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Three essays on empirical asset pricing

Xueying BIAN
Singapore Management University

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XUEYING BIAN

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Three Essays on Empirical Asset Pricing

Xueying Bian

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Dissertation Committee:

Jun Yu (Supervisor / Chair)

Lee Kong Chian Professor of Economics and Finance

Singapore Management University

Jun Tu (Co-chair)

Associate Professor of Finance

Singapore Management University

Daniel Preve

Associate Professor of Economics (Education)

Singapore Management University

Weikai Li

Assistant Professor of Finance

Singapore Management University

Singapore Management University 2021

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Xueying Bian

Abstract

The dissertation consists of three essays on empirical asset pricing. The first chapter proposes a novel inter-firm link - similar employee satisfaction. Based on the employee satisfaction data on Glassdoor, the returns of similar employee satisfaction (SES) firms are documented to predict focal firm stock returns. A long-short portfolio sorted on the lagged returns of SES firms yields the Fama-French six-factor alpha of 135 bps per month. The observed predictability cannot be explained by risk-based arguments or subsumed by other known inter-firm momentums. According to the international tests, we observe stronger return predictability in countries with more flexible labor markets. The return predictability across SES firms may reflect a new type of cross-firm link derived from the knowledge spillover about employee welfare policies via social transmissions.

The second chapter discovers a novel firm characteristic that contains information about firm stock performance. Inspired by the psychological findings that demographic similarity can promote trust and coordination within a team, we propose and find that firm performance is positively related to the facial resemblance between top management team (TMT) members due to the higher managerial efficiency. A long-short value-weighted portfolio sorted on the TMT facial similarity yields a significant Fama and French (2018) six-factor alpha of 40

bps per month. In addition, the firm TMT facial similarity is also documented to be informative in firm operating performance. In addition, our tests suggest that investors' limited attention and limits of arbitrage are the potential mechanisms behind the documented return predictability.

The last chapter studies the effects of CEO tweeting on firm stock performance by creating a measure of CEO tweeting skill. Based on the U.S. public firms sample from 2012 to 2018, we discover that if CEOs are good at communicating on social media, firms can benefit from CEOs' high exposure on Twitter. However, if CEOs cannot handle well on social media, tweeting frequently can be harmful to the firm stock performance. We find the results hold across different countries (such as France, Germany, and the United Kingdom). The possible mechanisms behind our documented findings are shown to be limited attention and limits to arbitrage. And our documented effects are more likely to be explained by the behavioral bias other than risk explanations.

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I dedicate this thesis to my family for their unconditional love and constant support!

Chapter 1

Return Cross-Predictability in Firms with Similar Employee Satisfaction[1]

This study uses Glassdoor data and finds that the returns of similar employee satisfaction (SES) firms predict focal firm returns. A long-short portfolio sorted on the lagged returns of SES firms yields the Fama-French six-factor alpha of 135 bps per month. The observed predictability is distinct from existing inter-firm momentum effects and cannot be explained by risk-based arguments. The return predictability across SES firms may reflect a new type of cross-firm link derived from the knowledge spillovers about employee welfare policies via social transmissions (e.g., personal interchange among employees from different firms).

1. Introduction

Employee welfare policies are not only important to both firm performance (Edmans, 2011) and personal wellbeing[2] but also relatively easy to understand and discuss (even for average person without any domain knowledge). Therefore, those polices seem always to be hot topics both for in-person interactions among employees and their family members/friends, and for general public information sources (e.g., social media). These social transmission activities may drive a knowledge spillover of employee welfare policies across firms (Jaffe et al., 1993).[3]

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[1] This is joint work with Sergei Sarkissian, Jun Tu and Ran Zhang.

[2] According to *USA Today* from September 16, 2015, even snacks may "lure employees to new companies: 48% of respondents said that if they were looking for a new job, they would weigh company perks, including availability of snacks, in their decision."

[3] For example, in its August 6, 2018 issue, *The Wall Street Journal* writes: "General Motors Co. has struck a deal with a Detroit-based hospital system to offer a new coverage option to employees…in an attempt to lower costs and improve care… A smaller number of companies, including Walt Disney Co., Boeing Co. and Intel Corp. have taken the more-ambitious approach of having the health-care provider manage nearly all of the care of enrolled employees... GM is the latest of a growing list of employers that are choosing to negotiate their own terms with health-care providers…"

This may spiritually echo "the new intellectual paradigm, social economics and finance … people observe and talk to each other" (David A. Hirshleifer, 2020 AFA Presidential Address).[4] Moreover, firms gauge whom to imitate by assessing each other's resource similarity (Chen, 1996). Strategic management scholars highlight that firms imitate others to maintain competitive parity (Lieberman and Asaba, 2006) and they keep track with those firms possess similar strategic resources but may operate in other markets (Bergen and Peteraf, 2002; Chen, 1996). As a result, the spillover of welfare policies is more likely to happen among firms with similar employee satisfaction (SES) due to potential better compatibility.

In this study, we explore the implications of the knowledge spillover about employee welfare policies on firm stock performance. Corporate wellness and employee satisfaction are found to be positively correlated with employee productivity, firm value and stock returns (Edmans, 2011; Bapna et al., 2013; Edmans et al. 2017; Gubler et al., 2018; Green et al., 2019; Sheng, 2019). Therefore, the adoption of similar welfare policies due to the knowledge spillover from the SES firms may in turn affect focal firms' stock performance. For example, for a focal firm, mimicking a better compensation system of SES peer firms can further motivate its employees' incentives on working, and improve its productivity (Bapna et al., 2013). Owing to investors' limited attention, this impact may be incorporated into focal firm's stock price with a delay. Therefore, one can expect a return predictability among firms with similar employee satisfaction (SES). Moreover, the return predictability across SES firms is associated with an implicit type of cross-firm link due to knowledge spillovers about employee welfare policies via social

[4] David A. Hirshleifer's 2020 AFA Presidential Address focuses on the biases generated by social transmissions. In contrast, we hypothesize a knowledge spillover via social transmissions.

transmission. In contrast, existing studies on cross-firm return predictability mainly focus on peer firms with explicit economic links or industry, technology or product similarities (e.g., Cohen and Frazzini, 2008; Cao et al., 2016; Lee et al., 2019).[5]

We use Glassdoor data – the largest career website that publishes company reviews written by former and current employees. The overall rating of a firm's employee satisfaction is based on the following five sub-categories: Culture & Values, Work/Life Balance, Senior Management, Compensation & Benefits, and Career Opportunities. Based on each firm's ratings on Glassdoor in June of the previous year, we obtain and rank top 1,000 listed firms (excluding financial firms) and test them for return predictability in the current year.[6] Our predictor is the average portfolio return of SES peer firms based on the proximity- or equally-weighted measure of closeness of 20 neighbor companies (before and after the focal firm) with the employee satisfaction level similar to that of the focal firm. Figure 1 illustrates one snapshot of this setting for The Walt Disney Company as the focal firm.

We start by testing whether SES firms have a lead-lag effect in employee satisfaction due to the welfare policy spillover. We find that the annual change in the employee satisfaction of the focal firm can be predicted by the annual change in the employee satisfaction of its SES peer firms in the previous year. We also find that SES peers' growth in employment, revenues, and profitability predicts the focal firm's growth in each of these three characteristics. This evidence shows that

[5] Some of the existing cross-firm links may also be tied to knowledge spillovers. For instance, the cross-firm technology link may be due to knowledge spillovers about certain technologies. However, different from the knowledge spillovers of employ policies, those knowledge spillovers are not likely to be boosted up by social transmissions since the professional domain knowledge related to industry or technology are usually required.

[6] Among all the US listed firms on Glassdoor, we focus on the top 1,000 listed firms with a high employee satisfaction, because human capital is relatively less valuable in firms with a low employee satisfaction.

implicit and less transparent SES link has a material impact on the economic fundamentals.

Then, we empirically demonstrate a striking relation wherein the stock returns of the focal firms exhibit a predictable lag corresponding to the portfolio return of their respective peer firms with SES. Focal firms with SES peer firms that earn higher (lower) returns will similarly earn higher (lower) returns in subsequent months. A long-short trading strategy based on the lagged monthly return of the proximity-weighted SES peer firms yields a monthly Fama and French (2018) six-factor alpha of 135 (value-weighted) and 179 (equally-weighted) basis points. Moreover, we observe a similar predictability in bivariate portfolio tests using the focal firm's own employee satisfaction score or its changes, as well as for each of the five sub-ratings of employee satisfaction. The results of cross-sectional regressions in the presence of various controls demonstrate that returns of SES firms predict focal firms' returns. Furthermore, we find that the predictive power of SES firms decreases with distance of peer firms from the focal firm in Glassdoor ratings. We explain these results by suggesting that, while firms with SES learn from each other, investors do not always promptly respond to this intangible information.

