. But are return patterns really driven by diversity, or by some other, potentially unobserved, variable correlated with it? The aim of this section is to raise the bar for alternative explanations by looking at within-firm variation in diversity.

We start by looking at executive turnover. We search news items in the Ravenpack dataset for executive turnover events. We define a turnover month $j = 0$ as the month in which Ravenpack first reports an executive leaving her firm,[2] and we compute a diversity measure before and after the change. Our tests focus on two sets of firms: D-UP, comprising firms that, starting from a lower diversity quintile, move into the top quintile after the turnover event; and D-DOWN, comprising firms that move into the bottom diversity quintile.

To assess the impact of changes in diversity on stock returns in the months surrounding the event, we use the Ibbotson (1975) returns across time and security (IRATS) method combined with the Fama-French-Carhart 4 factor model, as in Peyer and Vermaelen (2009). Separately for stocks in the D-UP and D-DOWN groups, we run the following cross-sectional regression for each event month j:

$$R_{ijt} - R_{ft} = a_j + b_j RMKT_t + c_j SMB_t + d_j HML_t + e_j UMD_t + \varepsilon_{it}. \tag{3}$$

Our tests are conducted in event time, relative to the event month defined as $j = 0$. R_{ijt} is the monthly return of stock i associated with event month j, t is the associated calendar month, R_{ft} is the risk-free rate, and RMKT, SMB, HML, and UMD are the Fama-French-Carhart factor returns.

Table 7, Panel A, shows the cumulative abnormal returns, defined as the sum of a_j across different horizons. We consider both pre-event horizons (–6, –4, and –2 months) as well as post-event horizons, starting at $j = 0$ for the full sample. As expected, both the D-UP and D-DOWN group have negative performance before turnover events, since executives are fired, or resign, mostly after bad performance. The key result is that stock returns are systematically higher for firms in which the top management team becomes more diverse.

Figure 4, Panel A, plots the cumulative abnormal returns, and highlights two key results.

[2]These are identified by the Ravenpack news categories executive–death, executive–firing, and executive–resignation.

First, the difference between the D-UP and D-DOWN groups is essentially zero before the event. This lack of a pre–trend suggests that the divergence between the two groups is indeed due to the change in diversity. Second, while the negative price drift continues on stocks in the D-DOWN group, it stops for the D-UP stocks, and the wedge between the two groups increases to 7.8% by month $j = 12$. The increase is statistically significant for all post-event months, but not pre-event, supporting the view that the patterns are caused by the change in diversity.

To attenuate concerns about the potential endogeneity of executive turnover, we also restrict the attention to executive deaths (Ravenpack category executive–death), which are less likely to be planned by management or driven by the firm's performance. Panel B of Table 7 and figure 4 report our findings. In this case too, the stock prices of the D-UP and D-DOWN move closely together prior to the change in diversity, and diverge following the event, with the wedge between D-UP and D-DOWN firms rising to over 10% one year after the executive death event.

These finding raise the bar for alternative explanations, since they rule out a scenario under which diversity investing works because diversity proxies for a time-invariant unobserved variable. If diversity returns obtain because of a correlation with some other driver of returns, then the results in Figure 4 imply this underlying driver needs to change exactly when diversity changes.

We directly examine in Table 8, specification (5), whether changes in diversity are related to contemporaneous changes in firm fundamentals (we discuss the other specifications in that table later). We find changes in diversity are not related to changes in size, leverage, capital expenditure, cash holdings, payout, R&D expenses, investment opportunities (proxied by Tobin's Q), and the presence of negative earnings. Hence, many natural variables that may act as underlying drivers of diversity returns are not changing when diversity changes, and therefore cannot explain the evidence we present in this section.

Two variables in Table 8, specification (5), change alongside diversity. One variable is idiosyncratic volatility, which increases when diversity increases. Ang, Hodrick, Xing, and Zhang (2006) show that higher idiosyncratic volatility is related to *lower* returns. Hence, even though volatility changes, that change cannot explain why we see *higher* returns after diversity increases.

The second variable which changes with diversity is the probability of a given firm taking over another firm. Since a takeover may reshuffle the top management team, and combine management teams with different backgrounds, this association makes intuitive sense. To make sure our results are not contaminated by takeover events, we rerun our analysis on the subsample of firms without a takeover event. Panel B of Table 7 shows that the results are effectively unchanged.

We conclude that changes in diversity are positively associated with changes in abnormal returns. The previously documented returns to diversity investing, therefore, cannot be due to a time-invariant omitted variable. The results provide support for the view that it really is the diversity of the top management team which matters for stock returns.

3.5 Determinants of Diversity

The high returns to diversity investing are striking. To start thinking about potential drivers, we analyze which firm level variables are correlated with diversity.

Table 8 regresses diversity on a large set of potential correlates. Specification (1) estimates pooled OLS, while specifications (2) to (4) add year, industry, and industry $\times$ year fixed effects, respectively. For almost all variables we find that the results are quite similar across specifications (1) to (4), so we mostly discuss these specification jointly. Specification (5) includes firm fixed effects, which means that we are trying to explain changes in the diversity measure by changes in the covariates within firms.

The results in Table 8 show that diversity is strongly correlated with the number of executives in the top management team reported in the 10-K ("team size"). Larger teams are, all else equal, more diverse. This is partly mechanical, because the smallest teams are single-manager teams which are maximally homogenous. The second variable we consider is the length of managerial biographies measured by the number of words in the biographical text ("bio length"). While bio length is not significantly related to diversity in the cross-sectional tests (specifications (1) to (4)), bio length is significantly related to diversity when we include fixed effects (specification (5)). We show below these two variables are not driving any of our results.

We next consider a number of firm characteristics. Across specifications (1) to (4), firms with diverse top management teams are smaller, more leveraged, have higher capital expenditures, higher cash holdings, lower payout ratios, and higher gross profitability. We find weak evidence suggesting that diverse firms have lower Tobin's Q and are more likely to take over another company. R&D expenditure, accounting losses, and idiosyncratic volatility are unrelated to diversity.

The observed differences between diverse and homogenous firms in specifications (1) to (4) are interesting, because they show our text-based diversity measure is actually related to economically important variation in corporate outcome variables. This variation is consistent with the existing management literature that suggests team diversity matters for decision-making in firms. The last column in Table 8 shows, however, that none of these firm level variables survives when we include firm fixed effects, i.e., changes in diversity are therefore not correlated with changes in the firm level variables within a given firm, a fact we have already used for interpreting the change-in-diversity tests in the previous section. There, we have also shown that while the takeover variable and volatility increase when diversity increases (as can be seen from specification (5)), these variables cannot explain the fact that returns drift up after a change in diversity.

In the next section, we show that the diversity returns in our baseline tests are not driven by the correlated variables in Table 8.

3.6 Robustness

This section presents robustness checks.

Team Size. Table 8 shows that our measure of diversity is strongly positively related to the number of executives. Table 9, Panel A, repeats our sorting results from Table 3, Panel C, but uses team size, rather than diversity as a sorting variable. The table shows that team size does not generate any meaningful spread in returns, so diversity returns do not simply reflect returns associated with larger or smaller top management teams.

Biography Length. A concern may be that diversity somehow captures biography length. Three points argue against this. First, the cosine similarity measure is normalized with respect to text length, which should largely eliminate the impact of text length. Second, Table 8 shows text length is at best weakly related to the level of diversity. Third, Table 9, Panel B, sorts on biography length directly and shows that our previous results are not induced by it.

Firm Characteristics. Table 8 shows that several firm characteristics are correlated with the diversity measure in the cross-section. We show in Panel C of Table 9, that the diversity strategy also works when we sort on diversity *within* groups formed on leverage, capital expenditure, cash holdings, and payout ratio. As for the other two significant variables, size is already captured in the Fama-French model and we have examined the impact of gross profitability already in Table 5. Hence, while there is correlation, the diversity strategy does not simply capture returns associated with leverage, capital expenditure, cash holdings, and the payout ratio.

Variation Across Industries. A reasonable question is whether diversity of the top management teams varies across industries. Figure 5 presents average diversity by Fama-French 12 industry. With the exception of Utilities and Finance, diversity scores across industries are very similar. Unreported results indicate that the diversity strategy returns are unaffected if we drop Utilities and Finance. In Table 9, Panel D, we run an even finer test. We first regress the distraction measure on dummies for 48 Fama-French industries, and then sort returns on the residual. We still obtain large and significant diversity returns. We conclude that the diversity strategy does not capture industry returns.

Single-Manager Firms. Our sample contains firms with only one reported top executive. By construction, those firms are assigned a diversity score of zero. To make sure our results are not driven by these firms, we repeat our baseline sorting results on a sample that excludes single-manager firms. The results in Panel E of Table 9 show that our results get even stronger in that case.

