Diversity Investing

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Abstract

Top management team diversity matters for stock returns. We develop a new text–based measure of team diversity and apply it to a sample of over 40,000 top executives in S&P 1,500 firms from 2001 to 2014. Buying firms with diverse teams and selling firms with homogenous teams—a strategy we call "diversity investing"—outperforms leading asset pricing anomalies over our sample period on a value-weighted basis. We examine a range of possible explanations and find strong evidence for the view that analysts and investors have downward-biased return expectations on firms with diverse teams, consistent with a mispricing explanation for diversity returns.

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

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1. Introduction

A large management literature analyzes how the 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 an extensive body of work on diversity in other fields, there is relatively little work on top management team diversity in the finance literature. Existing studies suggest diversity may play an important role for understanding financial outcomes, but, despite significant progress, many first-order questions are still unanswered.

Our paper studies the impact of top management team diversity on stock returns. Direct evidence shows that important stock market investors care about the diversity of corporate leadership. For example, in March 2015, a group of public investment funds, collectively managing assets in excess of one trillion dollars, submitted a petition to the SEC which asks for enhanced diversity disclosure for board nominees.[1] As another example, BlackRock Inc.'s proxy voting guidelines explicitly encourage firms to "take into consideration the diversity of experience and expertise" when determining the structure of their leadership team, and threatens to oppose director nominations if firms pay "insufficient attention to diversity."[2]

If prominent investors care about the diversity of top management teams, two questions emerge: Is top management team diversity related to stock returns? And if it is: Are returns driven by differences in what firms with diverse top management teams do, or by differences in how such teams are perceived by investors?

To answer these questions, we exploit a new source of data, managerial biographies firms are

[1] "We believe better disclosure about the board's skills, experiences, gender, race, and ethnic diversity can help us as investors determine whether the board has the appropriate mix to manage risk and avoid groupthink. For these reasons, we urge the Commission to initiate a rulemaking process to require better disclosure." The signatories included the California Public Employees Retirement System (CalPERS), the Washington State Investment Fund, the Connecticut Retirement Plans and Trust Fund, the California State Teacher's Retirement System, the Illinois State Board of Investment, the Ohio Public Employees Retirement Systems, the New York State Common Retiremen Fund, and the North Carolina Department of State Treasurer. The full text can be found at: https://www.sec.gov/rules/petitions/2015/petn4-682.pdf.

[2] Source: https://www.blackrock.com/corporate/en-br/literature/fact-sheet/blk-responsible-investment-guidelines-us.pdf

required to disclose to the Securities and Exchange Commission (SEC), and use them to develop a novel text–based measure of team diversity (explained in detail below). These new data allow us to cover almost all firms in the S&P 1,500 over the period from 2001 to 2014, i.e., more than 40,000 individual executives in more than 2,500 unique firms.

Our central result, based on our new measure, is that firms with diverse top management teams ("diverse firms") dramatically outperform firms with non-diverse top management teams ("homogenous firms"). For value-weighted raw returns, buying diverse firms and selling homogenous firms – a strategy we label "diversity investing" – yields a 53bps average monthly return over our sample period, with an annualized Sharpe ratio of 0.63, and a t-statistic of 3.20. This remarkable performance is robust to a range of standard risk-adjustments. For example, using value-weighted Fama-French-Carhart adjusted returns, diversity investing yields 44bps, with a t-statistic of 3.36.

Figure 1 presents cumulative size and book-to-market adjusted returns for a set of well-known investment strategies over our 13-year sample period. The diversity strategy delivers a cumulative risk-adjusted return of 60%, which exceeds value-weighted returns from Momentum, Profitability, Asset Growth, and Accrual strategies, and is only slightly lower than the return from a Net Stock Issuance strategy (we discuss details on the construction of these return series below). A remarkable feature of diversity investing, visible from Figure 1, is that it combines high returns with low volatility, which leads to the Sharpe ratio from diversity investing dominating all other investment strategies we consider.

For investors, diversity investing has several attractive features. Most importantly, it works best on a value-weighted basis. This is interesting because a common concern about anomalies is that most of them produce alphas only for small stocks, which make up a minor part of market wealth and are costly to trade. Adding to the likely tradeability of the diversity strategy is that its returns are not exclusive to the short leg of the strategy's investment portfolio, and that implementing the strategy does not require large portfolio turnover. For example, the required turnover is similar to implementing a value strategy, but an order of magnitude less than implementing momentum.

The returns to diversity investing are robust to a number of changes to our baseline setup: diversity returns are not subsumed by a combination of other anomaly strategies; and they are not driven by a battery of observable firm-level or industry-level characteristics. We also show that diversity returns are not driven by top management team diversity being correlated with corporate governance, workforce diversity, firm complexity, or measures of managerial skill. While risk-based explanations are impossible to rule out completely, we show that diversity returns are not captured by a large range of standard risk-adjustments.

Having established large positive returns to diversity investing in a first step, our second step is to examine a range of potential explanations. The main result in this second part of the paper is that diversity returns are driven, at least partly, by mispricing. Two pieces of evidence lead to this conclusion. First, using a direct test of mispricing due to Engelberg, McLean, and Pontiff (2017b), we find evidence suggesting the market is systematically positively surprised about diverse stocks on days when new firm-specific information becomes available. Second, we provide *direct* evidence for downward-biased expectations of important stock market participants, by showing that security analysts' forecasts are systematically more pessimistic for diverse firms than homogenous firms. Hence, similar to recent work by Engelberg, McLean, and Pontiff (2017a), and Bouchaud, Ciliberti, Landier, Simon, and Thesmar (2016), downward-biased analyst expectations appear tightly linked to return anomalies.

We also examine a range of alternative channels for diversity returns. Notably, we find some evidence supporting a role for profitability. A strand of the related literature in management and finance argues that diverse teams will often make better decisions (e.g., Landier, Sauvagnat, Sraer, and Thesmar (2013)). Diverse firms may therefore be more profitable, which, in turn, may lead to higher returns, following the valuation equation logic in, for example, Fama and French (2014) and Novy-Marx (2014). We show this channel may indeed be operative and that it explains up to one fifth of the returns to diversity investing, depending on the estimation method we use.

Combined, our paper proposes a simple rationale for why professional investors care about top management team diversity: diversity predicts subsequent stock returns and diversity investing is profitable relative to standard return benchmarks. We provide strong evidence suggesting that biased investor expectations, and therefore mispricing, are important drivers of diversity returns. We find only weaker evidence for fundamental differences between diverse and homogenous firms driving diversity returns. We thus conclude that investor perceptions are important for understanding the impact of top management team diversity on stock returns. This investor perception channel is, to the best of our knowledge, new to the literature on diversity in top management teams.

In terms of methodology, a key empirical challenge our paper addresses is measuring diversity of the top management team for a large set of firms. We propose using textual analysis on a new source of managerial background data. Specifically, we exploit the fact that the SEC requires all 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 standard textual analysis tools (e.g., Hanley and Hoberg (2010), Hoberg and Phillips (2016)). One advantage of this approach is that we can build a very large dataset on diverse management teams.

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 age, tenure, nationality, or gender. Such studies capture some relevant dimensions of diversity, but at the same time miss many others. By contrast, our text–based measure allows us to capture many dimensions of diversity simultaneously (to be specific, up to 55,000 for the average firm-year), without limiting ourselves to a pre-specified, and usually small, set of dimensions.

1.1 Relation to Existing Literature

Our paper contributes to the empirical asset pricing literature by documenting a particularly striking stock market pattern: diversity investing delivers high returns, with low volatility, for large-cap stocks, and at low portfolio turnover. Over our sample period, diversity returns match, if not surpass, some of the most prominent anomalies in the literature. A second contribution is to show that diversity returns may be a quantitatively substantial case of mispricing (even though rational explanations may still explain part of diversity alphas).

Studying the link between diversity and returns is motivated by two facts. First, the idea that the diversity of corporate leadership teams matters for corporate outcomes is long standing, and firmly rooted in a large management literature, as well as a growing literature in finance (see e.g., Jackson, Joshi, and Erhardt (2003), Harrison and Klein (2007), Nielsen (2010) for surveys of the management literature; see below for references in finance). Second, there is both anecdotal and scientific evidence suggesting sophisticated 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), Gompers, Gornall, Kaplan, and Strebulaev (2016)), and in particular the diversity of the leadership team (see, for example the petition to the SEC or BlackRock Inc.'s proxy voting guidelines mentioned in the introduction). A natural assumption is that sophisticated investors care about diversity because they believe it impacts stock returns. We believe these facts provide a priori grounds to study the link between diversity and returns, and our study is, to the best of our knowledge, one of the most comprehensive on this link.

Our study is related to the asset pricing literature on the role of biased investor expectations for stock market anomalies (e.g., Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998)). Specifically, closely related to our paper, Engelberg, McLean, and Pontiff (2017b) study the role of biased cash-flow expectations on a broad set of 97 anomalies. Engelberg, McLean, and Pontiff (2017a) document that analysts have downward-biased expectations about firms in anomaly portfolios and argue that one channel through which anomalies manifest is investors following biased analyst expectations. In a similar vein, Bouchaud, Ciliberti, Landier, Simon, and Thesmar (2016) and Asness, Frazzini, and Pedersen (2017) study biased analyst expectations as a source of the returns to "quality" investing. Our paper provides new and complementary evidence supporting the view that downward-biased analyst expectations are linked to return anomalies.

Our paper is related to an important corporate finance literature on the diversity of corporate boards (see e.g., Ferreira (2010) for a survey). Examples include studies on the effects of women on boards (e.g., Adams and Ferreira (2009), Ahern and Dittmar (2012), Adams (2015), Kim and Starks (2016)), studies on CEO power vis-á-vis the board (e.g., Adams, Almeida, and Ferreira (2005), Fahlenbrach (2009), Bebchuk, Cremers, and Peyer (2011)), studies on nationality of board members (e.g., Masulis, Wang, and Xie (2012)), studies on variation in expertise and prior work history (e.g., Güner, Malmendier, and Tate (2008), Coles, Daniel, and Naveen (2015)), and studies that combine several characteristics into an index (e.g., Gompers, Mukharlyamov, and Xuan (2016), Giannetti and Zhao (2016), Adams, Akyol, and Verwijmeren (2017)).

There are four key differences between our study and most of the existing literature on diversity in finance. First, almost all papers in the literature use a bottom-up approach, i.e., they measure diversity by relying on one or more variables hypothesized to capture the relevant dimension of group heterogeneity (e.g., age, gender, education etc.). By contrast, our approach is top-down, i.e., we use similarities in biographical texts, which eliminates the need to limit ourselves to a small, pre-specified set of dimensions and allows us to capture similarities on a very detailed level. By using a top-down approach, our study complements the bottom-up approach in the existing literature, and contributes fundamentally new evidence on the impact of diversity on financial outcomes.

The second difference from the existing literature is our focus on stock returns, and investment strategies to be used by stock market investors. Only a subset of the studies in the literature focuses on performance. Those that do, almost exclusively focus on accounting performance and stock market valuations. But, importantly, differences in accounting performance, or differences in valuation levels, do not necessarily imply differences in stock returns. Specifically, in the benchmark case of an efficient market, if diverse top management teams were systematically able to generate higher cash flows, then accounting profits and valuations would be higher, but stock returns would not differ between diverse and homogenous firms; the effects of diversity would already be priced in, generating no excess performance going forward. What sets our study apart is the focus on whether and how stock market investors can profit from diversity investing.