We then conduct a number of tests to ensure that the predictive effect of SES firms cannot be subsumed by the well-known industry momentum effect (Moskowitz and Grinblatt, 1999) or various inter-firm momentum effects, including: supplier and customer industry returns (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), "pseudo-conglomerate" peer firms' returns (Cohen and Lou, 2012), strategic alliance partners' returns (Cao et al., 2016), technological partners' returns (Lee et al., 2019), geographic (headquartered in the same US county) peers' returns (Parsons et al., 2020), firm returns with common board members (Burt et al., 2020), the shared analyst coverage peers' returns (Ali and Hirshleifer, 2020), or the common institutional investors peers' returns (Gao et al, 2017). Also, our documented predictability effect cannot be replicated with other firm characteristics, most notably ESG (Environmental, Social, and Governance) scores. Taken together, the results of all these tests convincingly demonstrate that the return predictability across SES firms is distinct from the return predictability arising from industry linkages or other inter-firm connections and is unique to the employee satisfaction (welfare policy) similarity link.

We also test the return predictability among SES firms internationally. To prevent biases caused by a small number of multinational firms that are on the top employee satisfaction companies list of many countries, we use the top 1,000 listed firms (excluding financial ones) headquartered and primarily listed in Canada, France, Germany, and the UK. Our results are mixed. In Canada and the UK, the returns of SES peer firms predict the focal firm's returns. However, in France and Germany, such return predictability is not observed. These results are consistent with those reported by Edmans et al. (2017) who find that employee satisfaction is associated with larger economic values only in more flexible labor markets (e.g., Canada, the UK, and the US). In these markets, since firms face lower hiring and firing constraints, and employees have a larger flexibility to respond to higher employee satisfaction, employee satisfaction can improve recruitment, retention, and motivation.

Next, we analyze the stock price reaction around earnings announcements. This setting is often used to test whether risk factors or mispricing can explain the existence of an anomalous return behavior (e.g., Bernard and Thomas 1989; La Porta et al., 1997; Gleason and Lee, 2003; Engelberg et al., 2018; Lee et al., 2019).

We find that the SES peer firms' anomaly spread is 800% larger on the earnings announcement days than on other days, suggesting that mispricing is the more likely driver of SES firm predictability. However, as argued by Lee and So (2015), return predictability can still be attributed to risk, even if the source of risk is unidentifiable. To test this possibility, we analyze the impact of lagged returns of SES firms on focal firm's standardized unexpected earnings (SUEs). This setting is not confounded by the possible existence of non-measurable risks. Our results show that the lagged returns of SES firms can indeed predict SUEs, but with a decreasing predictive power over time that becomes insignificant after three quarters. This result provides further support to the conclusion that our return predictability pattern is unlikely to be related to risk.

We further examine whether this predictability can be related to three commonly documented mechanisms, namely, investors' inattention (proxied by firm turnover, analyst coverage, and institutional ownership), limits to arbitrage (proxied by firm size, volatility, and liquidity), and information complexity (proxied by firm analysts' dispersion, industry concentration, and existence of dividends). Based on the empirical results, we show that, focal firms exhibit a slow price response due to the investors' inattention, limits to arbitrage and information complexity, which again are largely consistent to a mispricing story than a risk factor story.

Furthermore, we offer empirical evidence that the observed predictability could be especially strong in locations with high population density and highly educated people (Jacobs, 1969; Lucas, 1988; Glaeser, 1999; Christoffersen and Sarkissian, 2009). This is consistent with that the SES firm predictability may come from the employee welfare policy spillover via the channels of social transmissions, including open information sources, social networks, or personal interchange.

The contribution of our results to the literature is three-fold. First, our paper contributes to the growing literature on cross-firm links. Due to investors' limited attention, the return predictability has been found among firms that are economically linked (e.g. the customer-supplier link (Cohen and Frazzini, 2008) and the strategic alliance link (Cao et al., 2016)), technologically linked (Lee et al., 2019), or fundamentally linked (Ali and Hirshleifer, 2020). Our study focuses on an implicit and less transparent link, which is associated with spillovers of employee welfare policies across SES firms via social transmissions, and we show that our proposed link is distinct from other well-documented inter-firm links.

Second, we add to the growing research on the impact of corporate wellness and employee satisfaction on firm performance. As shown by Edmans (2011, 2012), the stock market does not promptly value intangibles, such as employee satisfaction. Bapna et al. (2013) and Gubler et al. (2018) show a direct impact of human capital investment and corporate wellness programs on employee productivity. Furthermore, Green et al. (2019) and Sheng (2019) argue that employee satisfaction can be one important source of fundamental information about the firm. Psychological and sociological scholars found the reciprocal effect between employee satisfaction and own firm's performance (Weitz and Nuckols, 1955; Brayfield and Crockett, 1955; McGregor, 1960; Akerlof, 1982; Shapiro and Stiglitz, 1984; Akerlof and Yellen, 1986; Schneider et al., 2003). All these studies highlight the importance of employee satisfaction to their *own* firms. In contrast, we examine the impact of knowledge spillover of employee satisfaction policies of *other* firms with SES on the focal firm's performance and find this relation to be distinct from other well-documented inter-firm links.

Third, we add to the studies on inter-firm employee competition. According to the extant strategy theory (Hall, 1993; Coff, 1997), human capital is a source of sustainable competitive advantage for firms. Furthermore, Yu and Cannella (2007) found that the theory of rivalry for employees is limited to the firms within the same industry, but Markman et al. (2009) and Liu and Wu (2018) point out that it goes beyond the boundaries of the same product market and the same industry.[7] We find inter-firm return predictability based on employee satisfaction and provide new evidence on human capital competition that transcends industry boundaries.

The rest of the paper is organized as follows. Section 2 describes the data and variables. Section 3 presents our main empirical results on return predictability among SES firms. Tests with international market data are also included in this section. Section 4 analyses risk-based versus mispricing nature of return predictability. Section 5 explores the underlying mechanisms of SES firm predictability. Conclusions are drawn in Section 6.

2. Data and Variables

We use Glassdoor data, which are available from 2009 onwards, to obtain the time-varying employee satisfaction ratings of top 1,000 listed firms (excluding financial firms), headquartered and primarily listed in the US market at the end of June each year, from 2009 (beginning year) to 2017 (end year). The overall rating of each firm

[7] Liu and Wu (2018) find that the overlap between product market rivals and firm's labor competitors is less than 20%. This makes sense. For instance, in its December 2, 2018 issue, *The Wall Street Journal* writes: "Some of the biggest recruiters of people with robotics expertise aren't just tech outfits or manufacturers, for instance, but also banks and real-estate firms. Auto makers and a slew of Silicon Valley firms are hiring autonomous-driving technicians, but so is insurance giant Allstate Corp. And health-care company Johnson & Johnson has been recruiting experts in three-dimensional printing … to develop customized orthopedics and surgical tools."

is calculated based on the following five employee satisfaction sub-category ratings: Culture & Values, Work/Life Balance, Senior Management, Compensation & Benefits, and Career Opportunities. In this paper, we use Glassdoor's firm ratings to rank firms and to study their return predictability. Less than 10% firms have the same overall rating. If two firms have the same overall rating, we compare their standard errors across the aforementioned five sub-category ratings. The firm with a smaller standard error is ranked ahead of the firm with a larger standard error. We use each firm's Glassdoor ranking in June of year $t-1$ to test the return predictability from January to December of year *t*.

We collect price, volume, and return data of US firms from the Center for Research in Security Prices (CRSP) and accounting information from Compustat. For non-US firms, we collect price, volume, and return data from Thomson Reuters Eikon and accounting information from Worldscope. Institutional ownership data and analyst coverage for all firms in the sample are obtained from Thomson Reuters Institutional Holdings (13F) and Thomson Reuters IBES, respectively. The sample period is from January 2010 to December 2018. Following Fama and French (1993), we use the one-month US T-bill rate to calculate monthly excess returns.