4. Why Does Diversity Investing Work?

4.1 Potential Drivers

The central contribution of this paper is showing diversity investing generates large, stable abnormal returns among the largest firms (Section 3.). In this section we provide some initial evidence on the potential economic drivers. Several, not mutually exclusive, drivers may be responsible.

Omitted Risk Factor. It is possible that the diversity characteristic is correlated with some priced risk-factor. If high diversity stocks are riskier, they would naturally command a return premium. While this is a theoretical possibility, we use the set of standard risk-adjustments in the literature, so it is not obvious what the omitted risk factor should be.

Diversity as a Proxy for Quality. Several recent papers argue prominently that investors pay a premium for "quality" stocks (e.g., Asness, Frazzini, and Pedersen (2013), Fama and French (2014), Novy-Marx (2014)). While papers differ in their empirical approaches, and the definitions of quality, the common intuition is based on the dividend discount model, which can be written as: $P/B = [\text{Profitability} \times \text{Payout ratio}] \, / \, [r - g]$. This identity implies, for example, that fixing price-to-book, more profitable stocks should, all else equal, have higher returns.

This logic may explain the diversity returns, if diversity is positively correlated with quality. For example, if diversity is a good predictor of future profitability, then, all else equal, diverse firms should outperform homogenous ones. An attractive feature of this explanation is that a part of the related management literature emphasizes the potential of diverse teams to make better, less biased, decisions. If this is true, then our results may even reflect a causal effect: we see positive returns from diversity investing because diverse teams, on average, make better decisions. Of course, it is also possible that there is a matching process by which diverse teams get matched with quality firms, and it is not our aim to rigorously identify the direction of causality. We simply point out that the large management literature which suggests diverse teams may make better decisions, and our evidence of abnormal returns from diversity investing, may be compatible.

Mispricing. There are several ways in which mispricing could explain diversity returns. One is that diverse teams make better corporate decisions than other teams, but that the market underestimates how valuable the diversity characteristic is. A variant of this argument is that diversity matters for the quality of decisions, but that a subset of investors is simply unaware of the top management team and its level of diversity. In equilibrium, investors would require returns that are too high relative to fundamentals.

A second way in which mispricing could explain diversity returns is that investors dislike diverse teams, and therefore require extra returns for holding such stocks. For example, investors may be more confident assessing the quality of a homogenous team, because they feel that team is easier to understand, and because of higher perceived ambiguity in the expected performance of a diverse team. If investor dislike the diversity attribute, firms with diverse teams would have higher required returns *even if diversity itself is unrelated to firm fundamentals.*

4.2 Empirical Evidence

Several pieces of empirical evidence are informative for distinguishing between potential drivers.

Stronger Effects for Large Firms. Diversity investing is a large-cap phenomenon, as we have shown in all previous tests. This fact is informative, because it rules out some simple stories about the drivers of diversity returns. In particular, if firms with diverse management teams were systematically more risky, and therefore had higher discount rates, we would expect returns from diversity investing across the full spectrum of firm sizes.

The stronger results for larger firms may be consistent with the diversity-as-quality hypothesis, if diverse management teams lead to better decisions only in large, complex, firms. This may be plausible: a large management team with diverse backgrounds can be very useful for large multi-national company, whereas diversity may even be hampering performance for "Joe's Pizza Place." Stronger results for larger firms are also consistent with mispricing if investors pay attention to the top management team only for sufficiently large companies. As it is much easier to obtain information on top management teams for the largest firms, this may again be plausible.

In sum, the fact that diversity returns are stronger for larger firms appears less consistent with an omitted risk factor channel, but compatible with the diversity-as-quality and mispricing channels.

Stronger Effects for High Idiosyncratic Volatility Firms. To make the diversity-as-quality and mispricing hypotheses less ad hoc, we seek to exploit variation orthogonal to size. The first variable we look at, to that end, is idiosyncratic volatility, which is motivated by its prior use as proxy for stocks that are, all else equal, harder to arbitrage, and therefore more likely to be mispriced (e.g., Baker and Wurgler (2007)). Moreover, more volatile firms may be more complex and harder to manage, which is why diverse top management teams may be particularly valuable in those firms. As a result, both the diversity-as-quality hypothesis, as well as the mispricing hypothesis would predict that, all else equal, diversity returns should be more pronounced for high volatility firms.

To satisfy the all-else-equal condition, we construct a Size-Adjusted Idiosyncratic Volatility variable as follows. We first compute idiosyncratic volatility for each firm as the standard deviation of residuals from a Fama-French-Carhart four-factor model estimated from daily returns over the previous 12 months. We then define Size-Adjusted Idiosyncratic Volatility as the residual from a regression of idiosyncratic volatility on size and size-squared.

Table 10, Panel A, presents results when we sort on the Size-Adjusted Idiosyncratic Volatility variable. While the difference between diverse and homogenous firms is not different from zero in the other groups, diversity investing yields an economically large 110bps monthly four-factor risk-adjusted alpha for the high volatility group. This outperformance is highly significant, despite our small sample (t-statistic = 3.28). Note that, because we have removed variation in size, high residual volatility firms are not small at all. The average market cap in the high volatility group is \$4.1 bn.

In sum, finding that, all else equal, diversity returns are concentrated in high volatility firms provides support for both the diversity-as-quality hypothesis, as well as the mispricing hypothesis.

We next try to find some more direct evidence for the diversity-as-quality channel.

More Direct Tests for Diversity-As-Quality. We first investigate if diversity is correlated with contemporaneous variables that are linked to quality by the previous literature. Specifically, Asness, Frazzini, and Pedersen (2013) suggest that, all else equal, high profitability, high payout ratios, and low volatility are characteristics of quality stocks.

The correlations we presented in Table 8 show mixed evidence for the diversity-as-quality hypothesis. Volatility has the correct sign but is statistically insignificant once we control for year or industry. Payout ratio is highly significant, but with the opposite sign compared with what the diversity-as-quality hypothesis would predict. By contrast, gross profitability is strongly positively related to diversity in line with a diversity-as-quality story.

We provide two additional tests to explore the diversity-quality link. First, we use the five-factor model of Fama and French (2014) as a benchmark. That model includes a profitability and an investment factor, which may both be related to quality. Second, we add Asness, Frazzini, and Pedersen's quality-minus-junk factor, which was developed to proxy for quality directly (we obtain the factor returns data from the homepages of Kenneth French and Lasse Pedersen, respectively). Table 11, Panels A and B, present results. While statistical significance weakens somewhat relative to our benchmark, we continue find an economically large return to diversity investing for both sets of results, and we continue to find stronger results for large stocks. Compared with the four factor model in Table 3, Panel C, controlling for quality reduces the alpha from diversity investing by about 25%. If we include the quality-minus-junk factor in our spanning regressions in Table 6, specification (1), we find QMJ reduces the baseline alpha of 43bps in that table to 35bps, i.e., by about 18%. We had already shown that including gross profitability in those regressions reduces alpha by about 25%.

We conclude from the evidence above that the diversity measure is related to some variables suggested to measure quality by the extant literature (gross profitability), but not to other variables (payout ratio). Standard measures – gross profitability from Novy-Marx (2013), the Fama and French (2014) investment and profitability factors, and the Asness, Frazzini, and Pedersen (2013) quality-minus-junk factor – capture up to 25% of the diversity alphas. Hence, most of the returns from diversity investing are not explained by standard variables used to measure quality stocks.

An interesting possibility is that diversity is a quality characteristic which investors care about *over and above* the proxies used in the existing literature. To further explore this possibility we run two tests. First, we investigate whether analyst recommendations are related to the diversity measure. Table 12, specifications (1) to (3) show that, all else equal, analysts have more positive views on firms with diverse top management teams. They are more likely to issue a buy recommendation (specification (1)) and they are in general issuing more positive recommendations on those firms (specification (3)). Note that we include industry $\times$ year fixed effects in those regressions, so we eliminate a lot of potentially confounding variation by comparing firms in the same industry at the same point in time. The evidence in Table 12 is consistent with the view that analysts take note of the diversity characteristic in their recommendations, and also with the view that diversity may be proxying for managerial quality over and above standard variables.

As a second test, we construct an alternative measure to capture the quality of a top management team, and investigate whether that variable is correlated with the diversity measure. To that end, we determine, for each executive in our dataset, whether they obtained a degree from a top 20 U.S. university. We label the fraction of executives in the team that went to a top university *Top University*. Table 8 shows that the Top University variable is indeed positively related to diversity. This is consistent with the idea that diverse teams are on average smarter, higher quality, teams. However, this correlation notwithstanding, we find no meaningful spread in returns when we sort on the Top University variable directly in Table 11, Panel C. Hence, while diversity is positively correlated with the Top University variable, arguably a direct measure of managerial quality, it is not the Top University characteristic per se which drives returns. The Top university test therefore fails to support the diversity-as-quality hypothesis.