That change in focus is consequential also for another reason. Most existing work analyzes the relation between diversity and performance on an individual firm basis. However, an investor can form *portfolios*, which can have different properties than individual stocks. To see why this is important, consider the case of firm risk. In our sample, individual stocks with diverse top management teams have higher stock return volatility. However, we show that a diversity investing strategy which goes long a portfolio of diverse firms and short a portfolio of homogenous firms yields returns with particularly low volatility, and particularly high Sharpe ratios, compared with other prominent investment strategies.

A third difference between our paper and most of the prior literature in finance is that we focus on the top management team of executives, rather than corporate boards. While boards may matter more for the broad strategic direction of a company, the top management team is more likely relevant for the firm's day-to-day operations. Compared with the literature on corporate boards, few papers focus on top management teams, even though good theoretical and empirical reasons suggest looking at top management teams can be incrementally valuable (see e.g., Landier, Sauvagnat, Sraer, and Thesmar (2013)). Our findings thus provide new evidence from top management teams to complement existing work on corporate boards.

Finally, our results suggest top management team diversity induces differential investor perceptions and promotes misvaluation. The role for investor perceptions is specific to the stock market setting and thus a new contribution relative to existing work which focuses on firm-level corporate outcomes.

2. Background, Measurement, 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.

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 for each top executive and year with the SEC under Regulation S-K of the U.S. Securities Act of 1933. Items 401(b), (c), and (e) require firms to identify each executive officer or other significant (non-director) employee, and report their principal occupations and employment over the past five years plus any material information on relevant business experience and professional competence. The following is one example of a text firms provide in response to this SEC requirement. It is from General Electric's 2009 proxy statement and describes the company's CEO, Jeffrey Immelt:

> Mr. Immelt joined GE in corporate marketing in 1982 after receiving a degree in applied mathematics from Dartmouth College and an MBA from Harvard University. He then held a series of leadership positions with GE Plastics in sales, marketing and global product development. He became a vice president of GE in 1989, responsible for consumer services for GE Appliances. He subsequently became vice president of worldwide marketing product management for GE Appliances in 1991, vice president and general manager of GE Plastics Americas commercial division in 1992, and vice president and general manager of GE Plastics Americas in 1993. He became senior vice president of GE and president and chief executive officer of GE Medical Systems in 1996. Mr. Immelt became GEs president and chairman-elect in 2000, and chairman and chief executive officer in 2001. He is a director of the Federal Reserve Bank of New York, a trustee of Dartmouth College, and was recently named a member of President Obamas Economic Recovery Advisory Board.

For each firm, information about each of its top management team members is provided in filings available in electronic form from the SEC on its EDGAR website. We use a web crawler to retrieve these data, going back until 2001 (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, a well-established method widely used in a recent strand of the finance literature (e.g., Hanley and Hoberg (2010), Hoberg and Phillips (2016)).

Firms provide biographies either in the annual report, or in the proxy statement. We thus electronically scan forms "10-K," "10KSB," or "DEF 14A" in the SEC EDGAR database for each firm and year. In 10-Ks, the biographies are usually provided in Item 10 or Item 4A. In proxy statements (DEF 14A), which have a less standardized structure, the biographies can often be found in a specific section whose title refers to "Executive Officers" or "Management." We employ a web-crawling algorithm written using Python to collect and process the biographies. We use human intervention whenever the non-standard format of a firm's filing does not allow the program to extract the biographies. Using this approach, we obtain a raw sample of 59,863 firm-year observations, consisting of 420,428 executive biography-year observations.

Next, we build the main dictionary. To this end, we take the list of all unique words used in all biographies in year t. Following Hoberg and Phillips (2016) we restrict attention to words classified as either nouns or proper nouns. We also keep adjectives, because words like "international" can carry informational value in our context. Also following Hoberg and Phillips (2016), we exclude words that appear in more than 25% of all biographies in a given year because such words are unlikely to convey meaning (e.g., "company"). The resulting list of N words is the "main dictionary" and it is represented by a vector of length N. We then summarize each biography's usage of the N words of the "main dictionary" by means of an N-vector. The n-th entry of a biography's N-vector is 0 if the n-th dictionary word is not used in the biography, or x, where x is the number of times the n-th word appears in the biography. The output is, for firm k in year t, a $M \times N$ matrix, where M is the number of executives in the top management team of firm k in year t.

Appendix B illustrates typical words in the biographies by showing the 100 most frequently used words in the "main dictionary" for the year 2011. As is evident from this list, texts relate to many different areas that are plausibly related to similarities between executives, including: industries ("technology", "bank", "engineering"), functional backgrounds ("operations", "marketing", "sales"), job titles ("controller", "treasurer", "CEO"), geography ("international", "global", "California"), education ("degree", "bachelor", "MBA"). Frequent words also cover dimensions of similarity that are potentially relevant, but harder to measure ("leadership", "responsibility", "governance"). Overall, the list highlights an advantage of the text-based approach: we get a very detailed and, at the same time, high dimensional, image of similarities across executives.

Some words in the list also illustrate a disadvantage of text-based methods: measurement error. For example, the most used word in the year 2011 is "position," which is unlikely to signal similarity among executives.[3] A word like "position," which is commonly used but likely unrelated to diversity, will noise up our diversity measure, and therefore work against us finding

[3]The Hoberg and Phillips (2016) 25% filter is designed to delete most of such common words. The word "position" in the year 2011 apparently just missed the 25% cutoff.

strong effects, but it should not otherwise bias our findings.

For each biographical text associated with executive i, company k, and year t, vector T_{ikt} is a row in the $M \times N$ matrix and describes the biography's word usage. 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 $[M \times (M-1)]/2$ executive pairs in firm k in year t. We consider firms with only one reported top executive as maximally homogenous and thus set $D = 0$.

To get an intuition for the diversity measure, consider a simple example with only two executives and a word dictionary of only two words "Blue" and "Red." If executive i's biography reads "Blue," her vector T_{ikt} is (1 0). If executive j's biography is also "Blue," 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, $D = 0$, i.e., diversity for this top management team is zero. Suppose now that executive j's biography reads "Red." Then, $T_{jkt} = (0\ 1)$ and $CS_{ijkt} = (1 \times 0 + 0 \times 1)/\left(\sqrt{1} \times \sqrt{1}\right) = 0$. It follows that $D = 1$, which means this team of top executives is maximally diverse.

A potential concern with analyzing texts in SEC filings is that the executives may not write the biographies themselves. We do not believe this is a serious limitation in our setting. First, while executives are not writing the bios, it is likely that many, if not most, would at least read them, given this is detailed personal information to be widely distributed among investors in a formal document. Second, the underlying biographical information (e.g., where the executive obtained her MBA or whether she has worked for a given company in the past) does not depend on who writes the biography. Third, the SEC requires certain items to be part of the bio, so the ability to "cherry-pick" entries is limited. Fourth, 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. Finally, even if diversity were picking up some correlated variable related to who writes the bios, that would not take anything away from the main result of our paper: sorting stocks based on our diversity measure yields exceptionally high risk-adjusted returns.

2.3 Data

We merge the firm-level diversity measures with the CRSP-Compustat Merged database. We drop all firms with missing or negative book value of equity, firms with less than 12 months of previous stock returns, firms with missing data to compute market cap in June year t, and utilities (sic codes 4900-4999). Because we are particularly interested in diversity returns for the investable universe of stocks, and because we want to ensure completeness of the data, we restrict attention to stocks in the S&P 1,500 in each year. Restricting to the S&P 1,500 allows us to hand-collect biographies for all firms for which we cannot automatically retrieve them with our webcrawler (e.g., because of formatting issues), and thus helps us minimize the risk of selection issues related to availability of texts. In the average cross-section we have useable data, after searching for biographical texts, and after applying our filters above, for almost 90% of all S&P 1,500 firms.[4] Our final sample has data on 42,927 individual executives, in 2,550 unique firms, and has 20,249 useable firm-years. All returns and firm level variables are winsorized at the 1^{st} and 99^{th} percentiles.

Table 1 presents summary statistics. Panel A shows time-series averages for various variables of interest when firms are sorted, each year, by their diversity measure (all variables are defined in the appendix.) Diverse firms are associated with higher returns than homogenous firms, which is the focus of our analysis below. Diverse firms are also smaller, although, at $5.0

[4] The majority of missing firm-years are due to firms not passing one of our filters above. The remainder is due to us not finding a biographical text in either 10K, or 10KSB, or DEF14A.

billion of average market capitalization, they are not small in absolute terms. Diverse firms are similar to homogenous firms in their book-to-market ratio, and have higher gross profitability (constructed as in Novy-Marx (2013) as revenues minus cost of goods sold divided by total assets) and idiosyncratic volatility (measured from the residual of a Fama-French-Carhart four-factor model).

Diverse firms do not differ much from homogenous firms in terms of leverage, but they have higher cash holdings, a lower payout ratio, and higher R&D expenditures. Finally, diverse firms tend to have smaller top management teams, but longer biographical texts for each executive.

We will show below that diversity returns are not due to any of the variables in Panel A.

2.4 Team-Level Correlates of Text-Based Diversity

Building on the large literature on textual analysis and studies that employ textual analysis in economics, we argue that similarities in biographical texts provide meaningful information on similarities between individuals. To bolster this case, we now show that the text-based diversity measure is correlated with a range of individual variables that are plausibly associated with the diversity of a top management team.

We obtain individual measures from two sources: (i) BoardEX, which has data on executives in the S&P 1,500 over our sample period, and (ii) the biographical texts themselves. We first construct two employment-related variables (details on the definitions are provided in the appendix): company overlap, which measures for each firm-year the number of unique company names that appear in the biographies of at least two executives, and thus captures prior work experience; tenure overlap, which captures the average time executives have spent together in the top management team at the current company. We also include an education-related variable, university overlap, which captures whether executives on the team went to the same universities. Finally, we include three variables on demographic diversity within the top management team: nationality mix, age standard deviation, and gender standard deviation.

Table 1, Panel B, presents correlations between the various individual measures and the text-based diversity measure. Just as one would expect, the diversity measure is lower for teams in which multiple executives are linked to the same set of companies, and for teams whose members have greater overlap in their tenures as top executives in the current firm. Also in line with expectations, diversity is lower in teams in which multiple executives have obtained their education from the same universities. The pairwise correlations across all three dimensions are significant at the 1% level.

Among demographic variables, we find that diverse teams are more likely to have members with different nationalities (significant at the 5% level), which accords well with intuition. Age standard deviation and gender standard deviation do not significantly correlate with text-based diversity, but note that the correlations of the demographic variables, even among themselves, do not consistently line up with standard diversity interpretations (for example, greater nationality mix is negatively related to greater gender standard deviation, even though both measures could reasonably measure relevant dimensions of diversity.)

Overall, we conclude that the text-based measure aligns well with a number of observable dimensions of diversity. The text-based diversity measure seems to capture in particular 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 pure demographic variables. Combining the examples we provided above, and the results in this section, we are therefore confident that text-based cosine similarity provides a useful gauge of the diversity of a top management team.

While it is reassuring to see the text-based top-down measure broadly lines up with individual bottom-up measures, it bears emphasizing that a key advantage of the top-down text-based measure is that it can capture information from many dimensions simultaneously – to be precise, it can capture N dimensions, the length of the word dictionary, which is around $55,000$ in the average year in our sample, and thus much larger than the number of bottom-up categories a researcher can reasonably pre-specify. The top-down measure may therefore capture a lot of information which individual bottom-up measures may miss. A second advantage of the text-based approach to measuring diversity is that it aggregates this large number of individual dimensions into one index (see equation (2) above.) The results in the following sections suggest that this information aggregation mechanism is very efficient for investment purposes.