The independent variable is the lagged monthly return of peer firm with SES, $SES_{i,t-1}$. This variable is constructed as the proximity-weighted or equally-weighted portfolio returns of peer firms with SES with the focal firm:

$$SES_{i,t-1} = \sum_{j \neq i} \frac{PWP_{i,j,t-1}}{\sum_{j \neq i} PWP_{i,j,t-1}} R_{j,t-1}$$

or

$$SES_{i,t-1} = \sum_{j \neq i} \frac{EWP_{i,j,t-1}}{\sum_{j \neq i} EWP_{i,j,t-1}} R_{j,t-1},$$

where $R_{j,t-1}$ is the gross stock returns of firm j in month $t-1$. $PWP_{i,j,t-1}$ is the proximity-weighted peer closeness measure between firms i and j at $t-1$, and it equals to the total number of neighbor firms minus the absolute value of ranking difference between firms i and j. When firms i and j have closer rankings, the predictive effect from firm j to firm i is stronger. For example, if firms A, B, C, D, E are ranked 1, 2, 3, 4, 5, and have SES, then firm C's predictor $SES_{C,t-1} = (5 - |3-1|/14)R_{A,t-1} + (5 - |3-2|/14)R_{B,t-1} + (5 - |3-4|/14)R_{D,t-1} + (5 - |3-5|/14)R_{E,t-1}$.[8] $EWP_{i,j,t-1}$ is the equally-weighted peer closeness measure between firms i and j at $t-1$. For example, if firms A, B, C, D, E are ranked 1, 2, 3, 4, 5, and have SES, then firm C's predictor $SES_{C,t-1} = 0.25R_{A,t-1} + 0.25R_{B,t-1} + 0.25R_{D,t-1} + 0.25R_{E,t-1}$. In our sample, for each focal firm, we use 20 neighbor firms with ranking above and 20 neighbor firms with ranking below the focal firm to construct the SES predictor based both on proximity-weighted and equally-weighted measures.

Table 1 shows summary statistics of the sample coverage, firm characteristics and employee ratings. Panel A reports the coverage of our sample as a fraction of the CRSP universe. The firms in the sample cover 24% in terms of the total number of the listed firms and 65% of the CRSP common stock universe in terms of market capitalization. The average proportions of SES firms within the same industry and state with the focal firm are 0.16 and 0.07, respectively. Panel B reports the main statistics of five firm characteristics: Market capitalization (in billion US dollars), book-to-market ratio (B/M), asset growth (AG), gross profitability (GP), and momentum. Asset growth is defined as year-over-year

[8] The number 14 in the denominator is the sum of four numerators ($14 = 3 + 4 + 4 + 3$).

growth rate of the total assets; gross profitability is defined as the revenue minus the cost of goods sold scaled by the assets; momentum is defined as the cumulative stock return from month $t-12$ to month $t-2$ as in Jegadeesh and Titman (1993). Not surprisingly, we observe that the average firm size exceeds \$5bln, while the minimal size is above \$0.6bln. Panel C reports the summary statistics of overall employer rating and sub-category ratings, on a scale of one to five with five being the top rating. In our sample, the mean value of overall employer rating is 3.5 stars, and the sub-category rating means range from 2.95 (Senior Management) to 3.47 (Work/Life Balance). The median for each rating is 3.0 and the standard deviation is around 1.20. The summary statistics help mitigate the concerns that reviews are only from those highly satisfied or unsatisfied employers. Panel D reports the correlations among the ratings. The top half of Panel D presents Spearman rank correlation coefficients, and the bottom half of the panel reports Pearson correlation coefficients. All correlation coefficients are significantly different from zero at the 1% level.

3. Empirical Results

In this section, we report our main empirical results. We first examine whether there is knowledge spillover on employee policies, and whether they are fundamentally related to each other. To this end, we use the data on changes in employee satisfaction as well as employment, revenue, and profit growth. Then we show the existence of SES firm return predictability in the settings of univariate portfolio sorts and multivariate cross-sectional tests when controlling for a series of firm characteristics and alternative inter-firm momentum effects. Finally, we report the results of international tests.

3.1 Fundamental linkages among SES firms

As discussed above, we start by testing whether SES firms are fundamentally interrelated. First, we examine the existence of direct spillover effects on employee policies among SES firms. We test for these effects by regressing focal firm's different employee satisfaction ratings on corresponding lagged ratings of SES firms. The dependent variable is focal firm's changes in the overall employee satisfaction rating ($\Delta OS_{i,t}$), as well as changes in sub-ratings based on Culture & Values ($\Delta CV_{i,t}$), Work/Life Balance ($\Delta WL_{i,t}$), Senior Management ($\Delta SM_{i,t}$), Compensation & Benefits ($\Delta CB_{i,t}$), and Career Opportunities ($\Delta CO_{i,t}$), respectively. The independent variables are the corresponding lagged changes in ratings of SES firms, namely, $SES\_\Delta OS_{i,t-1}$, $SES\_\Delta CV_{i,t-1}$, $SES\_\Delta WL_{i,t-1}$, $SES\_\Delta SM_{i,t-1}$, $SES\_\Delta CB_{i,t-1}$, and $SES\_\Delta CO_{i,t-1}$. They are constructed as the proximity-weighted average change in the overall employee satisfaction rating and five sub-category ratings. The control variables include the focal firm's lagged respective employee satisfaction rating, as well as the focal firm's size, book-to-market ratio, asset growth, gross profitability, and momentum, and year and industry fixed effects, measured at two-digit SIC codes. All variables are measured at the end of each calendar year and are winsorized at 1% and 99% levels.

Panel A of Table 2 reports the results of pooled OLS regressions. The significantly positive coefficients on the SES peer firms' lagged changes in various measures of employee satisfaction indicate that when the SES peer firms improve their ratings in a given year, focal firms experience an increase in the corresponding employee satisfaction ratings in following year. For example, for the overall employee satisfaction rating, the estimated coefficient on $SES\_\Delta OS_{i,t-1}$ is 0.162 (t = 2.85), implying that one unit increase in SES firms' average employee satisfaction rating in year $t-1$ predicts a 0.162 increase in focal firm's overall employee satisfaction rating in year t. Across five sub-category ratings, the predictability is markedly stronger for the Compensation & Benefit rating, which may be due to the fact that compensation is relatively easy to mimic among peer firms. Therefore, our results provide strong evidence of spillover effects in employee satisfaction activities among SES peer firms.

Next, we regress the annual employment growth of focal firms (a growth in annual number of employees) on both the contemporaneous and the lagged one period average employment growth of their SES peer firms, *SES_ΔEmployment*. Similarly, we regress focal firms' annual revenues and profitability growth on either the contemporaneous or the lagged one period corresponding average growth measures of their SES peer firms, *SES_ΔRevenue* and *SES_ΔProfit*, respectively. In all predictive regressions, we also control for the corresponding contemporaneous firm characteristics. Other control variables include the focal firm's size, book-to-market ratio, asset growth, gross profitability, and momentum. Again, all variables are measured at the end of each calendar year and are winsorized at 1% and 99% levels. To facilitate interpretation, all variables are cross-sectionally standardized to have zero mean and unit variance.

The test results are summarized in Panel B of Table 2. The dependent variables are industry-adjusted using two-digit SIC codes. The standard errors are clustered by year. Due to space constraints, the coefficients on control variables and fixed effects are not reported.[9] Columns (1-2) show that the proximity-weighted SES peer firms' employment growth explains and positively predicts the current

[9] Adding firm fixed effects does not materially affect Table 2 estimations. These results are available on request.

and next year focal firm's employment growth, respectively: all estimates are significant at least at the 5% level. Likewise, columns (3-4) show that the proximity-weighted SES peer firms' revenues growth explains and positively predicts the focal firm's revenues growth. The last two columns show that the proximity-weighted SES peer firms' profitability growth is a significant predictor for the focal firm's profitability growth. Taken together, the test results in Table 2 suggest that there are strong employee policy spillovers among SES firms, and such firms are fundamentally related to each other.

3.2 Univariate portfolio sorts

In this section, we design a trading strategy among SES firms. To conduct the test, we construct proximity-weighted and equally-weighted portfolio returns of peer firms with SES as two predictors according to the Glassdoor firm ranking in year $t - 1$. Then we classify stocks into five quintiles based on the predictor. In Quintile 1, focal firms have the lowest SES peer firms' portfolio returns in the last month. In Quintile 5, focal firms have the highest SES peer firms' portfolio returns in the last month. Then, we calculate the value- and equally-weighted portfolio returns of the lowest and highest quintiles, as well as the hedged portfolio return of Quintile 5 minus Quintile 1. Finally, we compute the corresponding statistical significance level of abnormal returns. We use three measures of abnormal returns for focal firms: (1) the excess return, *ret*; (2) the risk-adjusted return from the Fama and French (2018) six-factor model, α_6; and (3) the industry-adjusted return, α_ind. To compute *ret*, we subtract the one-month T-bill rate from the focal firm return. To compute α_6, we use risk factors from Ken French's webpage. Following Fama and French (1993) and Cao et al. (2016), we compute the factor loadings for each focal firm by using a time-series regression over the entire sample period.[10] To compute α_ind, we subtract from the focal firm return its value-weighted industry return based on the two-digit SIC code. This adjustment eliminates any predictability that could arise from monthly industry-wide auto-correlation in returns.