We conclude that some of the reported diversity returns are likely to be explained by the diversity-as quality hypothesis. However, the largest part of the returns to diversity investing are not explained by standard variables in the literature. We obtain some suggestive evidence that the diversity characteristic may capture quality over and above what is captured by standard variables from looking at analyst recommendations.

Stronger Effects if Analyst Coverage is Low. Finally, we look for more direct evidence on the mispricing hypothesis by analyzing variation in analyst coverage. Looking at analysts may be interesting because they frequently mention that the "quality of the top management team" is a relevant factor for their assessment of a given company, and our result from Table 12, that diversity increases the chance of a buy recommendations, is consistent with this idea. We conjecture that, all else equal, the potential for mispricing may be greater in firms with less analyst coverage, because fewer experts are trying to assess the quality of the top management team.

Table 12, specification (4), is in line with this conjecture. It shows that analysts are not less accurate in their forecasts for diverse firms. Statistically, the coefficient on diversity is not significant, and economically it is tiny: a one-standard-deviation shift in diversity changes the absolute forecast error (actual minus predicted EPS divided by current share price) by 0.02 standard deviations. Hence, combined, the evidence in Table 12 is consistent with the view that analysts take note of the diversity characteristic in their recommendations, and that they correctly factor this information in their earnings forecasts. Therefore, analyst coverage may bring useful information to the table which reduces mispricing potential.

Following the above logic, higher analyst coverage should *all else equal* be associated with weaker diversity returns if diversity returns are driven by mispricing. Because analyst coverage is highly correlated with firm size, and because diversity may matter more in large firms, it is particularly important to remove the impact of size to satisfy the all-else-equal criterion. We do this by regressing analyst coverage on size and size-squared, and by using the residual of this regression as our size-adjusted sorting variable. We label this variable Size-Adjusted Analyst

Coverage.

Table 10, Panel B presents returns consistent with the mispricing hypothesis. The returns from diversity investing decrease monotonically in Size-Adjusted Analyst Coverage. For the low analyst coverage group, the returns from diversity investing are 67pbs per month, and therefore higher than in our baseline. When analyst coverage is high, and the additional information provided by analysts should reduce mispricing potential, we observe no meaningful difference between the diverse and homogenous firms.

In sum, our evidence suggests the substantial returns to diversity investing may be driven by a combination of two things. First, diversity of the top management team may be a previously underemphasized dimension of "quality" stocks which is important *over and above* the quality variables used in the literature. Existing quality measures explain at best about 25% of the diversity returns we observe. Second, we find evidence for the notion that some of the diversity returns may be due to the market mispricing the diversity of the top management team by showing that returns are, all else equal, coming from stocks with lower analyst coverage and higher idiosyncratic volatility.

5. Conclusion

We show that top management team diversity – a new text-based measure of how different managers are in terms of personal characteristics and prior experiences – is related to stock returns, using a new dataset of more than 50,000 top executives in US firms from 2002 to 2014. Firms with diverse management teams have up to 57bps higher risk-adjusted returns per month than firms with homogenous management teams, which is larger than effects obtained from most other leading asset pricing anomalies over our sample period. In contrast to most other anomalies, the effect is stronger for large-cap stocks, so investing on diversity seems feasible for investors. Our paper is among the first to focus on top management team diversity in the finance literature, and among the few papers that document a return anomaly concentrated in the largest stocks.

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Table 1: Summary Statistics

The table presents summary statistics for the whole sample and for samples of firms in different quintiles of Diversity. At each date, Homogenous firms are defined as those firms with a value of diversity in the bottom quintile by date, while Diverse firms are those firms with a value of diversity in the top quintile, where diversity in measured according to equation (2). The first column shows the monthly average number of sample firms with non-missing values of each of the listed variables. The second column presents monthly averages for sample firms of each of the listed variables. The third through seventh columns show monthly group averages of each of the listed variables for firms in different quintiles of D. Finally, the last column shows the t-statistic for the difference between diverse and homogenous averages. Equal-weighted (EW) and value-weighted (VW) returns are expressed as percentages per month. Size is the market capitalization in June year t, expressed in billions of dollars. Book-to-Market is the ratio of the book value of equity to the market value of equity. Idiosyncratic volatility is the standard deviation of residuals from 4–factors model estimated from daily returns over the previous 12 months, expressed in percentage points. Net stock issues is the natural log of the ratio of the split-adjusted shares outstanding at the end of December year $t-1$ divided by the split-adjusted shares outstanding at the end of December year $t-2$. Asset growth is the natural log of the ratio of assets per split-adjusted share at the end of December year $t-1$ divided by assets per split-adjusted share at the end of December year $t-2$. Accruals is the change in operating working capital per split-adjusted share from $t-2$ to $t-1$, divided by book equity per split-adjusted share at the end of December $t-1$, and it is expressed as percentage. Gross Profitability is revenue minus cost of goods sold at the end of December $t-1$ divided by assets at the end of December $t-2$, and it is expressed as percentage. Momentum is the cumulated continuously compounded stock return from month $j-12$ to month $j-2$. Team Size refers to the size of the top management team. Biography length is the average number of words in the biographies of the top management team members. Top University is the number of executives team members that attended a top 20 US university, divided by the number of executives. Analyst Coverage is the number of analysts covering a specific firm at the end of each month.

	No. Firms	All	Diverse	2	3	4	Homog.	t-stat
Diversity	2,428	0.75	0.93	0.88	0.83	0.75	0.33	–
EW returns (%)	2,428	0.92	0.95	0.94	0.93	0.95	0.92	0.18
VW returns (%)	2,428	0.85	1.05	0.80	0.65	0.70	0.51	2.84
Size (B$)	2,428	4.33	3.08	2.43	4.11	4.90	7.22	4.97
Book-to-Market Ratio	2,428	0.82	0.85	0.77	0.73	0.83	0.90	1.12
Idiosyncratic Volatility (%)	2,425	2.41	2.62	2.60	2.49	2.25	2.10	13.97
Net Stock Issues (%)	2,428	6.42	6.57	8.01	7.47	6.28	3.75	6.62
Asset growth (%)	2,428	9.52	9.58	11.72	10.62	9.52	6.14	4.79
Accruals (%)	2,051	-97.13	53.29	-5.59	-510.20	-0.22	-2.13	0.98
Gross Profitability (%)	2,428	32.69	37.22	34.10	34.03	31.52	26.37	9.54
Momentum (%)	2,416	12.75	11.92	13.03	14.40	13.26	11.19	0.92
Team Size	2,293	7.10	6.75	7.84	7.80	7.34	5.57	6.61
Biography Length (words)	2,307	101.89	99.53	112.89	112.13	103.43	80.49	8.35
Ivy League fraction (%)	2,293	0.12	0.12	0.16	0.15	0.11	0.05	10.42
Analyst Coverage	1,939	8.09	7.39	7.56	8.29	8.72	8.52	3.97

Table 2: Long-Short Strategy Raw Returns

The table shows the performance of the long-short Diversity strategy, in terms of raw returns, relative to a set of well-known alternatives. For Diversity, Book-to-Market (BTM), Gross Profitability (PROF) and Momentum (Mom) we sort stocks into quintiles. For Net Stock Issues (NSI), Accruals (AC) and Asset Growth (AG) we sort firms with negative values into two portfolios, and we sort firms with positive values into five quintiles, resulting in seven portfolios in total. The mean (E[R]) and standard deviation (std[R]) shown are based on raw returns, which pertain to going long a value-weighted portfolio of stocks in the highest and short a value-weighted portfolio of stocks in the lowest group for each sorting variable.

	Diversity	BTM	Mom	NSI	AC	AG	PROF
E[R]	0.55	0.64	0.46	0.44	0.25	0.03	0.31
t-statistic	2.84	2.45	0.81	1.77	1.34	0.19	0.94
std[R]	2.40	3.27	7.02	3.09	2.31	2.25	4.07
Annualized Sharpe Ratio	0.79	0.68	0.22	0.49	0.37	0.05	0.26

Table 3: Sorting on Diversity

The table shows abnormal returns to portfolios that follow the Diversity strategy for our sample of stocks from 2002 to 2014. We sort stocks into Diversity portfolios in December of each year $t-1$, and compute average abnormal returns for July year t to June year $t+1$. Panel A shows the average Size-and-Book-to-market adjusted returns; Panel B shows Fama-French three-factor alphas; and Panel C Fama-French-Carhart four-factor alphas. In each panel, the third column (D−H) shows the difference between the highest quintile of Diversity (Diverse) and the lowest quintile of Diversity (Homogenous). The last three columns of each panel show the t-statistic for the corresponding quintiles and for the D−H difference. We present results for our whole universe of firms, for S&P500 ("Big") stocks, and for non-S&P500 ("Small") stocks.