3. Main Result

This section presents our main result: diversity investing yields high risk-adjusted returns, on par with, or even exceeding, the returns of a set of well-known investment strategies. We first establish this fact in the data. We then present a battery of robustness checks. We explore why diverse and homogenous firms have different returns in later sections.

3.1 The Returns to Diversity Investing

We define "diversity investing" as the strategy of going long a portfolio of stocks in the top diversity quintile and short a portfolio of stocks in the bottom quintile. Following the standard approach of Fama and French (2008), we predict returns from July in year t through June in year $t+1$ using values of diversity as of December in year $t-1$. A common critique of anomalies is that most of them produce alphas only for small stocks, which make up a minor part of market wealth and are costly to trade (e.g., Novy-Marx and Velikov (2015)). To show diversity returns obtain for the economically most relevant set of stocks, and to show diversity investing may be a tradable strategy even for large investors, we focus on value-weighted returns throughout.

Table 2, Panel A, presents raw strategy returns. The first column shows that diversity investing yields average monthly value-weighted raw returns of 53 basis points, which is economically large. With a t-statistic of 3.20 this outperformance is highly statistically significant and crosses the threshold of 3.0 recently advocated by Harvey, Liu, and Zhu (2016) to attenuate data mining concerns. Diversity investing has a substantial annualized Sharpe ratio of 0.63.

Availability of usable text to create the diversity measure restricts our analysis to the sample period from 2001 to 2014. To gauge the economic and statistical significance of diversity returns, it is useful to compare them with the returns of a set of well-known trading strategies over the same period. We use value, momentum, net stock issuance, accruals, asset growth, and gross profitability as comparison strategies and call them "anomalies" for brevity. We obtain value-weighted return data on those strategies until 2013 from Robert Novy-Marx's website and extend them to 2014 following the methodology of Novy-Marx and Velikov (2015).[5]

Table 2, Panel A, shows raw diversity returns alongside the raw anomaly returns. The key finding is that the average value-weighted raw return of the diversity strategy exceeds that of the other strategies. Moreover, the annualized Sharpe Ratio of the diversity strategy is higher than the Sharpe Ratio of all of the prominent alternatives we consider. Diversity investing thus yields returns that are economically first order.

Panel B of Table 2 presents results when we risk-adjust using the Fama-French-Carhart four-factor model. For value and momentum, we present CAPM-adjusted and Fama-French-adjusted returns, respectively. The panel shows that returns from diversity investing, at 44bps per month ($t = 3.36$), continue to be in the same range as those from the leading anomalies. Both momentum and net stock issuance have higher risk-adjusted returns (63bps), but both have lower t-values (1.13 and 2.85.) The other anomalies have lower risk-adjusted returns and lower statistical significance than diversity investing.

Figure 1 shows that the diversity strategy also performs well when we use size/book-to-market adjusted returns. That figure also shows that diversity returns are not driven by particular time periods within our sample. Rather, diversity returns accrue in a remarkably stable manner across the 14 year sample period. There is no trace of crash risk or substantial return skewness for diversity returns.

If diversity investing combines high returns and low volatility, an important remaining question for investors is how costly it is to trade the strategy. Since we focus on value-weighted

[5]Note that using these data, which are not restricted to S&P 1,500 stocks, gives a slight advantage to the other anomalies, because those anomalies are known to be weaker for larger stocks (e.g., Fama and French (2008)). In any case, since we are value-weighting, this should not matter much quantitatively. We have verified that following the Fama and French (2008) methodology in constructing the return series yields essentially unchanged results, independent of whether we restrict to stocks in the S&P 1,500 or not.

returns, and since diversity, which is based on the managers in a top management team, is a slow-moving variable, transaction costs from diversity are likely low. In Panel C of Table 2 we present supporting evidence from portfolio turnover. For strategies with annual rebalancing (all strategies in Table 2, Panel A, except momentum), we define turnover in year t as:

$$Turnover_t = \sum_i \mid w_{i,t+1} - w_{i,t^+} \mid, \tag{3}$$

where $w_{i,t+1}$ is the weight of stock i at the start of year $t+1$ (i.e., just after rebalancing) and w_{i,t^+} is the weight of stock i in the portfolio at the end of year t (i.e., just before rebalancing). We apply equation (3) separately to the long and the short leg of each strategy and then average across all periods, to obtain an average turnover for each leg of the portfolio. Finally, we take the average of the turnover values for the long and short legs and divide by 12 to get an estimate of monthly turnover. For momentum, which rebalances monthly, we perform an analogous calculation on a monthly basis. Panel C shows that turnover required for diversity investing is low. It is in the same ballpark as turnover for the value and profitability strategies, requires less turnover than net stock issuance, accruals, and asset growth, and substantially less turnover than momentum.

Panel D presents a more detailed look at the portfolios underlying a diversity strategy. While both the long and the short leg of the strategy contribute to the 44bps alpha of the diversity strategy, the 28bps outperformance of the long leg (diverse stocks) is almost twice as high as the 16bps underperformance of the short leg (homogenous firms). The outperformance of the long leg is also statistically more significant (t-value of 2.65 vs. 1.97). Figure 2, which decomposes the performance of the diversity strategy shown in Figure 1 into the long and short legs, shows that diverse firms outperform homogenous firms for most of the years in the sample. Panel D also shows that the portfolio of diverse firms loads more on size and less on value than the portfolio of homogenous firms. Diverse firms also load less on momentum, but the momentum loadings are closer to zero for both legs. There is no difference in market exposure, which implies that diversity investing is effectively market neutral.

Overall, we conclude diversity investing yields economically large outperformance when compared with the leading anomalies in the literature, both in magnitude and statistical significance. It does so for raw returns, risk-adjusted returns, and when comparing Sharpe ratios. Transaction costs required for trading diversity seem small, because diversity investing is a value-weighted strategy with low required turnover. A substantial fraction of the returns to diversity investing come from the log leg (diverse firms), which implies that diversity investing may be attractive even to long-only investors like mutual funds.

3.2 Robustness

3.2.1 Does Diversity Proxy for Other Anomalies?

We start our robustness section by showing that diversity returns are not simply a repackaged version of existing anomalies. To that end, we conduct spanning tests as in, for example, Novy-Marx (2014). In these tests, we regress the time series of diversity strategy returns on the Fama-French-Carhart factors and returns from the set of anomalies we have previously considered. Specifically, we run:

$$y_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \beta_x x_t + \varepsilon_t, \qquad (4)$$

where y_t is the return to the diversity strategy in month t, x_t is the return to an alternative strategy we call the "control strategy," and α is what we label the "diversity alpha." As shown by Huberman and Kandel (1987), $\alpha = 0$ in the above regression is a necessary condition for the set of assets on the right hand side to dominate asset y in a mean-variance sense. If $\alpha > 0$, then the RHS assets do not span asset y. Intuitively, the test asks whether an investor who is already trading on the four factors and the known anomalies would find it attractive to also trade on diversity. A second, more stringent, interpretation of this test is that the variables on the right hand side proxy for sources of priced risk.

As a starting point, Table 3, specification (1), shows our earlier result that diversity investing yields 44bps with a t-statistic of 3.36 when controlling for the Fama-French-Carhart factors. In the next specifications, we add the anomaly strategy returns previously considered. The results in specifications (2) to (5) show that the alpha on diversity investing is not subsumed by net stock issuance, asset growth, accruals, and gross profitability strategies, if we add them to the standard four factors. We estimate diversity alphas between 38bps and 46bps per month, all highly economically and statistically significant.

The positive correlation between the profitability returns and diversity returns in specification (5) is notable, and we will discuss the potential link between profitability and diversity in greater detail below. (We will also discuss specification (6) there.)

Looking at the factor loadings, diversity returns are largely market neutral, load positively on size, and momentum factors, and negatively on value. We conclude from the tests in specifications (1) to (5) that diversity returns are not explained by correlation with previously documented anomalies.

3.2.2 Alternative Factor Models

Specifications (7) to (9) in Table 3 show that our results are robust to risk-adjusting returns with three alternative factor models. First, we include the Pastor and Stambaugh (2003) liquidity factor. Second, we use the Fama and French (2014) five factor model, which includes a profitability factor (RMW) and an investment factor (CMA) alongside the market, size and value factors. Third, we use the Cremers, Petajisto, and Zitzewitz (2013) four-factor model. Diversity alphas remain essentially unchanged for all three alternatives to the FFC four factor model.

3.2.3 Fama-MacBeth Regressions

As an alternative to the portfolio sorts we present results from Fama-MacBeth cross-sectional regressions in Table 4. We present both value-weighted results (specifications (1) and (2)) and equal-weighted results (specifications (3) and (4)). For the former, we weigh each observation by its market capitalization in June of year t, to predict returns from July year t to June year $t+1$.

Table 4, specification (1), shows diversity is positively related to returns with a slope coefficient of 0.78 ($t = 3.55$) before adding controls. Specification (2) controls for market capitalization, book-to-market, momentum, previous-month returns (to control for reversal effects in monthly stock returns documented by Jegadeesh (1990)), idiosyncratic volatility, and turnover. The slope estimate is then 0.59 with a t-statistic of 2.80. To compare the economic significance implied by this regression with the sorting results, note that the difference in diversity between top and bottom quintile is about 0.5. Applying a change of the diversity measure of 0.5 to the slope estimates in specifications (1) and (2), we obtain a monthly difference in returns of about 39bps without controls and 30bps with controls, which is smaller than in the sorts, but economically still very large.

Similar results obtain for equal-weighted returns. Diverse firms have a slope coefficient of 0.47 with a t-statistic of 2.49 without controls, and 0.40 with a t-statistic of 2.44 with controls.

We conclude that Fama-MacBeth regressions and sorts deliver the same message: returns to diversity investing are large and significant.

3.2.4 Does Diversity Proxy for Firm-Level Correlates?

Table 1, Panel A, indicates that diversity is correlated with a set of firm-level variables. Diverse firms tend to be smaller, have higher gross profitability, higher idiosyncratic volatility, higher cash holdings, lower payout ratios, and greater R&D expenditure. Leverage is largely uncorrelated with diversity.

To show that diversity returns are not driven by these correlated firm-level characteristics, we use two sets of tests. First, we use spanning tests, as in Table 3. To implement this test, we form a strategy portfolio for each firm-level variable which goes long the top quintile and short the bottom quintile, analogous to our construction of the diverse-minus-homogenous portfolio. (Since we want to explain variation in diversity returns, it does not matter which quintile we go long, and which quintile we go short.) Second, we run the Fama-MacBeth regressions from Table 4, specification (2), with the firm-level characteristics as additional controls.

Table 5 presents results when we include the firm-level strategies one-by-one, and then, in the bottom row of the panel, jointly. For brevity, we report only the diversity alpha for the spanning tests, and the coefficient on diversity from the Fama-MacBeth regression, respectively. Across both tests, the results show that the returns to diversity investing are very robust, even when we include all variables jointly.

One variable we would like to highlight is idiosyncratic volatility. We know from Ang, Hodrick, Xing, and Zhang (2006) that idiosyncratic volatility predicts returns. The results in Table 4, where we control for idiosyncratic volatility, and the results in Table 5 are useful because they show that diversity returns are not driven by idiosyncratic volatility. In fact, in our sample, idiosyncratic volatility is positively correlated with diversity (Table 1), which would, all else equal, predict lower rather than higher returns. This test is also useful, because it speaks to explanations in which diversity returns are induced by diverse top management teams altering the risk profiles of the businesses they run. Since diversity returns are robust to controls for both systematic and idiosyncratic risk, such an explanation appears unlikely.