The results of the implementation of this trading strategy are reported in Table 3. The standard errors are calculated using the Newey-West method with three lags.[11] Columns (1-2) show the monthly excess returns of focal firm stocks based on EWP and PWP portfolio returns of firms with SES, respectively. We observe that, as compared to SES firms with the lowest portfolio returns, firms with SES that have the highest portfolio returns are associated with a significantly higher focal firm excess return in the next period.[12] The long-short strategy based on the these EWP and PWP portfolio returns of peer firms with SES yields monthly excess returns of 102 bps and 117 bps, respectively, for value-weighted portfolios and 135 bps and 156 bps, respectively, for equal-weighted portfolios. Columns (3-4) report the monthly α_6 of focal firm stocks. The results are very similar to those for excess returns. For example, the long-short strategy based on the lagged one-month PWP yields a monthly α_6 of 135 bps (*t=3.03*) for value-weighted and 179 bps (*t=3.64*) for equally-weighted portfolios, respectively. Finally, the univariate tests using industry-adjusted returns in columns (5-6) again lead to the same predictability pattern irrespective of firm portfolio formation methods. As we show in the Internet

[10] Similar results are obtained using rolling estimates. These results are available on request.
[11] The choice of the lag length from 1 to 12 does not influence the significance of in any of our tests.
[12] Firm stock price is forward looking and takes all future firm performance improvements into account. Therefore, although the adoption of a new policy learned from peer firms may take a long time and the improvements of firm performance due to the new policy may be materialized at a later date, the firm price should be affected immediately if the market is efficient. When there is limited attention, the potential underreaction to this information may cause return predictability at a shorter horizon like next month.

Appendix, our results also hold with the Burt and Hrdlicka (2020) adjustment which accounts for correlated alphas across connected firms. Therefore, this table presents strong evidence that lagged returns of peer firms with SES can forecast the focal firm's stock returns, including those corrected for standard risk factors and industry averages.[13]

Before proceeding to other tests, it is important to establish whether SES firm predictability (1) is specific to Glassdoor's aggregate employee satisfaction rating, or whether its disaggregated ratings are equally informative, and (2) is specific to the immediate neighborhood of focal firms, or whether more distant firms also have some forecasting power. Therefore, as in Table 3, Panel A of Table 4 shows the estimates of α_6 based on PWP portfolio returns of firms with SES for each of the Glassdoor's five sub-ratings of Glassdoor. We again use both value-weighted and equal-weighted portfolio construction within each SES firm return quintile. In line with our expectation, the alphas are statistically significant in all five sub-ratings, confirming the unanimous existence of information diffusion and cross-learning on different factors among firms with SES. In particular, among all five cases, α_6 based on Compensations & Benefits is the largest, suggesting that the effect of the information diffusion and cross-learning (among SES firms) on this category is the strongest. This agrees with the intuitive assumption that the compensation level (or other benefits) of a firm is the most objective category, which makes it easier for firms to verify and learn from their peers and act accordingly. For example, if Facebook increases the salary level of its engineers, Google may want to follow up soon enough so that not to lose its existing engineers

[13] In the Internet Appendix we use abnormal returns based on the CAPM, the Daniel et al. (2020) behavioral factor model, and the Hou et al. (2020) q5-factor model. The results resemble those in Table 3.

and maintain its firm competitiveness. Other categories, such as Culture & Values, Work/Life Balance, are inherently more subjective.

In Panel B of Table 4, we examine the importance of the neighbor window in construction of SES return portfolios. In this panel, SES peer firms are defined based on five different distance segments relative to the focal firm. The first one is our benchmark window of [-20, +20] firms with SES around the focal firm. For the sake of consistency with other SES firm windows, we record it as {[-20,-1], [1,+20]}. We report the corresponding value-weighted and equal-weighted estimates from Table 3, column (4) into column (1) of the current panel. The other four windows are {[-40,-21], [21,+40]}, {[-60,-41], [41,+60]}, {[-80,-61], [61,+80]}, and {[-100,-81], [81,+100]}. Again, we report only the estimates of α_6 based on PWP portfolio returns of firms with SES. In the results, as neighbor windows become more distant from the focal firm, we observe a monotonic decrease in SES predictability in both economic and statistical terms. For instance, the long-short portfolio of SES firms using {[-20,-1], [1,+20]} window yields a monthly α_6 of 135 bps for value-weighted portfolio, the same estimate for {[-80,-61], [61,+80]} window is 74 bps, and that for {[-100,-81], [81,+100]} window is only 54 bps and insignificant. Therefore, in terms of employee satisfaction rating, neighbor firms indeed play a much more important role for the focal firm returns than more distant companies.[14]

Furthermore, we also test the long-run return pattern of the predictive effect of peer firms with SES. Our aim here is to examine whether the documented strong

[14] In the Internet Appendix we also examine the existence of predictability among SES firms using several sub-sample tests, namely, on two equal sub-periods, smaller and larger than 20 peer firms, same or different industry belonging, and same or different US state belonging. In all these estimations, the SES firm predictability is positive and significant. In addition, we show the differences in predictability across nine industries based on their one-digit SIC codes.

return predictability effect represents an overreaction in focal firm information, in which case we should expect a reversal in the longer run. Alternatively, if SES peer firms' information truly captures the focal firms' fundamental information, we should see no reversal.

To examine these two alternative explanations, we look at the cumulative excess returns (CERs) of the portfolio strategy described in Table 3 over the 12-month period. In Figure 2, we depict these long-run CERs delivered by both value-weighted and equally-weighted portfolios. As shown in the figure, there is a significant upward drift in CERs over the first six months. The CERs flatten for the later months, showing no signs of reversal in the long run. These findings imply that the SES firm predictability effect is not a simple overreaction to information. Rather, consistent with previous inter-firm return predictability studies (Cohen and Frazzini, 2008; Lee et al., 2019), our results reflect a delayed updating of focal firm prices to their fundamental values based on important information emanating from their SES peer firms.

3.3 Bivariate portfolio sorts

Edmans (2011) and Edmans et al. (2017) show that firms associated with high employee satisfaction generate positive abnormal returns. Then, our SES firm predictability effect may simply reflect this finding. To control for it, we construct portfolios sorted on both firm's own employee satisfaction score and portfolio returns of SES peer firms. In Table 5, Panel A reports the monthly Fama and French (2018) alphas of value-weighted (VW) and equally-weighted (EW) quintile portfolios (Q1 and Q5) as well as the Q5-Q1 difference portfolio for each quintile of firms sorted on employee satisfaction scores. The SES firm predictability exists across all the five quintiles of firms with different employee satisfaction scores.

Thus, our documented phenomenon reflects the return spillover among firms with SES rankings rather than abnormal returns of high employee satisfaction firms.

Furthermore, firms tend to learn and mimic those changes and innovations in employee policies that have value-enhancing firm effects. In contrast, an unsuccessful policy is not likely to be followed by other firms. Therefore, we expect the SES firm predictability to be stronger among firms with improved employee policies.[15] To test this hypothesis, we sort firms on their own changes in employee satisfaction score from year $t-2$ to year $t-1$ and group them into two groups based on the employee satisfaction score changes: "Negative" and "Positive," standing for decreased and increased scores, respectively. Panel B of Table 5 reports the monthly Fama and French (2018) alphas of value-weighted (VW) and equally-weighted (EW) quintile portfolios sorted on the SES predictor for both groups of changes in the firm's own employee satisfaction score as well as the Q5-Q1 difference portfolio. We observe that abnormal returns are significantly larger for firms with increased employee satisfaction scores. In addition, the difference in monthly alphas between "Positive" and "Negative" groups is significant for both VW and EW Q5-Q1 spread portfolios. These results indicate that, consistent with intuition, the return predictability among firms with SES scores is largely associated with the spillover of positive employee satisfaction practices.

[15] This does not imply that a firm never follows its peers with similar employee satisfaction if such companies cut employee welfare provisions to reduce their costs, especially during economic downturns. For instance, in its October 24, 2011 issue, *The Wall Street Journal* writes: "As the economy sputters and health-care costs rise, businesses large and small are eliminating benefits they consider nonessential and shifting more costs to employees for the benefits that are offered… Still, some company-funded perks are proving resilient, particularly those that are seen as providing value to the company, not just the staff."