Panel A: Size\BTM adjusted returns

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Risk-adjusted Value-Weighted Returns (alpha)				*t*-statistic	
All firms	0.37	-0.19	0.57	2.59	-1.74	2.95
Big firms	0.45	-0.23	0.68	2.52	-1.88	3.00
Small firms	-0.08	0.03	-0.11	-0.63	0.25	-0.55
	Risk-adjusted Equal-Weighted Returns				*t*-statistic	
All firms	-0.03	-0.04	0.01	-0.22	-0.42	0.07
Big firms	0.10	0.11	-0.01	0.50	1.23	-0.06
Small firms	-0.05	-0.08	0.03	-0.32	-0.69	0.22

Panel B: Fama-French three-factor alphas

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Risk-adjusted Value-Weighted Returns (alpha)				*t*-statistic	
All firms	0.33	-0.09	0.42	2.29	-1.08	2.41
Big firms	0.43	-0.12	0.55	2.41	-1.32	2.63
Small firms	-0.11	0.08	-0.19	-0.97	0.73	-1.17
	Risk-adjusted Equal-Weighted Returns				*t*-statistic	
All firms	-0.08	0.05	-0.12	-0.51	0.48	-0.96
Big firms	0.01	0.17	-0.16	0.07	1.99	-1.07
Small firms	-0.09	0.02	-0.11	-0.54	0.17	-0.79

Panel C: Fama-French-Carhart four-factor alphas

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Risk-adjusted Value-Weighted Returns (alpha)				*t*-statistic	
All firms	0.33	-0.10	0.43	2.22	-1.14	2.35
Big firms	0.42	-0.13	0.55	2.30	-1.40	2.54
Small firms	-0.10	0.10	-0.20	-0.89	0.88	-1.22
	Risk-adjusted Equal-Weighted Returns				*t*-statistic	
All firms	-0.00	0.09	-0.10	-0.03	1.10	-0.73
Big firms	0.08	0.19	-0.11	0.62	2.31	-0.73
Small firms	-0.02	0.07	-0.09	-0.10	0.73	-0.62

Table 4: Fama-MacBeth Regressions

The table presents monthly Fama and MacBeth (1973) regressions of returns on Diversity. To predict returns from July year t through June year $t+1$ we use values of Diversity, Net Stock Issues, Accruals, Asset Growth, Gross Profitability, Turnover, Idiosyncratic Volatility and Single Executive as of December year $t-1$. Market Capitalization is the log of market-cap in June year t, and Book-to-Market is log book to market defined and lagged as in Fama and French (1993). Momentum is defined as the cumulative return from month $t-12$ to month $t-2$. Return $(t-1)$ is the one-month lagged return. The last specification includes industry effects, based on 1-digit SIC codes. In all regressions we weight observations by market capitalization in June year t. t-statistics based on Newey and West (1987) standard errors with 12 monthly lags are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)
Diversity	0.386	0.562	0.381	0.732	0.592
	(2.06)	(3.04)	(2.84)	(3.76)	(3.72)
Market Capitalization	-0.050	-0.224	-0.225	-0.217	-0.218
	(-0.86)	(-4.27)	(-3.80)	(-4.20)	(-3.79)
Book-to-market	0.039	-0.012	-0.028	-0.003	-0.022
	(0.39)	(-0.15)	(-0.33)	(-0.04)	(-0.27)
Momentum	-0.075	-0.280	-0.119	-0.277	-0.112
	(-0.11)	(-0.39)	(-0.17)	(-0.38)	(-0.16)
Turnover		0.120	-0.089	0.059	-0.152
		(0.10)	(-0.06)	(0.05)	(-0.10)
Idiosyncratic Volatility		-0.861	-0.835	-0.860	-0.833
		(-3.30)	(-3.32)	(-3.32)	(-3.33)
Return $(t-1)$		-3.207	-3.319	-3.205	-3.287
		(-2.44)	(-2.49)	(-2.43)	(-2.46)
Net Stock Issues			-0.157		-0.148
			(-0.59)		(-0.57)
Asset growth			0.108		0.117
			(0.59)		(0.65)
Accruals			0.002		0.004
			(0.04)		(0.10)
Gross Profitability			0.244		0.232
			(0.86)		(0.82)
Single Executive				0.165	0.252
				(0.98)	(1.50)
Constant	0.758	3.658	3.633	3.473	3.403
	(0.87)	(5.93)	(4.91)	(5.66)	(4.74)
Observations	344693	342554	289867	342554	289867
R^2	0.09	0.15	0.17	0.16	0.17

Table 5: Conditional Sorts

The table reports monthly portfolio abnormal returns for conditional sorts. First, we sort stocks into quantiles of a given anomaly's signal, and then within these groups by Diversity quintile. In the last row we report the results of conditional sorts within each FF-12 industry. For Diversity, Momentum and Gross Profitability we sort stocks into quintiles. For Net Stock Issues, Accruals and Asset Growth we sort firms with negative values into two portfolios, and firms with positive values into five quintiles, resulting in seven portfolios in total. For Net Stock Issues, Accruals, Asset Growth, Gross Profitability and Diversity we use December year $t-1$ values, and then hold value-weighted portfolios from July year t through June year $t+1$. For Momentum we sort monthly. In each panel, we show Fama-French-Carhart four-factor alphas, except for momentum, where we show Fama-French three-factor alphas. In each panel the third column (D−H) shows the difference between the highest and the lowest quintile of diversity. The last three columns of each panel show the t-statistic for the corresponding quintiles and for the D−H difference.

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Value-Weighted Returns (alpha)			t-statistic		
Momentum	0.33	-0.12	0.45	2.38	-1.32	2.61
Net Stock Issues	0.32	-0.07	0.39	2.01	-0.80	2.04
Accruals	0.25	-0.09	0.34	1.83	-1.04	1.97
Asset Growth	0.34	-0.11	0.45	2.36	-1.35	2.60
Gross Profitability	0.27	-0.10	0.37	1.73	-1.27	2.09

Table 6: Spanning Tests

The table shows the performance of the Diversity strategy evaluated against the Fama-French-Carhart factors and other anomaly strategies. For Diversity and Gross Profitability (PROF) we sort stocks into quintiles. For Net Stock Issues (NSI), Accruals (AC) and Asset Growth (AG) we sort stocks with negative values into two portfolios, and stock with positive values into five quintiles, resulting in seven portfolios in total. In column (6) we add the Asness, Frazzini, and Pedersen (2013) quality-minus-junk factor (QMJ). Strategies are computed by going long the portfolio of stocks in the highest and short the portfolio of stocks in the lowest group for each sorting variable, and are based on raw returns. t-statistics are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
MKT	0.090	0.115	0.093	0.079	0.127	0.121
	(1.27)	(1.65)	(1.31)	(1.13)	(1.64)	(1.49)
SMB	0.402	0.418	0.423	0.408	0.405	0.482
	(4.87)	(5.12)	(5.03)	(4.91)	(4.80)	(5.21)
HML	-0.266	-0.278	-0.270	-0.238	-0.124	-0.232
	(-2.92)	(-3.06)	(-2.93)	(-2.62)	(-1.11)	(-2.10)
UMD	-0.015	-0.022	-0.018	-0.015	-0.051	-0.036
	(-0.23)	(-0.34)	(-0.29)	(-0.21)	(-0.74)	(-0.52)
NS		0.085				
		(1.34)				
AC			0.078			
			(0.97)			
AG				-0.147		
				(-1.88)		
PROF					0.146	
					(1.85)	
QMJ						0.115
						(0.83)
Constant	0.425	0.372	0.398	0.429	0.334	0.345
	(2.34)	(2.15)	(2.21)	(2.38)	(1.77)	(1.88)
Observations	156	156	156	156	156	132
R^2	0.25	0.26	0.25	0.27	0.27	0.27

Table 7: Changes in Diversity and Stock Returns

The table reports the cumulative monthly abnormal returns for portfolios sorted on Diversity events. We define two types of events: D-UP, when a firm moves into the top quintile of Diversity; and D-DOWN, when a firm moves into the bottom quintile. Both D-UP and D-DOWN are defined regardless of the Diversity quintile the firm belongs to prior to the event. In Panel A, the event date is the date of an Executive Turnover. In Panel B, the event date is the date of an Executive Death. Using the Ibbotson (1975) returns across time and securities (RATS) procedure, we construct D-UP and D-DOWN portfolios, and for each run a cross-sectional regression on the Fama-French-Carhart factors for the 6, 4 and 2 month pre–event horizons, and the 2, 4, 6, 8, 10 and 12 month post-event horizon, and compute the cumulative alphas. t-statistics are shown in parentheses.