In sum, we find no evidence to suggest diversity returns are due to diversity proxying for observable firm-level characteristics.

3.2.5 Industry-Level Determinants

Diversity returns could obtain because diverse firms cluster in particular industries. We use two tests to show that this is not the case. First, we use conditional sorts, in which we sort stocks within each month and Fama-French 12 industry by diversity. The associated value-weighted long-short diversity portfolio has an alpha of 37bps with a t-statistic of 2.65. Second, we add industry dummies to the Fama-Macbeth regression in Table 4, specification (2), which removes any industry-level effect from each cross-section. The coefficient on diversity is then 0.58 with a t-statistic of 3.03, i.e., effectively unchanged.

3.2.6 Text-Level Determinants: Biography Length and Team-Size

Finally, we check whether the diversity measure picks up other characteristics of the biographical texts a firm issues. One concern may be that it is the length of the biographical text that matters, rather than the content. We investigate this again using two tests: a long-short portfolio on biography length, which we add to the spanning tests; and adding biography length as a control to the Fama-MacBeth regressions. Both sets of results clearly indicate that biography length is not inducing diversity returns. In the spanning test, the diversity alpha is 46bps ($t = 3.52$), and, in the Fama-MacBeth regression, the slope coefficient on diversity is 0.58 ($t = 2.83$), which are both effectively identical to our baseline estimates.

A second variable which determines variation in the available texts, and which might be correlated with diversity, is the number of executives in the top management team. Making sure diversity returns are not reflecting team-size is particularly relevant because Boguth, Newton, and Simutin (2016) find that firms with small teams outperform firms with big teams. We again use a long-short portfolio in the spanning tests, as well as a direct control in the Fama-MacBeth regressions to determine whether diversity returns may be proxying for team-size effects. Both sets of tests indicate the answer is negative. In the spanning test, the diversity alpha is 43bps ($t = 3.32$), and, in the Fama-MacBeth regression, the slope coefficient on diversity is 0.57 ($t = 2.80$), when we control for team size effects.[6]

We conclude that the diversity measure does not pick up effects related to biography length or team size.

4. Diversity Returns and Mispricing

The results above establish large returns to diversity investing. These returns are not captured by a large set of standard risk factors, they are not reflecting known anomalies, and they are

[6]Boguth, Newton, and Simutin (2016) argue that team-size returns may be related to the risk permia associated with organizational capital (Eisfeldt and Papanikolaou (2013)). If we include the Eisfeldt and Papanikolaou (2013) measure of organizational capital directly, the diversity alpha is 40bps ($t = 3.11$) in the spanning tests, and the diversity coefficient is 0.59 ($t = 2.86$) in the Fama-Macbeth regressions. Hence we are capturing a different effect.

not captured by a large set of firm-level observables. So what explains diversity returns? In this section we present evidence consistent with the view that diversity returns, at least partially, reflect mispricing. We examine alternative explanations in Section 5.

4.1 Evidence from Firm-Specific Information Releases

We start by implementing a test recently proposed by Engelberg, McLean, and Pontiff (2017b), who argue that stock returns on earnings announcement days, and other corporate news days, can be used to detect mispricing. The key idea in this test is that systematic and economically large swings in the day-to-day return differences between stocks around information release days are less likely due to risk (i.e. changes in discount rates), because most risk factors are unlikely to show systematic and large day-to-day swings. Rather, predictable changes in return differences around information-release days are indicative of mispricing.

Engelberg, McLean, and Pontiff (2017b) propose a specific version of a mispricing model, motivated by the literature on biased investor expectations (e.g., Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998)). Namely, they propose that investors have downward-biased expectations on stocks in the long leg of anomaly portfolios (and vice versa for the short leg). Upon information releases, such as earnings announcements, investors partly correct their mistake, thus inducing higher stock returns for long-leg stocks precisely on days in which a firm releases information. The three authors show that this mispricing view is consistent with return patterns for a large set of documented anomalies from the recent finance literature. Our goal here is to see whether diversity returns follow the same pattern, which would indicate that biased expectations are at least partially driving diversity returns.

We follow Engelberg, McLean, and Pontiff (2017b) and run the regression:

$$R_{it} = \alpha_t + \beta_1 D_{it} + \beta_2 Eday_{it} + \beta_3 D_{it} \times Eday_{it} + \Gamma X_{i,t-1} + \epsilon_{it}, \tag{5}$$

where R_{it} is the return of stock i on day t, D_{it} is the last available diversity score for firm i, $Eday_{it}$ is an indicator variable equal to one if firm i announces earnings on day t, $X_{i,t-1}$ is a vector of controls, and α_t is a calendar-day fixed effect, which eliminates any day-specific variation such as, for example, macroeconomic shocks, or day-of-the-week effects.

The coefficient of interest is β_3, which measures whether return differences vary systematically with the level of diversity around announcement days. As Engelberg, McLean, and Pontiff (2017b) explain, rational expectations would predict $\beta_3 = 0$, because "in the rational expectations framework, return-predictability is explained by ex-ante differences in discount rates, which should not change in a predictable manner on firm-specific information days." By contrast, $\beta_3 \neq 0$ indicates mispricing.[7]

Table 6, specification (1), presents results. The coefficient on diversity (β_1) shows that diverse firms outperform homogenous firms on non-announcement days by about 1 basis point (calculated using a 0.5 difference in D, which is roughly the difference in D between the first and fifth quintiles from Table 1). As this return difference may reflect compensation for systematic risk, we do not use it to distinguish risk from mispricing.

The central result is that the coefficient on the interaction (β_3) is more than 10 times bigger, indicating that diverse firms outperform homogenous firms strongly on, and particularly on, earnings announcement days. At 14bps (assuming again a diversity difference of 0.5), and with a t-statistic of 2.71, the incremental effect is both statistically and economically large. This large difference in the return difference between diverse and homogenous stocks between earnings days and non-earnings days constitutes strong support for a mispricing explanation, since rational risk premia would need to vary systematically and by an extremely large magnitude to explain the results.[8]

While earnings days may be particularly informative, the underlying logic – that priors are

[7] Engelberg, McLean, and Pontiff (2017b) examine in detail two alternative possibilities for $\beta_3 \neq 0$: (i) rationally higher correlations with the market on earnings announcement days, and (ii) data mining, i.e. a mechanical effect by which outperforming companies are those that have positive news in a given period. While the joint hypotheses problem makes it impossible to completely rule out these alternative stories, the evidence in Engelberg, McLean, and Pontiff (2017b) suggests that they explain at best a part of the higher returns on earnings announcement days.

[8] For example, using the CAPM, and assuming a risk-free rate of 1%, a market risk premium of 4%, 250 trading days, and a beta of 1 for homogenous firms, would require the beta of diverse firms to increase from a level of 1.6 on non-announcement days to a level greater than 10 on announcement days to be consistent with the above results. After the announcement, the beta of diverse stocks would need to decrease again to its original level of 1.6.

updated on information release days – should apply also to other firms-specific news days. Specification (2) thus replaces the earnings announcement indicator in the above regression by an indicator variable for firm-specific news days, $Nday$. We define firm-specific news days as days for which we can find any news items linked to the firm in the Ravenpack dataset in which the company plays an important role in the main context of the story (as defined by Ravenpack). We find that the return difference between diverse and homogenous firms is significantly higher on news days (coefficient = 0.069, $t = 4.38$), which is again consistent with mispricing.

Because the news items used to construct $Nday$ include news about earnings announcements, specification (3) includes both the $Eday$ and $Nday$ variables and the interactions with diversity. The results are very similar to specifications (1) and (2).

Finally, specification (4) includes as control variables returns, volatility (returns squared), volume, as well as the lagged value of each variable over each of the last 10 days. The results remain unchanged.

It is difficult to determine with great confidence what fraction of returns are coming from mispricing. Nevertheless, to get a sense, consider the following back-of-the-envelope calculation. For the average firm in our sample about 76% of days each year are non-information release days, 22% are days with news other than earnings, and the remaining 2% are earnings release days. Assume that the 1bp outperformance of diverse firms on non-news days are a "rational" return premium due to risk. (Note this is conservative as those returns may also be due to mispricing.) Further assume that the incremental returns on news days and earnings announcement dates of 3.5bps and 14bps, respectively, are due to mispricing. Based on these assumptions, about 50% of the total return gap between diverse and homogenous firms in a year is due to mispricing, but the actual number could obviously be much higher. The predictable outperformance on the 4 earnings days alone contributes already 14%. While these numbers are crude, they clearly suggest that mispricing explains a substantial fraction of diversity returns.

In sum, the significant interaction terms in Table 6 show that diverse firms enjoy, all else equal, *predictably* higher returns on information release days. This is hard to square with rational expectations, and therefore provides evidence in favor of a mispricing explanation for diversity returns. In particular, the results are consistent with biased expectations of investors as emphasized in Engelberg, McLean, and Pontiff (2017b), which, in our setting, means that diversity returns are due to investors being too pessimistic on firms with diverse top management teams. We provide direct evidence supporting the biased expectation channel in the next section.

4.2 Direct Evidence on Biased Analyst Expectations

To investigate whether diversity returns obtain because investors have biased beliefs, we would, ideally, like to have data on investors' return expectations on a given stock and date. Because such data is unavailable, we make use of what we believe is the best available substitute: analyst forecasts. We directly test for downward-biased expectations on diverse firms relative to homogenous firms by comparing returns implied by target price forecasts to actually realized returns. We also present analogous results for earnings forecasts.

We start by looking at target price forecasts, a direct measure of analyst's return expectations. We compute for each stock i and month m the expected one-year ahead return implied by analysts' target price forecasts ("forecast"), and we compare it with the corresponding ex post realized one-year return ("actual"). The expected one-year ahead return is defined as $TP_{i,m+12}/P_{im} - 1$, where $TP_{i,m+12}$ is the average one-year ahead target price across all active analyst forecasts on firm i in month m in the IBES database, and P_{im} is the current stock price. Ex post realized return is the 12 months cumulative stock return ex-dividend as reported in CRSP.

Prior work shows that analyst forecasts are on average too optimistic, a fact that is often attributed to conflicts of interest (e.g., Michaely and Womack (1999), Hong and Kubik (2003)). The absolute level of the difference between actual and forecast returns is therefore not very informative in our setting. Instead, we base our tests on the *relative* level of actual minus forecast returns and ask whether analyst forecasts are, all else equal, more pessimistic for diverse firms than homogenous firms. We implement this test by regressing the actual minus forecast return difference on diversity; date fixed effects, which ensure we are comparing firms in the same year and month; control variables from Table 4, specification (2); the number of analysts issuing a target price estimate in the current month; and dispersion, defined as the standard deviation of the price targets divided by the average price target.

Table 7, columns (1) to (3), present results for target returns. Column (1) captures our previous finding that greater diversity is associated with higher returns ($t = 9.80$). If diversity is a predictor of returns, one would expect well-calibrated analysts to issue higher return forecasts on diverse firms. Strikingly, column (2) shows that this is not the case and, if anything, forecasts are decreasing in diversity ($t = -1.83$). Combining the evidence, column (3) shows that the gap between actual and forecast returns increases significantly with diversity. In other words, analysts are systematically too pessimistic in their return expectations for firms with diverse top management teams. The estimates in column (3) imply that, relative to a fully homogenous team ($D = 0$), the bias can be as high as 5.6 percentage points, so it is economically large. With a t-statistic of 6.56 is also highly statistically significant.