3.4 Multivariate regressions

In this section, we use Fama and MacBeth (1973)'s two-step procedure to analyze whether the SES peer firms' return predictability remains robust after accounting for various firm characteristics and industry momentum. The stock-level's Fama-Macbeth regression is consisted of two steps. We use the following cross-sectional regression each month:

$$RET_{i,t} = \lambda_{0,t} + \lambda_{1,t}\, SES_{i,t-1} + \lambda_{2,t}{}'\, X_{i,t-1} + \gamma_i + \varepsilon_{i,t}, \tag{1}$$

where $RET_{i,t}$, the dependent variable, is one of the return metrics on the focal firm's stock *i* in month *t*. As in Table 3, we use three different measures of returns of the focal firm: (1) the excess return, *ret*; (2) the risk-adjusted return based on the Fama and French (2018) six-factor model, α_6, and (3) the industry-adjusted return, α_ind. $SES_{i,t-1}$ is SES peer firms' stock return in month $t-1$; $X_{i,t-1}$ is a vector of firm-level controls that includes all five characteristics from Panel B in Table 1. In these estimations, firm size is taken as the natural log of market capitalization measured in million US dollars (Banz, 1981). Likewise, we use the natural log of book-to-market equity ratio (Basu, 1983). The control set also includes the lagged focal firm's excess return to account for short-term reversal, $ret_{i,t-1}$ (Jegadeesh, 1990; Lo and MacKinlay, 1990), and Ind_Mom to account for industry momentum (Moskowitz and Grinblatt, 1999). Additional control variables are the best 100 employee satisfaction company (BC) indicator,[16] which equals one if the focal firm is in the most recent top 100 employee satisfaction firm list, and zero otherwise; and the top 100 employee growth companies (EG) indicator, which equals one if

[16] We also test company's employee satisfaction rank as an alternative control instead of the best 100 employee satisfaction company indicator. Our results are not influenced.

the focal firm is among the top 100 employment growth firms in the previous year, and zero otherwise. Variable γ_i represents the industry fixed effect. It is included in Eq. (1) when the dependent variable is excess return or α_6. For each focal firm, the SES peer firms' portfolio is constructed based on [-20, +20] neighbor stocks using the proximity-weighted peer approach. We again use the Newey-West correction with three lags to calculate standard errors.

Table 6 presents the estimation results. Column (1) reports the results without control variables, but with industry-fixed effects. We find that the portfolio return of peer firms with SES can predict returns of focal firms: the coefficient on $SES_{i,t-1}$ is positive and significant at the 1% level. Regarding economic significance, a one-unit increase in the lagged proximity-weighted return of SES peer firms in month $t-1$ is associated with a 0.0728 unit increase in the focal firm's returns in month t. From column (2), we find that the predictive power of peer firms with SES cannot be subsumed by the series of firm characteristics and industry momentum. In column (3), instead of excess returns, we use the risk-adjusted returns of focal firms based on the Fama and French (2018) six-factor model. Again, we find that SES peer firms' lagged returns can predict risk-adjusted returns of focal firms with a very high significance level. In the final column, column (4), we use industry-adjusted returns as the dependent variable. In this estimation the magnitude and significant level coefficient for $SES_{i,t-1}$ remains virtually identical. Consistent with univariate and bivariate portfolio sorts in Tables 3 and 5, the results of Table 6 demonstrate that the portfolio return of peer firms with SES can predict the focal firm's future return.

To better visualize the consistency in the predictive power of firms with SES, in Figure 3, we show the time-series of estimated SES coefficients from the Fama-

MacBeth regressions over the entire sample period. These coefficients are estimated based on Regression (1) and averaged over a six-month window. We observe that these estimates are almost universally positive, while few negative values are much smaller in magnitude. Also, there is no trend in the dynamics of SES firm predictability coefficients. Therefore, Figure 3 shows that the observed SES firm predictability is a phenomenon that is rather consistent across time.

Furthermore, in Table 7, we test whether the predictive power of peer firms with SES can be subsumed by previously reported inter-firm momentum effects. We include the following inter-firm momentum variables: supplier industry returns and customer industry returns (Menzly and Ozbas, 2010), customers' returns (Cohen and Frazzini, 2008), "pseudo-conglomerate" portfolio returns (Cohen and Lou, 2012), strategic alliance partners' returns (Cao et al., 2016), technological partners' returns (Lee et al., 2019), geographic peers' returns (Parsons et al., 2020), firm returns with common board members (Burt et al., 2020), shared analyst coverage peers' returns (Ali and Hirshleifer, 2020), as well as common institutional investors peers' returns (Gao et al., 2017). We also add but do not report control variables from Table 6 in all regressions. Column (1) in Table 7 reposts the original results from Regression (2) of Table 6. Columns (2-11) show that the SES predictor is not subsumed by any other inter-firm links when they enter regressions individually.[17]

In the Internet Appendix, we also show that no predictability exists when the same procedure (as the one used for SES firm predictability) is applied to other firm characteristics. In particular, we show that our findings cannot be replicated

[17] The SES predictor remains significant even with simultaneous control for all other inter-firm effects, but the sample size reduces by 90%.

with such characteristics as size, B/M ratio, momentum, investment, profitability, or, most importantly, ESG (Environmental, Social, and Governance) score. Therefore, our results suggest that the new inter-firm predictor cannot be explained by the industry momentum, a series of firm characteristics, other known inter-firm predictors, and is unique to the employee satisfaction similarity (welfare policy) link.

3.5 International tests

In this section, we test the existence of SES firm return predictability in international markets. Our aim is to verify whether the return predictability between SES firms is unified or mixed in flexible and rigid labor markets. Our international data includes top 1,000 employee satisfaction firms (excluding financial firms) headquartered and primarily listed in Canada, France, Germany, and the United Kingdom. This choice of companies prevents our results being driven by a small number of multinational firms that are on the top employee satisfaction company list of many countries. As before, the dependent variable is the excess return of the focal firm, the risk-adjusted return of the focal firm based on the Fama and French (2018) six-factor model, or the industry-adjusted return of the focal firm.

The estimation results are summarized in Table 8. All are similar to those reported in columns (2-4) of Table 6. We find that return predictability between firms with SES exists in flexible labor markets of Canada and the United Kingdom, but is absent in rigid labor markets of France and Germany. These results indicate that return predictability depends on a country’s labor market flexibility. The return predictability and information diffusion among firms with SES in the US are not anomalous in the global context. The return predictability exists only in the countries with high labor market flexibility. In such labor markets, since firms face lower constraints on hiring and firing and people can easier move to companies with better employment policies, employee satisfaction can improve employee recruitment, retention, and motivation, and thus knowledge spillover of employee policies is more likely to happen. These results are consistent with the findings reported by Edmans et al. (2017) who found that investing in high employee satisfaction firms can generate abnormal returns only in the countries with high labor market flexibility.

4. Risk versus Mispricing

As discussed in Section 3, the observed return predictability among firms with SES cannot be explained by the standard asset pricing factors. However, this predictability could still be driven by some unobserved risks. We have previously shown that the six risk factors from the Fama French (2018) model, along with the industry momentum factor, cannot explain our results. Other possible factors, such as the ones related to the focal firm's discount rate, could also affect the firm's expected return. Following Bernard and Thomas (1989), Chopra et al. (1992), Lee et al. (2019) and others, we examine how stock price reacts around the subsequent earning announcements. The intuition behind this approach is that, if the anomaly is explained by changes in underlying risks, then the stock returns should smoothly adjust over subsequent periods. However, if the anomaly is related to mispricing, we should expect a stronger anomaly manifestation during the earnings announcement window, as the earnings' release helps to correct investors' prior expectation errors on firms' future cash flows.

Following Engelberg et al. (2018) and Lee et al. (2019), we conduct the test based on a simple regression analysis. In this regression model, the dependent variable is the daily return of the focal firm's stock instead of its monthly return, while independent variables are the SES peer firm portfolio return, a dummy for an earnings announcement window ($EDAY$), as well as the interaction term consisting of these two variables. Control variables include the lagged values of the focal firm's stock returns, stock returns squared, and its trading volume over the past 10 days.

Panel A of Table 9 summarizes the estimation results. In column (1), the earnings announcement window is defined for one day only, while in column (2) – over three days. According to the mispricing explanation, we expect larger returns on the SES firm strategy during the earnings announcement window. Consistent with this expectation, for one-day earnings announcement window, the SES coefficient is 0.004, but the $SES \times EDAY$ interaction term is 0.032. Said differently, the return spread based on the hedged SES firm strategy is more than eight times larger during the earnings news release. For the three-day earning announcement window, the results show a similar pattern. Therefore, these results suggest that standard risk models are unlikely to explain the return predictability among the firms with SES.

Lee and So (2015) show that anomaly return can still be attributed to risk, even if the source of risk has not been identifiable or measurable. Accordingly, in what follows, we test whether firms with SES have a predictive power to standardized unexpected earnings (SUEs) of focal firms. Since SUEs can capture unanticipated changes in the focal firm's earnings and are not return-based, the results of this test are not confounded by imperfect controls of risks. Furthermore, given that SUEs are also fundamental determinants of future cash flows of firms, the results of this test can further confirm whether the anomaly return is due to the changes of unexpected cash flows, instead of a risk compensation effect.

To test the focal firms' future earnings predictability, we use the Fama-MacBeth regressions. Specifically, we examine whether SES peer firms' returns can predict the focal firm's SUEs. The dependent variable is the unexpected earnings scaled by the standard deviation of unexpected earnings over past eight quarters, SUE.[18] The independent variable is the lagged by one quarter return of SES peer firms computed from the preceding three months. We also add the focal firm's own lagged SUEs (up to four quarters) as control variables. The dependent variable is winsorized at 1% and 99% in the cross-section, while all explanatory variables are scaled from 0 to 1 according to the assignment in deciles. For consistency, we restrict sample firms to those that have fiscal quarters ending in March, June, September, and December.