Panel A: Executive Turnover

	-6m	-4m	-2m	2m	4m	6m	8m	10m	12m
D-UP	-4.50	-4.37	-2.15	0.69	1.16	1.20	0.29	-0.16	0.59
	(-2.85)	(-3.39)	(-2.22)	(0.71)	(0.84)	(0.69)	(0.14)	(-0.10)	(0.26)
D-DOWN	-4.64	-3.06	-2.04	-2.45	-4.79	-5.28	-5.96	-5.66	-7.18
	(-2.28)	(-1.89)	(-1.89)	(-2.22)	(-2.99)	(-2.68)	(-2.56)	(-2.11)	(-2.46)
High - Low	0.14	-1.31	-0.10	3.14	5.95	6.48	6.25	5.50	7.76
	(0.03)	(0.63)	(0.10)	(2.14)	(2.82)	(2.48)	(2.05)	(1.61)	(2.09)
N	708	708	708	708	708	708	708	708	708

Panel B: Executive Deaths

	-6m	-4m	-2m	2m	4m	6m	8m	10m	12m
D-UP	2.56	0.76	0.17	0.94	3.52	3.19	5.08	7.68	5.78
	(1.49)	(0.53)	(0.20)	(0.81)	(2.36)	(1.82)	(2.46)	(3.25)	(2.18)
D-DOWN	1.45	-0.93	-0.33	0.71	-2.17	-3.52	-3.71	-3.25	-2.63
	(0.69)	(-0.50)	(-0.26)	(0.71)	(-1.49)	(-1.89)	(-1.69)	(-1.35)	(-0.98)
High - Low	1.11	1.69	0.50	0.24	5.69	6.72	8.79	10.92	8.41
	(0.41)	(0.72)	(0.33)	(0.14)	(2.73)	(2.63)	(2.92)	(3.25)	(2.24)
N	186	186	186	186	186	186	186	186	186

Table 8: Determinants of Top Management Team Diversity

The table presents correlations. In all columns the dependent variable is Diversity. Standard errors are clustered by firm. t-statistics are shown in parentheses. A detailed definition of all the variables is provided in the Appendix.

	(1)	(2)	(3)	(4)	(5)
Team Size	0.015	0.015	0.015	0.015	0.015
	(17.93)	(17.84)	(17.69)	(17.64)	(13.84)
Bio Length	-0.009	-0.004	-0.003	-0.003	-0.031
	(-1.94)	(-0.72)	(-0.65)	(-0.65)	(-4.63)
Size	-0.018	-0.018	-0.018	-0.017	-0.004
	(-9.96)	(-9.85)	(-9.39)	(-9.17)	(-0.84)
Leverage	0.050	0.051	0.054	0.054	-0.001
	(3.97)	(4.09)	(4.31)	(4.24)	(-0.08)
Capex	0.050	0.051	0.055	0.057	0.000
	(2.80)	(2.84)	(3.02)	(3.00)	(0.01)
Cash Holdings	0.047	0.046	0.036	0.036	0.013
	(4.25)	(4.21)	(3.23)	(3.18)	(0.74)
Payout	-0.312	-0.315	-0.243	-0.236	-0.095
	(-4.58)	(-4.64)	(-3.50)	(-3.37)	(-1.28)
Gross Profitability	0.041	0.042	0.015	0.015	-0.000
	(6.52)	(6.75)	(2.48)	(2.35)	(-0.04)
R&D Expenditure	-0.000	0.000	-0.001	-0.001	0.001
	(-0.29)	(0.03)	(-1.09)	(-1.15)	(0.86)
Tobin's Q	-0.002	-0.002	-0.002	-0.002	-0.001
	(-1.62)	(-2.09)	(-1.70)	(-1.57)	(-0.54)
Negative Earnings	0.004	0.005	0.000	0.000	-0.001
	(0.93)	(1.23)	(0.05)	(0.10)	(-0.29)
Takeover	0.015	0.016	0.014	0.013	0.015
	(1.71)	(1.82)	(1.61)	(1.51)	(2.28)
Idiosyncratic Volatility	0.641	0.317	0.201	0.213	0.396
	(3.92)	(1.45)	(0.93)	(0.96)	(2.52)
Top University	0.068	0.066	0.068	0.066	0.052
	(6.05)	(5.83)	(5.87)	(5.72)	(2.36)
Year FE	No	Yes	Yes	No	No
Industry FE	No	No	Yes	No	No
Industry × Year FE	No	No	No	Yes	No
Firm FE	No	No	No	No	Yes
Observations	17811	17811	17811	17811	17811
Adjusted R^2	0.12	0.13	0.14	0.14	0.07

Table 9: Robustness

The table presents robustness checks. Panels A and B sort stocks into quintiles by Team Size and Biography Length. Panel C presents conditional sorts where we first sort stocks into quintiles of a given firm characteristic, and then within these groups by Diversity quintile. Panel D presents results when we sort by residual Diversity, defined as the residual from the regression of Diversity on indicators for the Fama-French 48 industries. Diversity, Team Size, Biography Length, residual Diversity and firm characteristics are expressed in their December year $t-1$ values, for July year t to June year $t+1$. All panels report Fama-French-Carhart four-factor alphas for the bottom and top quintile of each variable, and for their difference. The last three columns of each panel show the t-statistic for the corresponding quintiles and for the difference between quintiles.

Panel A: Sorting on Team Size

	Low	High	L−H	Low	High	L−H
	Value-Weighted FFC alpha			t-statistic		
All firms	-0.06	0.03	-0.10	-0.69	0.32	-0.65
Big firms	0.00	0.02	-0.02	0.01	0.18	-0.09
Small firms	-0.03	0.09	-0.13	-0.24	0.70	-0.60

Panel B: Sorting on Biography Length

	Low	High	L−H	Low	High	L−H
	Value-Weighted FFC alpha			t-statistic		
All firms	0.04	0.09	-0.05	0.45	0.51	-0.26
Big firms	0.03	0.26	-0.23	0.33	1.20	-0.93
Small firms	0.14	-0.32	0.46	0.96	-1.92	2.03

Panel C: Conditional Sorts Using Firm Characteristics

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Value-Weighted FFC alpha			t-statistic		
All Firms						
Payout	0.24	-0.07	0.31	1.73	-0.85	1.91
Cash Holdings	0.32	-0.11	0.44	2.19	-1.37	2.53
Capex	0.27	-0.13	0.39	1.84	-1.45	2.16
Leverage	0.37	-0.07	0.44	2.50	-0.72	2.44
Big Firms						
Payout	0.26	-0.13	0.39	1.70	-1.25	2.05
Cash Holdings	0.39	-0.00	0.39	2.63	-0.03	2.00
Capex	0.40	-0.05	0.46	2.69	-0.52	2.40
Leverage	0.37	-0.10	0.47	2.45	-0.90	2.36

Panel D: Control for 48 Fama-French Industries

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Value-Weighted FFC alpha			t-statistic		
All firms	0.31	-0.08	0.39	1.93	-0.97	2.01
Big firms	0.38	-0.12	0.50	1.99	-1.24	2.19
Small firms	-0.10	0.11	-0.21	-0.88	0.92	-1.27

Panel E: Excluding Single Executives Firms

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Value-Weighted FFC alpha			t-statistic		
All firms	0.31	-0.09	0.41	2.24	-1.19	2.43
Big firms	0.40	-0.15	0.55	2.33	-1.62	2.66
Small firms	-0.10	0.26	-0.36	-0.89	2.56	-2.45

Table 10: Diversity Returns, Volatility, and Analyst Coverage

The table shows diversity sorts for various groups of Size-Adjusted Idiosyncratic Volatility and Size-Adjusted Analyst Coverage. Panel A presents results for 3×5 independent sorts, based on terciles of Size-Adjusted Idiosyncratic Volatility and quintiles of Diversity. Panel B shows analogous sorts using Size-Adjusted Analyst Coverage and Diversity. To adjust for size, we regress Idiosyncratic Volatility (or Analyst Coverage) on Size (market cap in June year t) and Size squared. Diversity and Idiosyncratic Volatility are expressed in their December year $t-1$ values, for July year t to June year $t+1$. Idiosyncratic Volatility is the standard deviation of residuals from a four-factor model estimated on daily returns over the previous 12 months. For Analyst Coverage we sort into portfolios with monthly frequency. All panels report Fama-French-Carhart four-factor alphas for the bottom and top quintile of Diversity, and for their difference. The last three columns of each panel show the t-statistic for the corresponding quintiles and for the difference between quintiles.