Columns (4) to (6) implement an analogous test for earnings per share (EPS) forecasts. We include as control variables the log of market-cap in June year t, log book-to-market ratio, log (1 + number of analysts), reporting lag, reporting lag squared and cubed, institutional ownership, earnings volatility, earnings persistence, and turnover as in Hirshleifer, Lim, and Teoh (2009) (all variables are defined in the appendix). As before, we include date fixed effects, which ensure we are comparing firms in the same year and quarter (since earnings are released on a quarterly basis). We scale both forecasts and actual reported earnings by the share price at the last quarter end before the earnings announcement, so the difference between scaled actual and scaled forecast in column (6) is equal to the widely used definition of standardized unexpected earnings.

Column (4) shows that reported EPS are not strongly related to diversity. The coefficient is negative, but we cannot reject that it is equal to zero (coefficient = -0.065, $t = 1.10$). In stark contrast, column (5) shows that analyst's EPS forecasts are strongly negatively related to diversity (coefficient = -0.147, $t = 3.20$). That is, analysts issue systematically lower EPS forecasts when diversity is high even though diverse firms do not differ substantially in their ex post reported EPS. Column (6) shows that this bias leads to *systematically* positive earnings surprises (coefficient = 0.081, $t = 3.03$).

These results are completely consistent with the evidence on earnings announcement day returns from the previous section. If analyst expectations reflected in columns (4) to (6) are a good proxy for investor expectations, or, alternatively, if investors lean on analyst recommendations for their stock market investments, we should see consistently positive surprises on earnings announcements, and therefore an extra return boost for diverse firms on days with earnings announcements. This is precisely what we had documented in Table 6 above.

It is quite remarkable that analysts, presumably experts in making forecasts, are biased so substantially. Even more remarkable is that the findings we document here for diversity are completely in line with several papers in the recent literature which use analyst forecasts to support mispricing explanations on stock market anomalies, including Bouchaud, Ciliberti, Landier, Simon, and Thesmar (2016), Engelberg, McLean, and Pontiff (2017b), and Asness, Frazzini, and Pedersen (2017). All three of these papers, just like ours, present results in which analysts get the sign wrong: even though a variable x is a positive predictor of returns, higher x leads to more pessimistic forecasts. Together, the findings in these papers and our paper suggest that examining biased expectations of investors and analysts is a fruitful way forward to understanding anomalous stock market patterns.

We conclude that the results in Tables 6 and 7 are strong evidence for the view that diversity returns are, at least in part, driven by biased expectations. Investors and analysts are not optimistic enough when judging the future performance of firms with diverse top management teams.

5. Alternative Explanations

The previous section presents strong evidence consistent with mispricing playing a role for understanding diversity returns. However, given that diversity is a complex construct which can have an influence on the firm and its investors through many channels, there is no a priori reason to expect diversity returns are due to just one underlying driver. In this section we thus examine a range of reasonable alternative explanations and show which ones do and do not find support in the data.

5.1 Diversity, Profitability, and Quality

A notable result in Table 3, specification (5), is that diversity returns are correlated with gross profitability returns. Controlling for profitability reduces diversity alphas by from 44bps to 36bps per month. Profitability thus "explains" about 20% of the diversity alpha.

Gross profitability has recently been suggested as a signature characteristic of "quality" stocks which have high risk-adjusted returns (e.g., Novy-Marx (2014), Asness, Frazzini, and Pedersen (2017)). While papers differ in their empirical approaches and definitions of quality, the common intuition is based on the dividend discount model, which can be written as: $P/B = \text{Profitability} \times \text{Payout ratio}/\left(r-g\right)$. This identity implies, for example, that *fixing price-to-book, the payout ratio, and the growth rate*, more profitable stocks should have higher returns.[9] Consistent with this idea, Table 1 shows that diverse firms are indeed associated with higher gross profits in our sample, and Table 3, specification (5), shows that diversity alphas get smaller once we account for profitability. An attractive feature of this explanation for diversity returns is that a part of the related literature emphasizes the potential of diverse teams to make better, less biased, decisions (e.g., Landier, Sauvagnat, Sraer, and Thesmar (2013)).

The test above uses the gross profitability measure of Novy-Marx (2014) which is designed to minimize the impact of accounting choices on reported profits. If we instead use the five-factor model of Fama and French (2014), which includes a profitability factor RMW, we do not observe

[9] This should not be confused with the view that "better firms have higher returns," which is a fallacy in a rational expectations equilibrium. The higher returns to profitability are either driven by diverse firms being more risky, which would be consistent with rational expectations, or by misvaluation (see e.g., Bouchaud, Krueger, Landier, and Thesmar (2016) for a recent mispricing explanation of the profitability anomaly). From the standard vantage point of rational expectations, results in the management and finance literatures on the link between diversity and performance measures other than stock returns do not in any way imply the positive diversity alphas we document in this paper.

a statistically significant relation between the returns on RMW and the diversity portfolio, so the power of profitability to capture diversity returns is measure specific.

Profitability is not the only attribute of quality stocks, so diversity returns may reflect those other quality attributes in addition to profitability. To explore this, we use the Asness, Frazzini, and Pedersen (2017) quality-minus-junk factor (QMJ), which is a portfolio formed on the empirical counterparts of three proxies for quality: profits, safety, and growth (we obtain data on QMJ from AQR's webpage and refer to Asness, Frazzini, and Pedersen (2017) for details on the construction of QMJ). If we include QMJ in our spanning regressions in Table 3, specification (6), we find QMJ is largely unrelated to returns from diversity investing.

We conclude that diversity returns are partially explained by higher profitability of diverse firms when we use the gross profitability measure of Novy-Marx (2014). On the other hand, diversity returns are not captured by QMJ, a more comprehensive proxy for quality. This may mean one of two things. Either diversity and quality are not closely related beyond gross profitability. Or diversity captures a dimension of quality stocks not captured by existing proxies like QMJ. This is possible because QMJ is constructed from past information (e.g., past sales growth rates), which may not fully capture investors' forward looking expectations. In either case, finding diversity is a successful predictor of stock returns is important.

5.2 Diversity and Complexity

Diversity returns could obtain because firms run by diverse teams are more complex and harder to understand. At least three channels may link complexity to higher returns. First, if complexity reflects fundamental risk, then complex assets may command an additional risk premium. While this is possible, we caution that our previous tests already adjust for an extensive set of standard risk factors, as well as other anomaly returns, so it is not obvious what additional risk may be captured by complexity and priced by investors. Second, ambiguity averse investors may require additional return premia for assets associated with more uncertainty and lower information quality (e.g., Epstein and Schneider (2008), Loughran and McDonald (2013)) Third, if investors find it harder to assimilate value-relevant information from financial disclosures, complexity may promote valuation mistakes.

We start by investigating whether diverse teams are associated with firms with greater complexity in the first place. Obviously, if diverse teams are not associated with more complex firms, the diversity-complexity channels above cannot be operative. We use two approaches to measure complexity: fundamental and text based. We propose two proxies for fundamental complexity. The first proxy is the prior year's idiosyncratic stock return volatility, computed from daily returns using the Fama-French-Carhart four-factor model. The second proxy we use is a Hirschman-Herfindahl index (HHI) over segment sales obtained from the Compustat Segments file, which has been used in prior work as a complexity proxy (e.g., Loughran and McDonald (2014)). The underlying motivation is that firms with substantial operations in multiple segments are more complex than firms which predominantly operate in one line of business.

We also propose a range of text-based complexity measures, building on a recent strand of the textual analysis literature in finance which analyzes texts in financial disclosures (e.g., Loughran and McDonald (2013)). We first test whether 10Ks of diverse firms differ in readability, defined as the ease with which investors and analysts "can assimilate value-relevant information from a financial disclosure" (Loughran and McDonald (2014), p.1649). Readability is thus a measure of textual complexity. We use two measures of readability: (i) the 10K file size in the SEC's EDGAR database, a measure advocated by Loughran and McDonald (2014); and (ii) the number of words in 10Ks, which is frequently used in the accounting literature (e.g., Li (2008)).[10]

A second textual dimension we analyze is the tone of the annual reports. We use two widely-used word lists that have recently been developed by Loughran and McDonald (2011) specifically to analyze financial texts such as those in 10Ks. *Uncertain Words* are words denoting uncertainty, with emphasis on the general notion of imprecision, for example: "approximate", "depend", "indefinite", or "uncertain." *Weak Modal Words* are words such as "could", "might", and "possibly." A greater use of uncertain or weak modal words is thus associated with information that is more

[10]Both file size and the number of words are simple measures. We use them because of the results in Loughran and McDonald (2014), who extensively analyze a range of simple and more complicated measures and find that these simple measures work better as readability measures in financial contexts than more complicated ones.

vague and therefore potentially harder to process for investors.

Table 8, Panel A, present results. The first four columns show that 10Ks are more complex, i.e. they are longer and use significantly more uncertain and weak modal words, when they are issued by firms with diverse top management teams. Two, not mutually exclusive, reasons may explain this. The first reason is that the texts reflect fundamentals, and that the companies themselves are more complex and have business models associated with greater uncertainty. A second possibility why text in diverse firms' 10Ks are more complex and uncertain relates to the inner workings of diverse teams. When evaluating a business opportunity, diverse teams are likely to have greater diversity of opinion than homogenous teams. If there is greater variation of opinions within the team, then this variation may be reflected in information the firm discloses to investors, thus leading to longer documents that use more uncertain language.

Among the fundamental complexity measures, the evidence is mixed. We find a strong relation between diversity and idiosyncratic volatility, but no relation between diversity and segment HHI. All results in Panel A control for industry $\times$ year fixed effects, so they are not simply reflecting reporting conventions in certain industries, or special events in certain industries, and all results control for market capitalization, book-to-market, and past returns for each firm.

After having established that there is indeed a link between measures of complexity and diversity, we next ask if diversity returns are due to complexity, rather than diversity. Table 8, Panel B therefore presents spanning tests and Fama-MacBeth regressions in which we control for returns associated with each complexity variable separately and jointly. The findings are clear: diversity returns are not due to greater complexity, either fundamental or text based.

5.3 Diversity as a Proxy for Corporate Governance

Firms with diverse top management teams may be firms with better corporate governance, which in turn may be associated with higher returns (e.g., Gompers, Ishii, and Metrick (2003)). To examine this possibility, we use the E-Index proposed by Bebchuk, Cohen, and Ferrell (2009) as a firm-level measure of corporate governance quality. Speaking against diversity returns being driven by governance, we find that the raw correlation between governance and diversity is negative and close to zero ($\rho = -0.02$). When we include a long-short governance portfolio as an additional regressor in our spanning tests in Table 3, specification (1), the diversity alpha remains essentially unchanged (coefficient = 0.44, $t = 3.31$).

One caveat is that the E-Index is available only until 2006. We thus use the last available value for each firm for our entire sample period in the test above. To make sure this is not inducing a bias, we replicate our tests using an alternative measure of governance strength, the Total Number of Governance Strengths index from the RiskMetrics KLD STATS database, which is available on the firm level throughout our sample period.[11] The raw correlation with diversity is again negative and close to zero ($\rho = -0.03$), and, when we include a long-short governance portfolio on this alternative governance variable in the spanning tests, the diversity alpha again decreases only marginally 39bps ($t = 2.99$).