Panel B of Table 9 shows the test results with unexpected earnings predictability over four subsequent future fiscal quarters; that is, the dependent variable, SUE, is estimated for quarters t to $t+3$. As can be seen from the table, the coefficients on the lagged returns of SES peer firms are positive, but significantly decrease from the first to the fourth fiscal quarter. The forecasting pattern decays over time. These results provide further support to our conclusion that return predictability among firms with SES is consistent with a gradual information diffusion of cash flows, instead of changes in underlying risk.

5. Forces Affecting SES Firm Predictability

In this section, we first investigate three commonly used mechanisms that may explain the documented SES firms' return predictability, namely, (1) investors'

[18] Unexpected earnings measure is the year-over-year change in quarterly earnings before extraordinary items.

inattention, (2) limits to arbitrage, and (3) information complexity. Then, we further examine and discuss other potential drivers of the SES firm predictability.

5.1 Three commonly used mechanisms

First, if the predictive power of peer firms with SES is related to investors' inattention, we should expect a stronger effect for firms with less investor attention. We use the following three investors' inattention measures in the literature: stock turnover, analyst coverage, and institutional ownership. We predict that firms with a lower stock turnover, analyst coverage, and institutional ownership will show a more sluggish stock price reaction to the information from peer firms with SES due to the less attention from investors. Turnover is the focal firm's turnover measured as the average daily turnover in the previous year. The analyst coverage is defined as the number of analysts following the focal firm in the previous year from the IBES database. We use the residual institutional ownership, which is the institutional ownership of the parent firm orthogonalized with regard to firm size at the end of December of each year. The firms' institutional investors' information is from Thomson Reuters institutional holdings (13F).

Second, we expect to see a stronger return effect for the firm stocks with more binding arbitrage costs, since investors are unable to freely trade and fully update these firms' stock prices (Hirshleifer et al., 2011; Beneish et al., 2015). We use the following three proxies for the limits to arbitrage: firm size, idiosyncratic volatility, and illiquidity. Size is the log value of market capitalization of the focal firm at the end of the previous month. Idiosyncratic volatility is the standard error of the residuals from a regression of daily stocks returns in the previous month based on the Fama and French (1993) three-factor model. Finally, illiquidity is the Amihud (2002) illiquidity measure based on the price impact.

Likewise, the firms with more information complexity should see larger SES firm return predictability, since investors with limited abilities to analyze such firms are unable to correctly update their stock prices (e.g., Cohen and Lou, 2012; Huang, 2015). We use the following three proxies of information complexity: analysts' dispersion; industry segmentation; and dividend payment. Analysts' dispersion is the analyst one-year-ahead earnings forecast dispersion at the end of the previous month. Industry segmentation is the reciprocal of Herfindahl index, which accounts for industry segment sales of a given firm in the previous year. The idea behind this measure is that the more dispersed are a firm's operations across its industry segments, the more complicated are the analyses needed to incorporate a given piece of information into its price.[19] Therefore, a higher industry segmentation implies a more complex (multi-segmented) firm. Dividend payment is a binary variable based on the splitting of firms into dividend paying and not paying. The logic behind this variable is that it is harder to value non-dividend paying firms than those that pay dividends.

Table 10 reports the results of our tests. Our dependent variable is the risk-adjusted return based on the Fama and French (2018) six-factor model, α_6. Each month, all stocks are sorted based on each proxy into two groups by the median and then independently sorted on peer firms' past returns into the five quintiles. For each focal firm, the portfolio of peer firms is constructed based on [-20, +20] neighbor stocks. The focal firm returns are reported for the Q5-Q1 difference portfolio only. The results are reported for both value-weighted and equally-weighed portfolios of firms with SES within ranking quintiles. Panel A shows the

[19] For example, suppose that BC, Inc., is a conglomerate firm that produces bicycles and computers. Bicycles amount to 40% of BC's sales, while computers correspond to 60% of its sales. The Herfindahl index of BC, Inc., is $(0.4)^2 + (0.6)^2 = 0.52$. And S, Inc. is a standalone that produces televisions. Televisions make up 100% of S's sales. The Herfindahl index of S, Inc., is $(1.0)^2 = 1.0$

differences in α_6 between high and low investor's inattention groups. These differences are statistically significant at the 1% level, with high inattention stocks displaying larger SES firm return predictability. Panel B reports the test results of the mechanism related to limits to arbitrage. Similar to the output in Panel A, we find that the differences in α_6 between high and low limits to arbitrage groups of stocks are statistically significant, with higher limits to arbitrage displaying larger return predictability. Finally, Panel C reports the results on information complexity tests. Similarly to the previous two panels, we find that the differences in α_6 between high and low information complexity groups are statistically significant with more complex firms (i.e., firms with high dispersion in analysts' forecasts, firms with a high industry segmentation, and non-dividend paying firms) displaying larger predictability effects. Overall, our results support the prediction that the SES return effect is stronger for the stocks with higher investors' limited attention, higher limits to arbitrage, and more information complexity.

5.2 Additional analysis on the drivers of the SES firm predictability

The return predictability across SES firms can be ascribed to the existence of common directors (Burt et al., 2020), common financial analysts (Ali and Hirshleifer, 2020), or common institutional investors (Anton and Polk, 2014; Gao et al, 2017), all of whom are likely to propagate and/or help enforcing similarities of firm policies and activities including employee satisfaction practices across firms that they oversee, analyze, or invest in. Specifically, the common directors are likely to induce the similar policies due to the commonality of managerial decision-making across firms. And the managers of two SES firms monitored and ranked by the same analyst pool are likely to consider similar corporate and employment policy decisions. In addition, if the same institutional investors hold two firms, large portfolio reallocations of such investors may affect firm policies and activities in those firms but not necessarily synchronously, even without common board members. In sum, common corporate board members, common analysts, and common institutional holdings can lead to return co-movement among firms linked by them due to not only the potential enforcement of similar firm policies and activities (not limited to only employee satisfaction practices) but also other possible reasons as documented in the literature (Burt et al., 2020; Ali and Hirshleifer, 2020; Anton and Polk, 2014; Gao et al, 2017). In this section, we further examine whether our documented return predictability of SES firms still exists after ruling out these potential universal type drivers of firm policy spillovers.

Panel A of Table 11 re-estimates Table 6 regression specifications separately on the subsamples of SES firms with no common board members (columns (1-3)), with no common analysts (columns (4-6)), and no common institutional investors (columns (7-9)). As in Table 6, the dependent variable is either the monthly excess return of the focal firm, the risk-adjusted return of the focal firm based on the Fama and French (2018) six-factor model, or the industry-adjusted return of the focal firm. All control variables are the same as in Table 6. The standard errors are Newey-West adjusted with three lags. The test results show that the SES firm return predictability is present even in these subsamples. The magnitude of coefficient on $SES_{i,t-1}$ across all estimations is lower than that in Table 6, but still statistically significant at the 5% level. This outcome is particularly remarkable in light of a very significant sample size drop in case of the tests with no common board members.[20]

[20] Due to a significant sample size reduction, the test of the SES predictability effect without any of the three decision commonality connections is unreliable.

Panel B of Table 11 re-estimates separately regression specifications of Panel A of Table 2 (predictability in employee satisfaction sub-ratings among SES firms) again for subsamples of SES firms with no common board members, no common analysts, or no common institutional investors. The variable $SES\_\Delta ES_{i,t}$ denotes the change in the specific employment satisfaction rating and stands for one of the six variables, $SES\_\Delta OS_{i,t}$, $SES\_\Delta CV_{i,t}$, $SES\_\Delta WL_{i,t}$, $SES\_\Delta SM_{i,t}$, $SES\_\Delta CB_{i,t}$, and $SES\_\Delta CO_{i,t}$, which are the proximity-weighted changes in the overall employee satisfaction and five sub-category ratings of SES firms, respectively. Control variables are from Panel B of Table 1. The standard errors are clustered by year. Again, we observe that the predictor, $SES\_\Delta ES_{i,t}$, remains significant in all but one out of 18 estimations. We note that certain statistical weakness of results in case of tests with no common board members is again due to a large reduction in the sample size.

Thus, the results of Table 11 show that the SES firm predictability for focal firm returns and its individual employee satisfaction sub-ratings is still there after controlling for common board members, common analysts, or common institutional investors. Although common directors, common financial analysts, and common institutional investors may be considered as sort of universal type drivers of firm policy spillovers, social transmissions (e.g., personal interchange among employees) may be considered as a specific type of driver that can help more to propagate and/or enforce similarities of employee satisfaction practices but do not fully explain the spillover of employee policies between SES peer firms.