Panel A: Size-Adjusted Idiosyncratic Volatility

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Risk-adjusted Value-Weighted Returns (alpha)				t-statistic	
Low	-0.00	-0.02	0.02	-0.02	-0.16	0.08
Mid	-0.17	-0.06	-0.11	-0.97	-0.47	-0.62
High	0.58	-0.52	1.10	2.21	-3.71	3.28

Panel B: Size-Adjusted Analyst Coverage

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Risk-adjusted Value-Weighted Returns (alpha)				t-statistic	
Low	0.18	-0.50	0.67	0.64	-2.34	1.92
Mid	0.29	-0.02	0.31	1.38	-0.11	1.09
High	0.24	0.16	0.08	1.35	1.16	0.33

Table 11: Diversity, Profitability, and Quality

Panel A shows abnormal returns from a Fama and French (2014) five-factor model, for portfolios that follow the Diversity strategy. Panel B reports abnormal returns from a model that combines the three Fama-French factors with the Asness, Frazzini, and Pedersen (2013) quality-minus-junk (QMJ) factor. Panel C sorts stocks into quintiles of Top University, and reports Fama-French-Carhart four-factor alphas. For Diversity and Top University we use values as of December year $t-1$, for July year t to June year $t+1$. All panels report abnormal returns for the bottom and top quintile of each variable, and for their difference. The last three columns of each panel show the t-statistic for the corresponding quintiles and for the difference between quintiles.

Panel A: Risk-Adjusting Using Fama-French (2014) Five-factor Model

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Value-Weighted FF (2014) alpha				t-statistic	
All firms	0.26	-0.08	0.34	1.74	-0.85	1.88
Big firms	0.31	-0.11	0.42	1.68	-1.17	1.97
Small firms	0.05	0.16	-0.11	0.45	1.44	-0.71

Panel B: Controlling for FF3 and Quality-Minus-Junk

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
	Value-Weighted alpha				t-statistic	
All firms	0.29	-0.07	0.36	1.93	-0.79	1.93
Big firms	0.35	-0.10	0.45	1.90	-1.00	2.03
Small firms	-0.01	0.15	-0.16	-0.13	1.00	-0.86

Panel C: Sorting on Top University Fraction

	Low	High	L−H	Low	High	L−H
	Value-Weighted FFC alpha				t-statistic	
All firms	-0.00	-0.05	0.04	-0.05	-0.29	0.23
Big firms	-0.02	0.05	-0.07	-0.24	0.26	-0.30
Small firms	0.07	-0.13	0.20	0.80	-0.87	1.14

Table 12: Diversity and Analyst Recommendations and Forecasts

The table reports estimates of regressions relating Buy and Sell Recommendation %, Mean Analyst Recommendation, and Analyst Error to Diversity and other control variables. Mean analyst recommendation takes values from 1 to 5, where 1 represents a strong buy and 5 a strong sell recommendation. Buy Recommendation % represents the percentage of buy recommendations issued by analysts covering the firm, and Sell Recommendation % the sell recommendation percentage. Analyst Error is the absolute value of the difference between estimate and actual EPS, divided by stock price. The EPS estimate is the median 1-year analyst forecast made in the 60 days prior to the earnings announcement date. All regressions include Industry × Year-Month fixed effects. In all regressions standard errors are clustered by firm. t-statistics are shown in parentheses.

	Buy Rec.-% (1)	Sell Rec.-% (2)	Mean Rec. (3)	Analyst Error (4)
Diversity	4.298	-0.022	-0.063	-0.026
	(3.49)	(-0.04)	(-2.77)	(-1.46)
Market Capitalization	-1.733	0.367	0.038	-0.000
	(-7.95)	(5.16)	(9.55)	(-0.14)
Book-to-Market	-4.880	1.205	0.087	0.008
	(-11.92)	(6.72)	(10.75)	(3.72)
Turnover	-0.060	0.079	0.003	0.000
	(-3.12)	(6.98)	(6.55)	(1.96)
Volatility	6.028	-0.095	-0.077	0.033
	(2.85)	(-0.24)	(-2.10)	(1.73)
Constant	57.293	3.148	2.115	0.036
	(30.70)	(4.73)	(62.19)	(4.93)
Industry × Year-Month FE	Yes	Yes	Yes	Yes
Observations	260265	260265	260265	75701
R^2	0.09	0.04	0.08	0.07

Figure 1: Cumulative Returns From Diversity Investing

This figure plots the cumulative returns for the diversity strategy and for other prominent anomalies (Momentum, Net Stock Issues, Accruals, Asset Growth, Profitability). The strategies are plotted as cumulative sum of Size\BTM-adjusted returns. Diversity is defined as in equation (2), and the diversity strategy goes long in diverse firms and short in homogenous firms. Each month, homogenous firms are stocks in the lowest diversity quintile, while diverse firms are stocks in the highest diversity quintile. The sample period runs from January 2002 to December 2014.

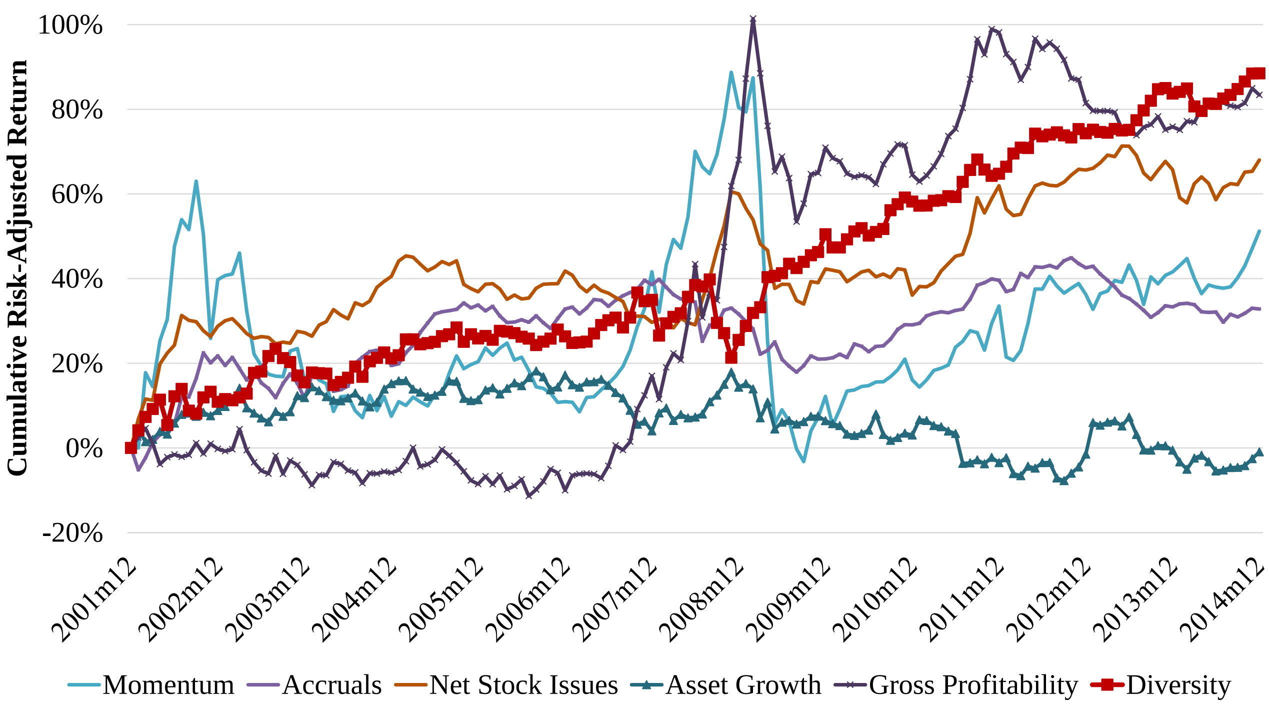


Figure 2: Long and Short Leg of the Diversity Strategy

This figure shows the cumulative return of value-weighted portfolios of diverse and homogenous firms, plotted as the cumulative sum of Size\BTM-adjusted returns. Each month, the portfolio of homogenous firms is composed of stocks in the lowest diversity quintile, while the portfolio of diverse firms includes stocks in the highest diversity quintile. Diversity is defined as in equation (2). The sample period runs from January 2002 to December 2014.