We conclude that diversity returns are unlikely to obtain because diversity proxies for good corporate governance.

5.4 Firm-Wide Diversity

Top management team diversity may proxy for the diversity of the workforce, or, more broadly, for awareness to diversity issues within the firm. More satisfied employees, or firms hiring the most talented employees irrespective of their background, may result in better performance and therefore higher returns (e.g., Edmans (2011)).

We measure firm-wide diversity based on six non-top management related diversity strengths provided in the KLD STATS dataset.[12] When we include a long-short governance portfolio on this measure of non-top management related diversity in the spanning tests, our original diversity alpha is virtually unchanged at 45bps ($t = 3.49$). Thus, the top management team diversity

[11] The Total Number of Governance Strengths is an index based on a set of underlying "governance strengths," which analyze, for example, compensation, ownership, and transparency.

[12] Specifically, we form an index by summing over the following 6 diversity strengths: (i) promotion of minorities and women, (ii) work-life-benefits at the company (iii) whether the firm does significant amounts of business with women or minority owed subcontractors or suppliers, (iv) employment of the disabled, (v) gay and lesbian policies, and (vi) other diversity strengths.

variable does not simply reflect the impact of diversity further down in the organization.

5.5 Diversity, Homophily, and Managerial Skill

Homophily is the tendency of individuals to bond with similar others. While collaborating with similar others can be beneficial (e.g., because of more efficient communication within the team), it can also be inefficient if an excessive focus on similarity leads to neglect of other performance-relevant considerations. Gompers, Mukharlyamov, and Xuan (2016) provide evidence on the adverse effects of homophily by showing that venture capitalists who share the same ethnic, educational, or career background are more likely to syndicate with each other, which reduces the probability of investment success. Hence, in our setting, diversity returns could obtain because homogenous teams are inherently less skilled than diverse teams.

We propose two tests. First, if diverse teams are better, this should, all else equal, be reflected in profitability levels. However, our findings from Table 3, specification (5), show that the bulk of the diversity alpha is left unexplained by profitability, and therefore, by extension, managerial skill differences.

As a second test, we construct a direct proxy for managerial skill: the fraction of executives on the team with a degree from an elite university, defined as Ivy League schools plus Chicago, MIT, and Stanford. Table 1 shows that homogenous teams indeed have the lowest fraction of elite university members. However, if we include the elite measure in our spanning regressions in Table 3, specification (1), the diversity alpha is, if anything, larger (coefficient = 0.49, $t = 3.74$). When we add it to the Fama-Macbeth regressions, we find effectively unchanged results for diversity (coefficient = 0.57, $t = 2.75$).

We conclude from these two tests that homophily and, more generally, differential managerial skill is unlikely to be a central driver of diversity returns.

6. 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. Our key innovation is that we measure diversity from within-team similarities in biographical texts which executives are required to file with the SEC. Using this new approach, we assemble a dataset which covers almost all firms in the S&P 1,500 from 2001 to 2014, and thus a total of more than 40,000 executives in more than 2,500 firms.

The main result in our paper is that the strategy of buying firms with diverse top management teams and selling firms with homogenous top management teams – an investment strategy we label diversity investing – yields value-weighted raw returns of 53bps per month over our sample period, with an annualized Sharpe ratio of 0.63. This significant outperformance of diverse firms is robust to standard risk-adjustments and a battery of robustness tests. Over our sample period, the strategy has delivered remarkably stable returns, on par with, and often exceeding, the returns from a set of leading stock market anomalies. Since the diversity characteristic is relatively slow moving, turnover required in implementing diversity investing is comparatively low. Our results suggest diversity investing may be feasible even for large long-only investors.

Issues of top management team diversity are virulent, capturing the attention of the media, consulting firms, scholars, and regulators. Likewise, the diversity of leadership teams is increasingly in the focus of large stock market investors. The positive returns on investing in diversity we document in this paper provide a clear rationale as to why investors might care, beyond reasons of fairness: diversity is a positive predictor of stock returns.

We also provide evidence on potential drivers. The key finding is that diversity returns are, at least partly, due to mispricing. To a lesser extent, diversity returns obtain because firms with diverse top management teams have higher gross profitability (which may itself be due to mispricing).

An important open question, beyond the scope of our paper, is which deeper drivers are causing downward-biased expectations on diverse firms. One potential explanation is motivated by recent experimental evidence showing that diverse teams are evaluated systematically too negatively because external evaluators tend to overestimate the level of conflict in diverse teams (Lount, Sheldon, Rink, and Phillips (2015)). In our setting, analysts, who routinely evaluate management quality as a basis for their forecasts, may thus also overestimate the potential for frictions in diverse teams and their associated adverse effects on firm performance. This may bias analyst expectations, and by extension, the expectations of investors downwards for firms with diverse top management teams. Shedding light on the deeper drivers, perhaps along those lines, is left for future research.

Finally, we note that our results are completely in line with several recent papers which also conjecture biased investor expectations are driving important stock market anomalies (e.g., Bouchaud, Ciliberti, Landier, Simon, and Thesmar (2016), Engelberg, McLean, and Pontiff (2017b), and Asness, Frazzini, and Pedersen (2017)). Despite the growing evidence for the importance of biased expectations, in our setting and similar settings in the recent literature, the deeper reasons for the bias in expectations remain elusive – and an important topic for future research.

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Table 1: Descriptive Statistics

Panel A presents summary statistics. Each month, homogenous firms are defined as firms in the bottom quintile of diversity; diverse firms are in the top quintile. Diversity is measured according to equation (2). The first column shows the monthly average number of firms in our baseline sample. The second column presents monthly averages. The third through seventh columns show monthly time-series averages for all variables by diversity quintile. The last column shows the t-statistic for the difference between diverse and homogenous, based on standard errors clustered by firm. Equal-weighted (EW) and value-weighted (VW) returns are expressed as percentages per month. Panel B shows correlation coefficients between Diversity and a set of team-level variables. a, b and c denote significance at the 1%, 5% and 10% levels, respectively. Definitions of all variables are provided in the Appendix.

Panel A: Summary Statistics

	Avg. N	Mean	Diverse	4	3	2	Homog.	t-stat
Diversity	1,323	0.80	0.94	0.89	0.85	0.79	0.50	
EW returns (%)	1,322	1.05	1.06	1.05	0.95	1.00	0.88	1.33
VW returns (%)	1,323	0.80	0.95	0.70	0.61	0.80	0.41	3.20
Market Capitalization (B$)	1,323	9.03	5.31	6.27	8.24	10.09	15.37	5.47
BTM	1,322	0.66	0.68	0.63	0.62	0.67	0.72	0.78
Gross Profitability (%)	1,323	36.59	40.86	39.67	38.94	34.42	28.92	8.76
Idiosyncratic Volatility (%)	1,323	1.80	1.95	1.89	1.81	1.74	1.62	11.86
Leverage	1,323	20.41	19.60	20.07	19.89	21.64	20.87	1.49
Cash Holdings	1,323	15.05	16.39	16.54	16.27	14.85	11.16	7.78
Payout	1,319	1.32	1.05	1.07	1.34	1.52	1.62	5.66
R&D Expenditures	1,323	4.37	4.36	5.52	4.73	4.89	2.37	5.31
Team Size	1,323	9.00	7.89	9.14	9.41	9.62	9.04	4.51
Net Biography Length (words)	1,323	36.89	35.59	40.15	39.50	38.80	30.59	5.87
Elite University	1,321	3.59	3.39	4.83	4.38	3.92	1.49	4.87

Panel B: Correlations between Team-Level Characteristics

Team Variable	Diversity	(1)	(2)	(3)	(4)	(5)
Employment-Related						
(1) Company Overlap	-0.12^a					
(2) Tenure Overlap	-0.06^a	-0.07^a				
Education-Related						
(3) University Overlap	-0.04^a	0.17^a	0.01^b			
Demographic						
(4) Nationality Mix	0.01^b	0.03^a	-0.11^a	0.04^a		
(5) Executive Age St. Dev.	-0.01	0.00	-0.05^a	0.01^c	0.03^a	
(6) Gender St. Dev.	0.00	0.02^a	-0.04^a	-0.01^c	-0.01^b	0.04^a

Table 2: Returns to Diversity Investing

This table presents the returns to diversity investing. In Panel A, the mean and standard deviation shown are based on raw returns from 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. For Diversity we sort stocks into quintiles. For book-to-market (BTM), gross profitability (PROF), momentum (Mom), net stock issues (NSI), accruals (AC) and asset growth (AG) we employ the data used in Novy-Marx and Velikov (2015), extended through December 2014. Annualized Sharpe Ratio is the annualized return in excess of the risk-free rate divided by the annualized volatility of monthly excess returns. Panel B presents Fama-French-Carhart risk-adjusted returns, except for BTM and momentum, which use the CAPM and the Fama-French (FF) three factor model, respectively. In Panel C, turnover is defined in the text and expressed as a percentage of portfolio value. Panel D presents Fama-French-Carhart portfolio alphas for the long–leg and short–leg of the strategy, the long–minus–short strategy as well as the loadings on the individual factors.

Panel A: Raw Returns of Value-Weighted Strategies

	Diversity	BTM	Mom	NSI	AC	AG	PROF
E[R]	0.53	0.30	0.23	0.49	−0.02	0.23	0.28
t-statistic	3.20	1.08	0.35	2.08	−0.09	0.95	1.13
std[R]	2.13	3.54	8.53	2.96	2.84	3.13	3.21
Annualized Sharpe Ratio	0.63	0.29	0.09	0.57	−0.03	0.26	0.31

Panel B: Fama-French-Carhart Four-Factor Alphas

	Diversity	BTM (CAPM)	Mom (FF)	NSI	AC	AG	PROF
FFC alpha	0.44	0.22	0.63	0.63	−0.05	0.14	0.33
t-statistic	3.36	0.79	1.13	2.85	−0.25	0.63	1.27

Panel C: Turnover

	Diversity	BTM	Mom	NSI	AC	AG	PROF
Monthly Turnover (%)	3.9	3.2	37.9	6.1	6.7	7.7	1.6

Panel D: Factor Loadings and Strategy-Legs

	Diverse	Homogenous	D−H	Diverse	Homogenous	D−H
		Risk-adjusted Returns			*t*-statistic	
FFC alpha	0.28	−0.16	0.44	2.65	−1.97	3.36
MKT	0.99	1.00	−0.01	34.02	37.28	−0.25
SMB	0.18	−0.26	0.44	4.40	−5.14	7.79
HML	−0.15	0.22	−0.37	−3.49	6.76	−6.76
UMD	0.02	−0.07	0.10	0.98	−2.26	3.29