In addition, we provide some supportive evidence that general information transfers via social transmissions can play an important role in the observed SES firm predictability. Based on the learning theory in urban economics developed by

Jacobs (1969), Lucas (1988), Glaeser (1999), higher population density and education level could offer better environment for information generation and transfer. To test this premise we collect the US demographic data on population density and university education across US metropolitan statistical areas from the 2010 US Census.[21] Then we conduct univariate and multivariate analysis of the SES firm return predictability on the subsamples divided by the median value of population density or the percentage of university degree holders across metro areas.

Table 12 shows the test results with two demographic variables. Panel A presents Fama and French (2018) six-factor abnormal returns for both value-weighted and equal-weighted portfolios based on SES predictor of each subsamples. Abnormal returns are reported for the lowest (Q1) and highest (Q5) quintile portfolios and the Q5-Q1 difference portfolio. We can see that the magnitude of the difference on portfolio return is substantially larger (50% or more) when focal firms are located in areas with high population density or high education level. In Panel B, tests are based on panel regressions with the same set of control variables as in Table 6. All estimations include time and firms fixed effects and the standard errors are clustered by time and firm. In separate tests for population density and education, we interactive the SES firm predictor, $SES_{i,t-1}$, with dummies $H\_Pop_{i,t-1}$ and $H\_Edu_{i,t-1}$, standing for metro areas with above median values of population density and education level, respectively. We conduct estimations for all three performance measures: excess returns in columns (1-2), the Fama and French (2018) six-factor alphas in columns (3-4), and industry-adjusted returns in columns (5-6), and report in the panel only the estimates of the SES firm predictor and its

[21] Besides learning within metro areas, distant social connections could also matter for information dissemination about firm welfare policies. However, the majority of social connections (share of friends) in the United States is observed within a 50-mile radius as documented in Bailey et al. (2018). This distance is largely similar to the coverage of many metro areas.

interactive terms. Consistent with the learning theory predictions, even after accounting for various controls, we observe positive, economically sizable, and statistically significant coefficients on interaction terms in all six estimations. In particular, the magnitude of coefficients on $SES_{i,t-1} \times H\_Pop_{i,t-1}$ and $SES_{i,t-1} \times H\_Edu_{i,t-1}$ is about 50% of that for coefficients on the stand-alone predictor term, $SES_{i,t-1}$. These tests, therefore, support the idea that the transfer of information on employee welfare policies across firms can be driven by social transmissions via public and/or private learning channels.

6. Conclusions

In this study, we report the evidence of return predictability among US firms with similar employee satisfaction (SES) by using a novel firm-ranking data based on employee satisfaction reviews from Glassdoor. This effect is distinct from industry and other known inter-firm momentum strategies. Moreover, as shown in the Internet Appendix, it cannot be replicated with other firm characteristics, most notably ESG (Environmental, Social, and Governance) scores. Besides the results based on the US firms, consistent with Edmans et al. (2017), we find that the predictability phenomenon is present in the flexible labor markets, such as those of Canada and the UK but not observed in the rigid labor markets of France and Germany. Further, we show that our documented return predictability pattern among SES firms cannot be explained by risk but is consistent with a gradual information diffusion of cash flows. Lastly, we show that the knowledge spillover about employee welfare policies can be due to social transmissions, especially in locations conductive for information generation. However, identifying exact social transmission channels is beyond the scope of this paper.

References

Akerlof, G. A., 1982, Labor contracts as partial gift exchange. Quarterly Journal of Economics 97, 543-569.

Akerlof, G. A., Yellen, J. L. (Eds.)., 1986. Efficiency wage models of the labor market. Cambridge University Press.

Ali, U., Hirshleifer, D., 2020. Shared analyst coverage: Unifying momentum spillover effects. Journal of Financial Economics 136, 649-675.

Anton, M., Polk C., 2014. Connected stocks. Journal of Finance 69, 1099-1127.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., Wong, A., 2018. Social connectedness: Measurement, determinants, and effects. Journal of Economic Perspectives 32, 259-280.

Banz, R. W., 1981. The relationship between return and market value of common stocks, Journal of Financial Economics 9, 3–18.

Bapna, R., Langer, N., Mehra, A., Gopal, R., Gupta A., 2013. Human capital investments and employee performance: An analysis of IT services industry. Management Science 59, 641–658.

Basu, S., 1983. The relationship between earnings' yield, market value and return for NYSE common stocks: further evidence, Journal of Financial Economics 12, 129–156.

Bergen, M., Peteraf, M. A., 2002. Competitor identification and competitor analysis: A broad-based managerial approach. Managerial and Decision Economics 23, 157–169.

Bernard, V. L., Thomas, J. K., 1989. Post-earnings-announcement drift: delayed price response or risk premium? Journal of Accounting Research 27, 1-36.

Beneish, M., Lee, C.M., Nichols, D., 2015. In short supply: short-sellers and stock returns. Journal of Accounting and Economics 60, 33–57.

Brayfield, A. H., Crockett, W. H., 1955. Employee attitudes and employee performance. Psychological Bulletin 52, 396.

Burt, A., Hrdlicka, C. M., 2020. Where does the predictability from sorting on returns of economically linked come from? Journal of Financial and Quantitative Analysis, forthcoming.

Burt, A., Hrdlicka, C., Harford, J., 2020. How Much Do Directors Influence Firm Value?. Review of Financial Studies 33, 1818-1847.

Cao, J., Tarun, C., Chen, L., 2016. Alliances and return predictability. Journal of Financial and Quantitative Analysis 51, 1689-1717.

Chen, M. J., 1996. Competitor analysis and interfirm rivalry: Toward a theoretical integration. Academy of Management Review 21, 100-134.

Chopra, N., Lakonishok, J., Ritter, J. R., 1992. Measuring abnormal performance: do stocks overreact? Journal of Financial Economics 31, 235–268.

Christoffersen, S., Sarkissian, S., 2009. City size and fund performance. Journal of Financial Economics 92, 252-275.

Coff, R. W., 1997. Human assets and management dilemmas: Coping with hazards on the road to resource-based theory. Academy of Management Review 22, 374-402.

Cohen, L., Lou, D., 2012. Complicated firms. Journal of Financial Economics 104, 383-400.

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. Journal of Finance 63, 1977-2011.

Daniel, K., Hirshleifer, D., Sun, L., 2020. Short-and long-horizon behavioral factors. Review of Financial Studies 33, 1673-1736.

Edmans, A., 2011. Does the stock market fully value intangibles? Employee satisfaction and equity prices. Journal of Financial Economics 101, 621-640.

Edmans, A., 2012. The link between job satisfaction and firm value, with implications for corporate social responsibility. Academy of Management Perspectives 26, 1-19.

Edmans, A., Li, L., Zhang, C., 2017. Employee satisfaction, labor market flexibility, and stock returns around the world. NBER working paper No. w20300.

Engelberg, J., McLean, R. D., Pontiff, J., 2018. Anomalies and news. Journal of Finance 73, 1971-2001.

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

Fama, E. F., French, K. R., 2018. Choosing factors. Journal of Financial Economics 128, 234-252.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: empirical tests, Journal of Political Economy 81, 607–636.

Gao, G., Moulton, P., Ng, D., 2017. Institutional ownership and return predictability across economically unrelated stocks. Journal of Financial Intermediation 31, 45-63.

Glaeser, E., 1999. Learning in cities. Journal of Urban Economics 46, 254-277.

Gleason, C. A., Lee, C. M., 2003. Analyst forecast revisions and market price discovery. The Accounting Review 78, 193-225.

Green, T. C., Huang, R., Wen, Q., Zhou, D., 2019. Crowdsourced employer reviews and stock returns. Journal of Financial Economics 134, 236-251.

Gubler, T., Larkin, I., Pierce, L., 2018. Doing well by making well: The impact of corporate wellness programs on employee productivity. Management Science 64, 4967–4987.

Hall, R., 1993. A framework linking intangible resources and capabilities to sustainable competitive advantage. Strategic Management Journal 14, 607-618.

Hirshleifer, D., Teoh, S.H., Yu, J., 2011. Short arbitrage, return asymmetry, and the accrual anomaly. Review of Financial Studies 24, 2429–2461.

Hou, K., Mo, H., Xue, C., Zhang, L., 2020. An augmented q-factor model with expected growth. Review of Finance, forthcoming.

Huang, X., 2015. Thinking outside the borders: investors' underreaction to foreign operations information. Review of Financial Studies 28, 3109-3152.

Jacobs, J., 1969. The Economy of Cities. Vintage, New York.

Jaffe, A. B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics 108, 577-598.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. Journal of Finance 45, 881-898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance, 48, 65-91.

La Porta, R., Lakonishok, J., Shleifer, A., Vishny, R., 1997. Good news for value stocks: further evidence on market efficiency. Journal of Finance 52, 859–874.