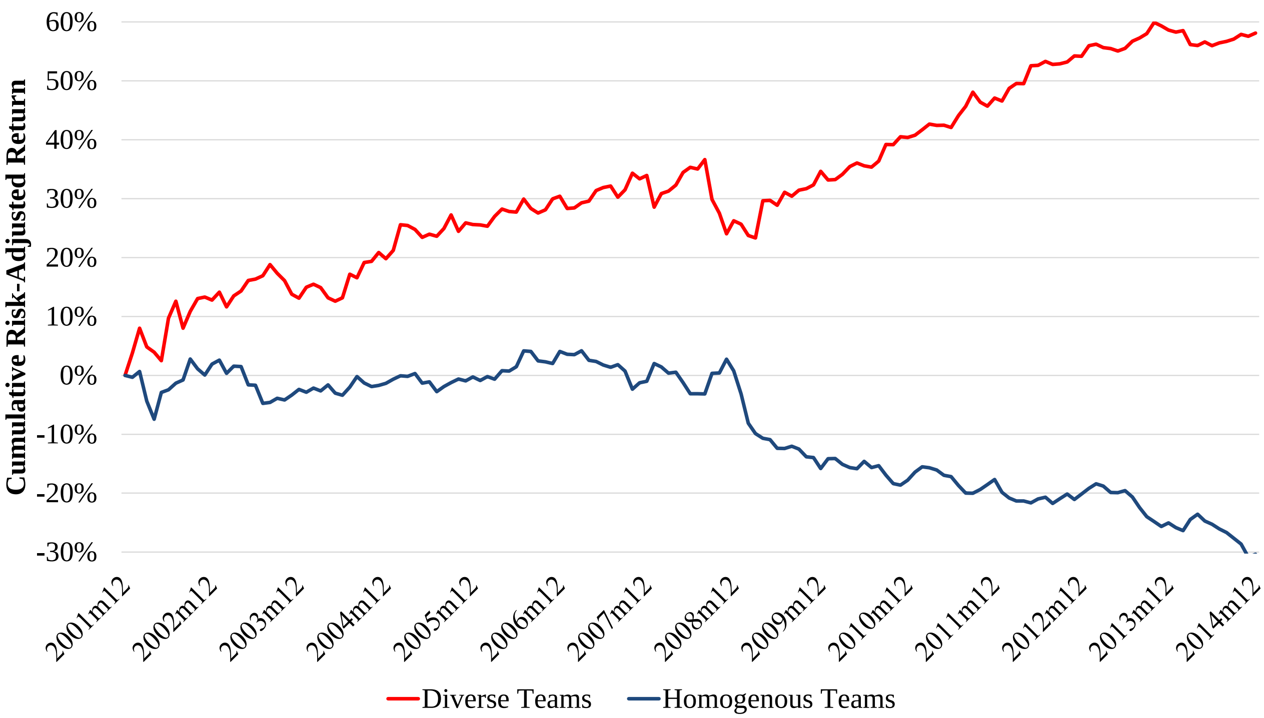


Figure 3: Average Value-Weighted Returns from Diversity Investing

This figure compares the average performance from the diversity strategy with other anomalies (Momentum, Net Stock Issues, Accruals, Asset Growth, Profitability). Performances is measured as the average of Size\BTM-adjusted monthly portfolio returns. Diversity is defined as in equation (2), and the diversity strategy goes long in diverse firms and short in homogenous firms. Each month, homogenous firms are stocks in the lowest diversity quintile, while diverse firms are stocks in the highest diversity quintile. The figure presents results for the full sample, and for subsamples of "large" firms (companies in the S&P500 index) and "small" firms (the residual sample). The sample period runs from January 2002 to December 2014.

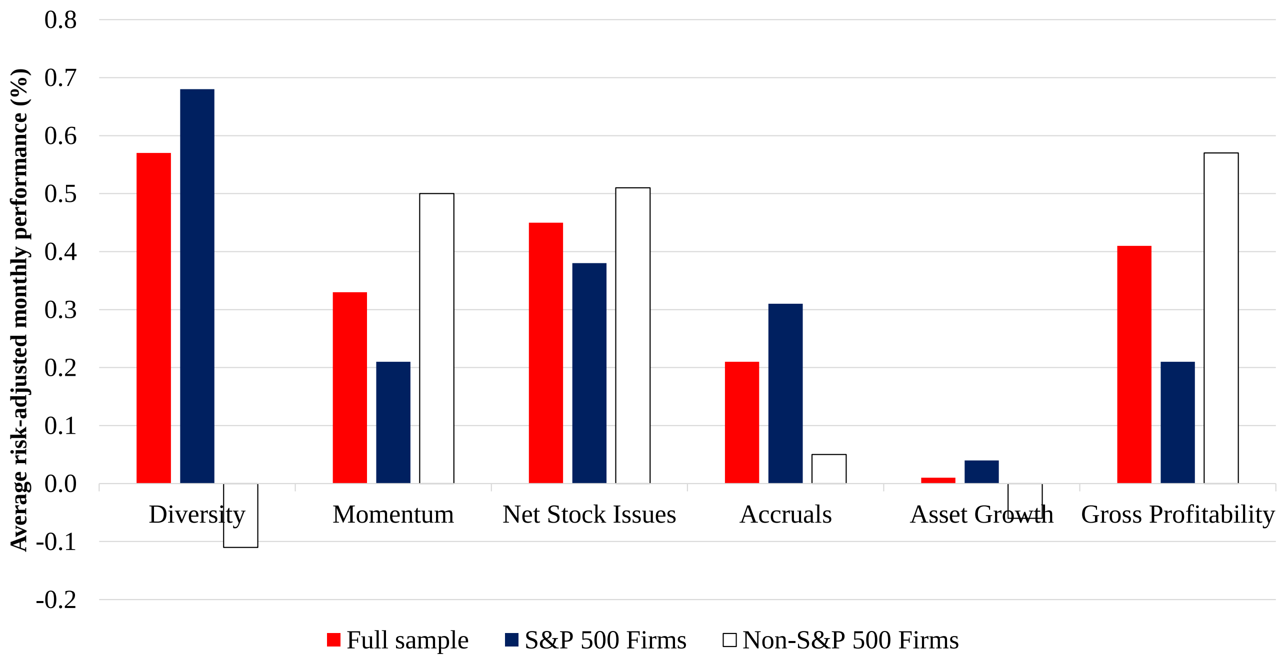
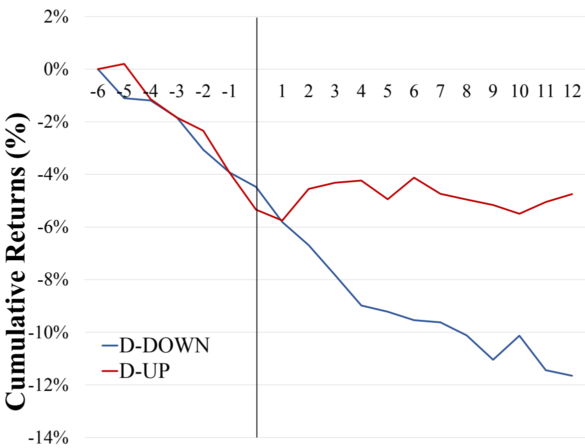
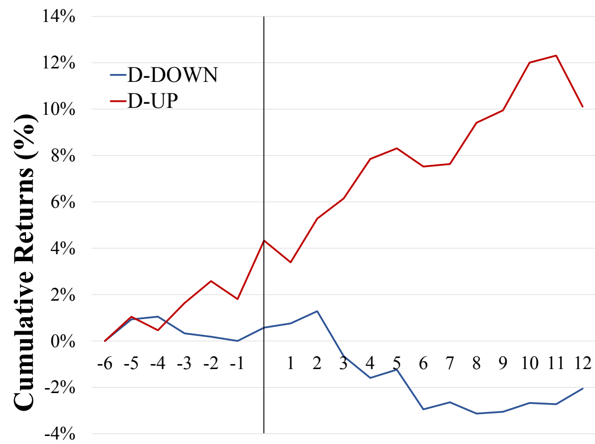


Figure 4: Returns Around Changes in Diversity

This figure shows cumulative abnormal returns from a Fama-French-Carhart four-factor model, for stocks in the D-UP and D-DOWN groups. The first group is composed of those firms that move to the top quintile of Diversity after the event, while the second group is composed of those stocks that move to the bottom quintile of Diversity. Panel A shows the cumulative IRATS four-factor alpha from month −6 to month 12 around the event "Executive Turnover". Panel B shows cumulative IRATS four-factors alpha from month −6 to month 12 around the event "Executive Death". The sample period runs from January 2002 to December 2014.