Table 3: Spanning Test

This table regresses returns from diversity investing on the Fama-French-Carhart factors and other factors or anomaly strategies. QMJ is the Asness, Frazzini, and Pedersen (2017) quality-minus-junk factor. PSL is the Pastor and Stambaugh (2003) liquidity factor. RMW and CMA are the Fama and French (2014) profitability and investment factors, respectively. In column (9) we use the Cremers, Petajisto, and Zitzewitz (2013) four-factor model. t-statistics, based on robust standard errors, are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MKT	−0.009	0.019	−0.012	−0.017	0.019	−0.044	−0.017	−0.041	−0.070
	(−0.25)	(0.49)	(−0.33)	(−0.44)	(0.51)	(−0.89)	(−0.46)	(−1.01)	(−1.71)
SMB	0.443	0.453	0.438	0.444	0.437	0.462	0.434	0.453	0.400
	(7.79)	(8.17)	(7.64)	(7.73)	(8.00)	(7.76)	(7.92)	(7.54)	(6.51)
HML	−0.367	−0.390	−0.368	−0.350	−0.234	−0.355	−0.353	−0.441	−0.405
	(−6.76)	(−6.31)	(−6.85)	(−5.69)	(−3.51)	(−6.58)	(−6.10)	(−7.17)	(−4.97)
UMD	0.097	0.083	0.095	0.096	0.054	0.101	0.092		0.090
	(3.29)	(2.74)	(3.20)	(3.17)	(1.75)	(3.23)	(3.08)		(2.50)
NSI		0.099							
		(2.18)							
AC			−0.034						
			(−0.51)						
AG				−0.079					
				(−0.98)					
PROF					0.183				
					(3.36)				
QMJ						−0.063			
						(−0.85)			
PSL							3.345		
							(0.86)		
RMW								0.034	
								(0.55)	
CMA								0.185	
								(2.37)	
Constant	0.442	0.378	0.449	0.456	0.356	0.476	0.428	0.416	0.474
	(3.46)	(2.92)	(3.38)	(3.52)	(2.77)	(3.53)	(3.19)	(3.09)	(3.33)
Observations	162	162	162	162	162	162	162	162	150
R^2	0.43	0.44	0.43	0.43	0.46	0.46	0.43	0.40	0.39

Table 4: Fama-MacBeth Regressions

This table presents monthly Fama and MacBeth (1973) regressions. To predict returns from July year t through June year $t+1$ we use values of Diversity 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 ratio defined in the appendix. Momentum is defined as the cumulative return from month $m-12$ to month $m-2$. Turnover is the average daily share turnover over calendar year $t-1$. Idiosyncratic volatility is the standard deviation of residuals from a Fama-French-Carhart four-factor model estimated on daily returns over calendar year $t-1$. Return$_{m-1}$ is the one-month lagged return. Columns (1) and (2) weight observations by market capitalization in June year t. Columns (3) and (4) use equal weighting. t-statistics based on Newey and West (1987) standard errors with 12 monthly lags are shown in parentheses.

	Value-Weighted		Equal-Weighted	
	(1)	(2)	(3)	(4)
Diversity	0.784	0.594	0.473	0.400
	(3.55)	(2.80)	(2.49)	(2.44)
Market Capitalization		-0.212		-0.190
		(-3.69)		(-3.02)
Book-to-market		-0.031		-0.012
		(-0.29)		(-0.16)
Momentum		-0.362		-0.449
		(-0.53)		(-0.77)
Return$_{m-1}$		-3.280		-2.344
		(-2.74)		(-2.86)
Idiosyncratic Volatility		-0.621		-0.475
		(-2.22)		(-2.15)
Turnover		0.813		-0.153
		(0.77)		(-0.20)
Constant	0.058	3.089	0.595	2.800
	(0.12)	(3.64)	(1.50)	(4.13)
Observations	215550	213931	215550	213931
R^2	0.01	0.15	0.00	0.08

Table 5: Diversity Returns and Firm-Level Observables

In the first three columns of the table we regress returns from diversity investing on the Fama-French-Carhart factors and control strategies. We rerun the regression in Table 3, specification (1), including control strategies based on each of the firm-level variables presented. Control strategies are the value-weighted returns from going long the portfolio of stocks in the highest and short the portfolio of stocks in the lowest group for each firm-level variable. Diversity alpha is the intercept from the regression of diversity returns on the standard four factors plus control strategy. t-statistics are based on robust standard errors. In the last two columns of the table, we run Fama and MacBeth (1973) regressions of monthly returns on Diversity and control variables. We present the coefficient of Diversity obtained by rerunning specification (2) of Table 4, with the addition of each firm-level variable. We weight observations by market capitalization in June year t. t-statistics are based on Newey and West (1987) standard errors with 12 monthly lags. Definitions of all variables are provided in the Appendix.

	Spanning Test			**FMB regression**	
	coefficient	t-stat	R^2	coefficient	t-stat
Only FFC	0.44	3.36	0.43	0.59	2.80
Gross Profitability	0.36	2.77	0.46	0.57	2.84
Idiosyncratic Volatility	0.51	3.85	0.44	0.59	2.80
Leverage	0.41	3.28	0.48	0.55	2.89
Cash Holdings	0.44	3.36	0.44	0.52	2.64
Payout	0.50	3.99	0.46	0.60	2.77
R&D Expenditures	0.43	3.34	0.45	0.57	2.84
All of the above	0.40	3.25	0.52	0.51	2.80

Table 6: Diversity Returns on Information-Release Days

This table reports results from a regression of daily returns on Diversity, information-release day dummy variables, interactions between Diversity and information-release day variables, day fixed effects and controls. Information-day variables are dummies equal to one on earning announcement dates (Eday), or corporate news release dates (Nday), respectively. Control variables included in specification (4) are lagged values for each of the past 10 days for stock returns, stock returns squared, and trading volume. Standard errors are clustered by day. t-statistics are shown in parentheses.

	(1)	(2)	(3)	(4)
Diversity	0.021	0.014	0.014	0.014
	(4.31)	(2.44)	(2.38)	(2.38)
Eday	0.015		−0.008	−0.010
	(0.18)		(−0.10)	(−0.11)
Eday × Diversity	0.288		0.248	0.249
	(2.71)		(2.32)	(2.33)
Nday		0.036	0.038	0.038
		(2.82)	(3.09)	(3.11)
Nday × Diversity		0.069	0.051	0.051
		(4.38)	(3.38)	(3.41)
Day FE	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes
Observations	4,162,572	4,162,572	4,162,572	4,162,159
Adjusted R^2	0.34	0.34	0.34	0.34

Table 7: Diversity and Analyst Forecasts

This table compares analyst forecast variables with ex-post realized values. In columns (1) to (3) focus on returns computed from analyst forecasts of target prices. Forecasts are computed as $TP_{m+12}/P_m - 1$, where TP_{m+12} is the average one-year ahead target price across all active forecasts in the current month, and P_m is the current stock price. Ex post realized return (Actual) is the 12 month cumulative stock return excluding dividends as reported in CRSP. In column (3), the dependent variable is the difference between actual ex post realized return and forecast. Columns (4) to (6) use consensus earnings forecasts. In column (5) forecasts are computed as the median of all 1- or 2-quarter-ahead forecasts issued or reviewed in the last 60 days before the earnings announcement by analysts covering the firm as reported by I/B/E/S, divided by the stock price at the end of the last quarter before the announcement. Actual is the announced earnings, divided by the stock price at the end of the last quarter before the announcement. In columns (6), the dependent variable is the scaled difference between actual and forecast. In columns (1) to (3), controls are from Table 4, specification (2), plus the number of analysts issuing a target price estimate in the current month, and dispersion, defined as the standard deviation of the price targets divided by the average price target. In columns (4) to (6), controls are from Hirshleifer, Lim, and Teoh (2009), and include log of market-cap in June year t, and log book-to-market ratio, log (1 + Number of Analysts), Reporting Lag, Reporting Lag squared and cubed, Institutional Ownership, Earnings Volatility, Earnings Persistence, Turnover. Date FE are based on year-month dates in columns (1) to (3), and on year-quarter dates in columns (4) to (6). Standard errors are clustered by date (year-month) in columns (1) to (3), and by date (year-quarter) in columns (4) to (6).

	Target Prices			**Earnings**		
	Actual	Forecast	A − F	Actual	Forecast	A − F
	(1)	(2)	(3)	(4)	(5)	(6)
Diversity	0.043	−0.012	0.056	−0.065	−0.147	0.081
	(9.70)	(−1.83)	(6.56)	(−1.10)	(−3.20)	(3.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	173,340	173,340	173,340	65,727	65,727	65,727
R^2	0.15	0.19	0.13	0.08	0.08	0.03

Table 8: Diversity and Complexity

Panel A regresses measures of firm complexity on Diversity and firm-level variables. The dependent variables are the logarithm of 10-K file size, the log of the number of words in the 10-K, the proportion of uncertain words, the proportion of weak modal words, idiosyncratic volatility and the HHI of firm business segments. In each column we include industry × year effects, based on Fama-French 12 industries. Additional controls are: log market cap, log book-to-market ratio, and continuously compounded stock return from months $t = -12$ to $t = -2$. Standard errors are clustered by firm. t-statistics are shown in parentheses. In the first three columns of Panel B, we rerun the regression in Table 3, specification (1), including control strategies based on each of the variables presented in Panel A. Control strategies are the value-weighted returns from going long the portfolio of stocks in the highest and short the portfolio of stocks in the lowest group for each variable. Diversity alpha is the intercept from that regression. In the last two columns of the table, we rerun specification (2) of Table 4, including each variable considered in Panel A. Definitions of all variables are provided in the Appendix.

Panel A: Diversity and Complexity

	10-K File Size	**10-K Word Count**	**Uncertain Words**	**Weak Modal Words**	**Volatility**	**Segment HHI**
	(1)	(2)	(3)	(4)	(5)	(6)
Diversity	0.012	0.038	0.042	0.049	0.034	-0.002
	(2.21)	(3.01)	(3.57)	(4.53)	(4.56)	(-0.45)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,224	17,224	17,224	17,224	17,224	17,224
Adjusted R^2	0.76	0.36	0.29	0.34	0.61	0.01

Panel B: Diversity Returns after Controlling for Complexity

	Spanning Test			**FMB regression**	
	coefficient	t-stat	R^2	coefficient	t-stat
Only FFC	0.44	3.36	0.43	0.59	2.80
10-K File Size	0.43	3.20	0.43	0.57	2.91
10-K Word Count	0.41	3.01	0.45	0.64	2.96
Uncertain Words	0.49	3.87	0.47	0.59	2.88
Weak Modal Words	0.45	3.59	0.51	0.55	2.79
Segment HHI	0.45	3.42	0.43	0.52	2.60
All of the above	0.43	3.21	0.53	0.53	2.98

Figure 1: Cumulative Returns From Diversity Investing

This figure plots cumulative returns for diversity investing and prominent anomalies (momentum, net stock issues, accruals, asset growth, and profitability). It shows, for each investment strategy, the cumulative sum of value-weighted 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; diverse firms are stocks in the highest diversity quintile. The sample period is July 2001 to December 2014.

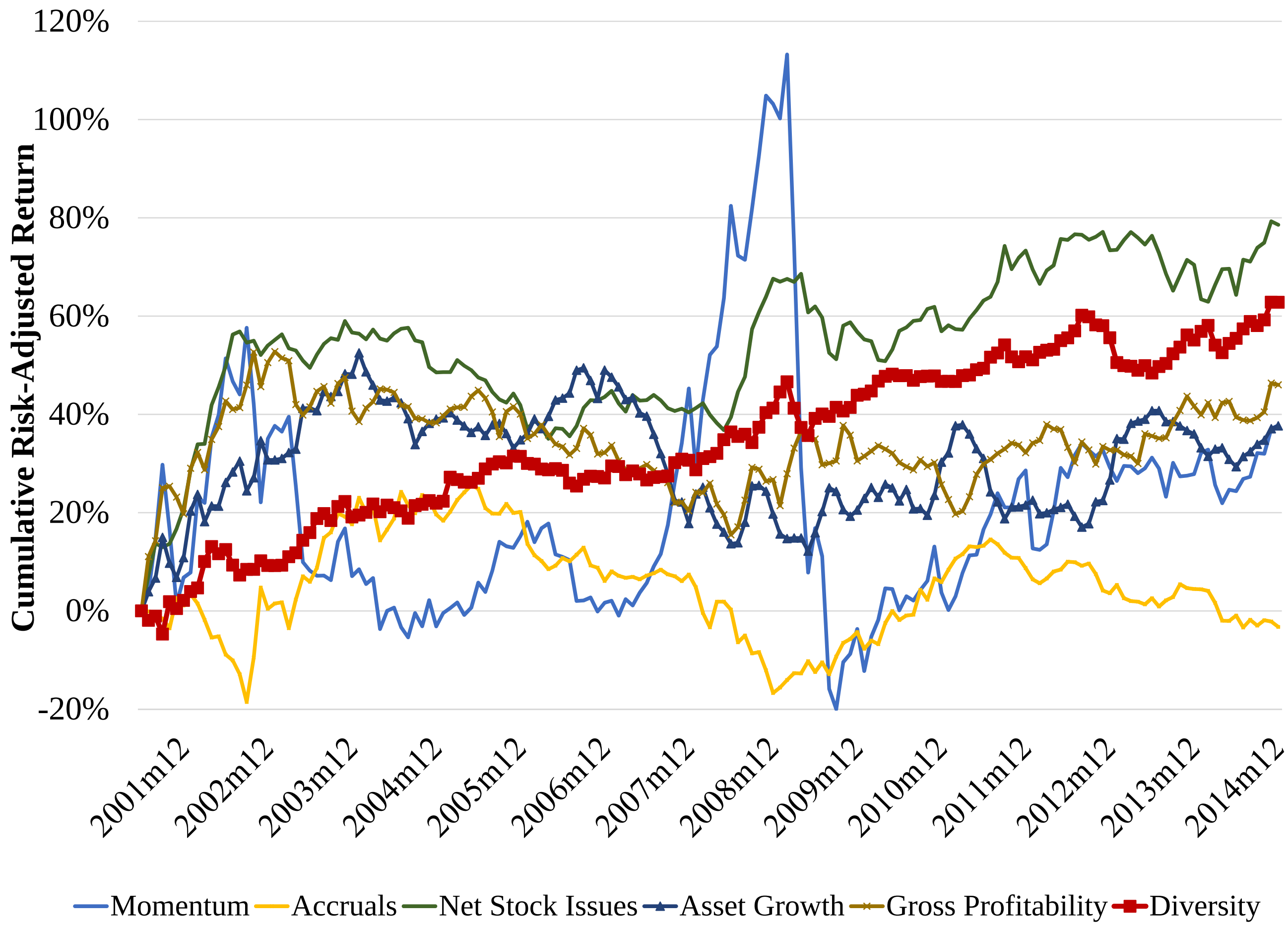
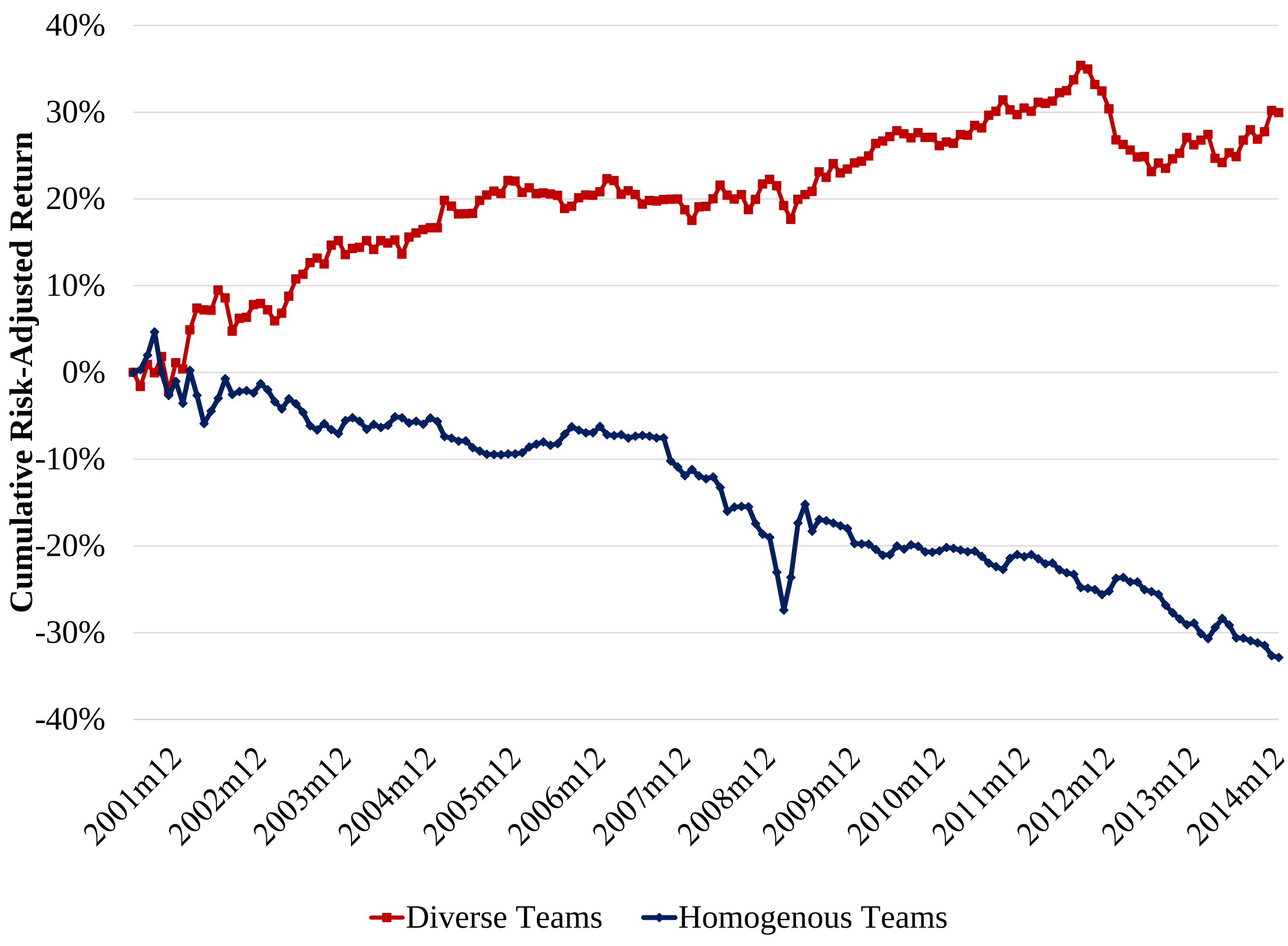


Figure 2: Long and Short Leg of the Diversity Strategy

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 is July 2001 to December 2014.



APPENDIX

A Additional Variable Descriptions

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 $t-1$.
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 $t-1$.
Momentum	Cumulated continuously compounded stock return from month $j-12$ to month $j-2$, where j is the month of the forecasted return.

Additional Variable Descriptions (Continued)

Variable	Description
Other variables in Table 1, Panel A	
Idiosyncratic Volatility	Standard deviation of residuals from 4–factors model estimated from daily returns over calendar year $t-1$.
Leverage	Ratio of the book value of long-term debt plus short-term debt over total assets.
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.
R&D Expenditures	Ratio of R&D expenditures over sales
Team Size	Natural logarithm of the number of executives constituting the top management team. Source: Executive biographies.
Net Biography length	Natural logarithm of the average number of words in the biographies of each top management team member. Computed after applying the filter described in Section **2.2**. Source: Executive biographies.
Elite University	Fraction of executives that attended one of the following university, at any academic level: MIT, Stanford University, University of Chicago, Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania, Yale University, and 0 otherwise. Source: Executive biographies.
Other variables in Table 1, Panel B	
Company Overlap	For every pair of executives in a given team we compute the number of company names that appear in the biographies of both executives, then we take the average over all executives pairs. Source: Executive biographies.
Tenure Overlap	For every pair of executives in a given team we compute the number of years that the pair has worked together on the team, then we take the average over all executives pairs. Source: Boardex supplemented by Execucomp.
University Overlap	For every pair of executives in a given team we compute the number of university names that appear in the biographies of both executives, then we take the average over all executives pairs. Source: Executive biographies.
Nationality Mix	One minus the Herfindahl concentration index for nationality. Source: Boardex.
Executive Age St. Dev.	Standard deviation of the age of the executives constituting the top management team. Source: Boardex supplemented by Execucomp.
Gender St. Dev.	Within executive team standard deviation of an indicator variable that takes value 1 when the executive is a woman and 0 otherwise. Source: Boardex supplemented by Executive biographies.

Additional Variable Descriptions (Continued)

Variable	Description
Other variables in Table 4	
Return_{m-1}	Stock return in month $m-1$.
Turnover	Average daily share turnover ($\times 100$) over calendar year $t-1$.
Other variables in Table 7	
Number of analysts (Prices)	Number of analysts issuing a target price estimate in the current month.
Dispersion	The standard deviation of the price target estimates divided by the average price target estimate.
Number of Analysts (EPS)	Natural logarithm of the number of analysts issuing an earning forecast in the current quarter.
Reporting Lag	Number of days between the the end of the current quarter and the earnings announcement date.
Earnings Volatility	The standard deviation during the previous 4 years of the deviations of quarterly earnings from the corresponding 1 year ago earnings.
Earnings Persistence	The first-order autocorrelation coefficient of quarterly earnings using 4 years of data.
Institutional Ownership	Natural logarithm of $IO/(1-IO)$. Where IO is the portion of shares outstanding held by institutional investors in a given quarter.
Other variables in Table 8	
10-K File Size	The natural logarithm of the file size in megabytes of the SEC EDGAR complete submission text file for the 10-K filing.
10-K Word Count	The natural logarithm of the word count from the 10-K.
Uncertain Words	Percentage of words within the 10-K that are classified as uncertain using the Loughran and McDonald (2011) word list.
Weak Modal Words	Percentage of words within the 10-K that are classified as weak modal using the Loughran and McDonald (2011) word list.
Segment HHI	The sum of the squared business segment shares reported for the firm in the COMPUSTAT Segment database based on company sales.

B Common Words in Executive Biographies

This table shows the list of the 100 most commonly occurring terms in the main dictionary based on executive biographies in the year 2011.

Rank	**Word**	**Rank**	**Word**	**Rank**	**Word**
1	position	35	administration	69	assistant
2	operations	36	state	70	health
3	finance	37	real	71	mba
4	public	38	science	72	communication
5	october	39	estate	73	software
6	committee	40	medical	74	subsidiary
7	firm	41	human	75	strategy
8	technology	42	information	76	oil
9	international	43	national	77	planning
10	investment	44	college	78	legal
11	degree	45	york	79	compensation
12	counsel	46	service	80	equity
13	marketing	47	american	81	association
14	secretary	48	research	82	llp
15	accounting	49	strategic	83	founder
16	sales	50	time	84	holding
17	global	51	llc	85	advisory
18	industry	52	extensive	86	addition
19	bank	53	leadership	87	institute
20	capital	54	career	88	provider
21	private	55	ceo	89	capacity
22	law	56	independent	90	america
23	engineering	57	principal	91	governance
24	division	58	banking	92	responsibility
25	school	59	california	93	shares
26	resource	60	commercial	94	effective
27	energy	61	united	95	department
28	systems	62	acquisition	96	consulting
29	product	63	consultant	97	present
30	controller	64	solutions	98	healthcare
31	treasurer	65	partner	99	market
32	responsible	66	securities	100	insurance
33	audit	67	gas		
34	bachelor	68	accountant		