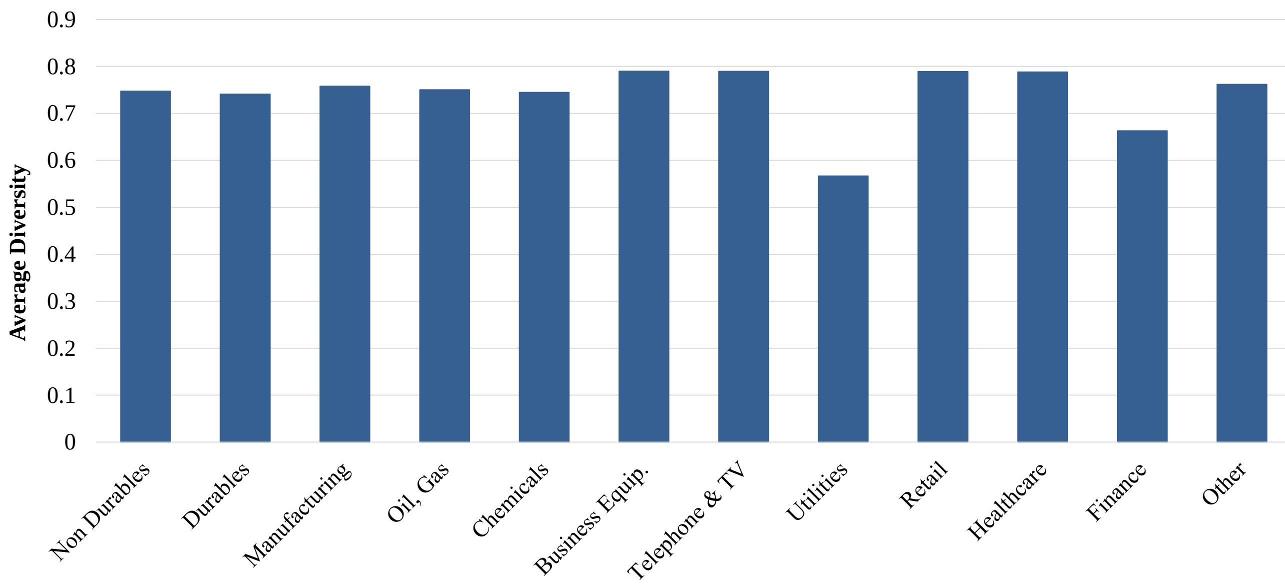
(a) Executive Turnover



(b) Executive Deaths

Figure 5: Average Diversity by Industry

This figure shows the average of diversity by industry across our sample. Industries are based on the Fama-French 12 classification.



APPENDIX

A Description of Variables Used

Variable	Description
Main independent variable	
Diversity	Degree of similarity among the members of the executives team. This variable is computed applying text-based analysis to executives biographies as reported in firms 10-K and DEF-14A SEC filings. It can take on values in the interval [0;1], with 0 representing the Homogenous firms and 1 Diverse firms.
Main sorting variables	
Book-to-market	The natural log of the ratio of the book value of equity to the market value of equity. Book equity is total assets at the end of December year $t-1$, minus total liabilities , plus balance sheet deferred taxes and investment tax credit if available, minus preferred stock liquidating value if available, or redemption value if available, or carrying value. Market equity is price times shares outstanding at the end of December of $t-1$.
Analyst Coverage	The number of analysts covering a particular firm at the end of each month
Net Stock Issues	The natural log of the ratio of the split–adjusted shares outstanding at the end of December year $t-1$ divided by the split–adjusted shares outstanding at the end of December year $t-2$. The split-adjusted shares outstanding is Compustat shares outstanding times the Compustat adjustment factor.
Asset growth	The natural log of the ratio of assets per split–adjusted share at the end of December year $t-1$ divided by assets per split–adjusted share at the end of December year $t-2$. This is equivalent to the natural log of the ratio of gross assets at $t-1$ divided by gross assets at $t-2$ minus net stock issues from $t-2$ to $t-1$.
Accruals	The change in operating working capital per split-adjusted share from $t-2$ to $t-1$ divided by book equity per split–adjusted share at the end of December $t-1$. Operating working capital is current assets minus cash and short–term investments minus current liabilities plus debt in current liabilities.
Gross Profitability	Revenues minus cost of goods sold at the end of December $t-1$ divided by book value of assets at the end of December $t-2$.
Momentum	Momentum, the cumulated continuously compounded stock return from month $j-12$ to month $j-2$, where j is the month of the forecasted return. We measure the momentum variable monthly.
Other variables	
Market Cap.	The natural logarithm of price times shares outstanding at the end of June of year t
Volatility	The standard deviation of daily returns over the previous 12 months.
Idiosyncratic Volatility	Standard deviation of residuals from 4–factors model estimated from daily returns over the previous 12 months.
Analyst Error	Absolute value of the difference between median analyst EPS forecast and actual EPS. Median analyst EPS forecast is computed by considering all the 1-year analyst forecasts made in the 60 days prior to the earnings announcement date
Mean Analyst Recomm.	Mean of analyst recommendation, it is calculated by assigning to each contributing analysts Recommendation an integer based on a scale from 1 to 5 and calculating a real number average.

Size	Natural logarithm of total book assets.
Tobin's Q	Ratio of the market value of assets over the book value of assets.
Leverage	Ratio of the book value of long-term debt plus short-term debt over total assets.
Capex	Ratio of capital expenditures over the book value of assets.
Acquisition Expenditures	Ratio of acquisition expenditures over book value of assets
R&D	Ratio of R&D expenditures over sales
Cash Holdings	Ratio of cash and short term investments over the book value of assets.
Payout	Ratio of total dividends over the book value of assets.
Neg. Earn.	Dummy variable that takes value 1 when firm presents negative earnings
Takeover	Dummy that takes value 1 if the firm is one of the parties in a M&A deal
Team Size	Number of executives constituting the top management team
Biography Length	Average number of words in the biographies of each top management team member
Top University	Ratio of the number of executives team members that attended a top 20 US university (irrespective of education level) over total number of executives
Single Executive	Dummy that takes value 1 when the firm reports only one executive in its top management team

B Examples of Low Diversity Biographies

Company Name	Executive Biography
ANAREN INC - 2012	Carl W. Gerst, Jr. has served as Chief Technical Officer and Vice Chairman of the Board since May 1995 and served as Treasurer from May 1992 to November 2001. Mr. Gerst previously served as Executive Vice President of the Company from its founding until May 1995, and has been a member of the Companys Board of Directors since its founding in 1967. He holds a Bachelor's Degree from Youngstown University and a Master's Degree in Business Administration from Syracuse University.
ANAREN INC - 2012	Lawrence A. Sala joined the Company in 1984. He has served as President since May 1995, as Chief Executive Officer since September 1997, and as Chairman of the Board of Directors since November 2001. Mr. Sala became a member of the Board of Directors of the Company in 1995. He holds a Bachelor's Degree in Computer Engineering, a Master's Degree in Electrical Engineering and a Master's Degree in Business Administration, all from Syracuse University.
ENBRIDGE ENERGY LLC - 2008	D.V. Krenz was elected Vice President of the General Partner and Enbridge Management in January 2005. Prior to that, he was President of Shell Gas Transmission, LLC (previously Shell Gas Pipelines Co.) from March 1996 to December 2004.
ENBRIDGE ENERGY LLC - 2008	A.M. Schneider was elected Vice President, Regulated Engineering and Operations of the General Partner and Enbridge Management in October 2007. Prior to his election he served as Director of Engineering and Operations for Regulated & Offshore and Director of Engineering Services from January 2005. Prior to that, Mr. Schneider was Vice President of Engineering and Operations for Shell Gas Transmission from December 2000.
GIANT MOTORSPORTS INC - 2008	Russell A. Haehn has been the Chairman, Chief Executive Officer and Secretary of the Company since the acquisition of W.W. Cycles, in January 2004, and holds the same positions with W.W. Cycles since such time. Prior to such acquisition, Mr. Haehn had been the Vice President and a director of W.W. Cycles since its inception in 1984. From 1990 to 2000, Mr. Haehn also was the founder, President, a director and the sole shareholder of Andrew Cycles Incorporated, which was an importer and exporter of motorcycles.
GIANT MOTORSPORTS INC - 2008	Gregory A. Haehn has been the President, Chief Operating Officer, Treasurer and a director of the Company since the acquisition of W.W. Cycles, in January 2004, and holds the same positions with W.W. Cycles since such time. Mr. Haehn, since its inception in 1998, also has been the President, director and sole shareholder of Yukon International Inc., a manufacturer, distributor and retailer of fitness equipment. From May 2000 to December 2000, Mr. Haehn was President of Interactive Marketing Technologies, Inc., a publicly-traded company in the direct marketing business. From 1988 to 1997, Mr. Haehn was the founder, President and sole shareholder of Midwest Motorsports Inc., a power sports dealership in Akron, Ohio which sold motorcycles. Additionally, from 1976 to 1997, Mr. Haehn was the President of Worldwide Auto Parts Inc., a leading regional auto parts supply business in Northeastern Ohio.