Lee, C. M., So, E. C., 2015. Alphanomics: The informational underpinnings of market efficiency. Foundations and Trends in Accounting 9, 59-258.

Lee, C. M., Sun, S. T., Wang, R., Zhang, R., 2019. Technological links and predictable returns. Journal of Financial Economics 132, 76-96.

Lieberman, M. B., Asaba, S., 2006. Why do firms imitate each other? Academy of Management Review 31, 366–385.

Liu, Y, Wu, X., 2018. Labor market competitor network and the transmission of shocks. Working paper, Yale University.

Lo, A. W., MacKinlay, A. C., 1990. When are contrarian profits due to stock market overreaction? Review of Financial Studies 3, 175–205.

Lucas, R., 1988. On the mechanics of economic development. Journal of Monetary Economics 22, 3-42.

Markman, G. D., Gianiodis, P. T., Buchholtz, A. K., 2009. Factor-market rivalry. Academy of Management Review 34, 423-441.

McGregor, D., 1960. Theory X and theory Y. Organization Theory 358, 374.

Menzly, L., Ozbas, O., 2010. Market segmentation and cross-predictability of returns. Journal of Finance 65, 1555-1580.

Moskowitz, T. J., Grinblatt, M., 1999. Do industries explain momentum? Journal of Finance 54, 1249-1290.

Parsons, C. A., Sabbatucci, R., Titman, S., 2020. Geographic lead-lag effects. Review of Financial Studies 33, 4721-4770.

Schneider, B., Hanges, P. J., Smith, D. B., Salvaggio, A. N., 2003. Which comes first: employee attitudes or organizational financial and market performance? Journal of Applied Psychology 88, 836-851.

Shapiro, C., Stiglitz, J. E., 1984. Equilibrium unemployment as a worker discipline device. American Economic Review 74, 433-444.

Sheng, J., 2019. Asset pricing in the information age: Employee expectations and stock returns. Working paper, UC Irvine.

Weitz, J., Nuckols, R. C., 1955. Job satisfaction and job survival. Journal of Applied Psychology 39, 294.

Yu, T., Cannella Jr, A. A., 2007. Rivalry between multinational enterprises: An event history approach. Academy of Management Journal 50, 665-686.

Table 1: Summary statistics

This table presents the summary statistics for the US sample coverage, firm characteristics, and employer ratings. The sample includes the top 1,000 employee satisfaction listed firms (excluding financials) based on time-varying Glassdoor firm ratings from January 2010 to December 2018. These firms are listed on the NYSE and NASDAQ and their share codes are 10 or 11 that are contained in the CRSP/COMPUSTAT merged data file. Financial firms (with one-digit SIC code = 6) and stocks with price less than $5 at the end of previous year are excluded. All variable definitions are in the Appendix Table. Panel A reports the sample coverage statistics as a fraction of the CRSP universe in terms of the total number of firms and total market capitalization and provides the statistics for similar employee satisfaction (SES) firms in the same industry and in the same US state. The SES firms are based on the employee satisfaction ranking of [-20, +20] neighbor stocks for each focal firm. Panel B reports the statistics of five firm characteristics: Market Capitalization ($bln), Book-to-Market Ratio (B/M), Asset Growth (AG), Gross Profitability (GP), and Momentum (Mom). Asset Growth is defined as year-over-year growth rate of total asset; Gross Profitability is defined as the revenue minus cost of goods sold scaled by assets; Momentum is defined as the cumulative stock return from month $t-12$ to month $t-2$ as in Jegadeesh and Titman (1993). Panel C reports the summary statistics of overall employer rating and sub-category ratings, on a scale of one to five with five being the top rating. Panel D reports the correlations among the ratings. The top half of Panel D presents Spearman rank correlation coefficients, and the bottom half of the panel reports Pearson correlation coefficients. All correlation coefficients are significantly different from zero at the 1% level.

Panel A: Sample coverage

	Mean	SD	Min	Median	Max
% of total number of stocks covered	0.24	0.03	0.23	0.25	0.27
% of total market capitalization covered	0.65	0.02	0.54	0.61	0.69
% SES stocks in the same industry	0.16	0.11	0.02	0.12	0.77
% SES stocks in the same US state	0.07	0.13	0.00	0.05	0.64

Panel B: Firm characteristics

	Mean	SD	Min	Median	Max
Market Capitalization ($ bln)	5.29	9.40	0.65	4.33	47.62
B/M	0.78	1.16	0.04	0.52	5.17
Asset Growth (AG)	0.23	0.43	-0.73	0.21	0.99
Gross Profitability (GP)	0.42	0.27	-0.96	0.40	1.07
Momentum (Mom)	0.19	0.66	-0.89	0.13	8.76

Table 1 (continued)

Panel C: Employee reviews

	Mean	SD	Min	Median	Max
Employer Rating	3.50	1.15	1.00	3.00	5.00
Career Opportunities	3.18	1.16	2.00	3.00	5.00
Compensation and Benefits	3.39	1.13	2.00	3.00	5.00
Senior Management	2.95	1.26	1.00	3.00	5.00
Work/Life Balance	3.47	1.18	1.00	3.00	5.00
Culture and Values	3.38	1.29	1.00	3.00	5.00

Panel D: Correlations among the ratings

	Employer Rating	Career Opportunities	Compensation & Benefits	Senior Management	Work/Life Balance	Culture & Values
Employer Rating		0.76	0.59	0.76	0.58	0.78
Career Opportunities	0.69		0.54	0.64	0.48	0.63
Compensation and Benefits	0.56	0.53		0.49	0.42	0.49
Senior Management	0.73	0.66	0.48		0.56	0.76
Work/Life Balance	0.61	0.46	0.41	0.55		0.60
Culture and Values	0.72	0.67	0.50	0.72	0.59	

Table 2: Fundamental linkages among SES firms

This table reports the results of panel regressions of the predictive power of similar employee satisfaction (SES) firms for focal firms' employee satisfaction in Panel A and their three fundamental characteristics: Employment growth (ΔEmployment), Revenue growth (ΔRevenue), and Profit growth (ΔProfit) in Panel B. The sample period is from January 2010 to December 2018. SES firms are constructed based on the proximity-weighted employee satisfaction ranking of [-20, +20] neighbor stocks for each focal firm. Panel A shows SES spillover effects on focal firm employee satisfaction. Variables $\Delta ES_{i,t}$, $\Delta CV_{i,t}$, $\Delta WL_{i,t}$, $\Delta SM_{i,t}$, $\Delta CB_{i,t}$, and $\Delta CO_{i,t}$ are the change in the focal firm's overall employee satisfaction and its five sub-category ratings, Culture & Values, Work/Life Balance, Senior Management, Compensation & Benefits, and Career Opportunities, respectively. Variables $SES\_\Delta OS_{i,t}$, $SES\_\Delta CV_{i,t}$, $SES\_\Delta WL_{i,t}$, $SES\_\Delta SM_{i,t}$, $SES\_\Delta CB_{i,t}$, and $SES\_\Delta CO_{i,t}$ are the proximity-weighted changes in the overall employee satisfaction and five sub-category ratings of SES firms, respectively. In Panel B, the dependent variable is the market-adjusted value of each characteristic. Variables $SES\_\Delta Employment_t$, $SES\_\Delta Revenue_t$, and $SES\_\Delta Profit_t$ are the proximity-weighted average growth in employment, revenue, and profit of SES firms, respectively. Regressions in Panel A include year and industry fixed effects, measured at two-digit SIC codes. All variables are measured at the end of each calendar year and are winsorized at 1% and 99% levels. Independent variables are cross-sectionally standardized to have zero mean and unit variance. Control variables are from Table 1-B. The standard errors are clustered by year. The *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Table 2 (continued)

Panel A: SES spillover effects on focal firm's employee satisfaction

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta OS_{i,t}$	$\Delta CV_{i,t}$	$\Delta WL_{i,t}$	$\Delta SM_{i,t}$	$\Delta CB_{i,t}$	$\Delta CO_{i,t}$
$SES\_\Delta OS_{i,t-1}$	0.162*** (2.85)					
$SES\_\Delta CV_{i,t-1}$		0.134** (2.56)				
$SES\_\Delta WL_{i,t-1}$			0.142** (2.47)			
$SES\_\Delta SM_{i,t-1}$				0.151*** (2.59)		
$SES\_\Delta CB_{i,t-1}$					0.184*** (3.28)	
$SES\_\Delta CO_{i,t-1}$						0.167 *** (2.77)
$\Delta OS_{i,t-1}$	0.373*** (3.28)					
$\Delta CV_{i,t-1}$		0.340*** (3.31)				
$\Delta WL_{i,t-1}$			0.322*** (2.79)			
$\Delta SM_{i,t-1}$				0.442*** (3.22)		
$\Delta CB_{i,t-1}$					0.540*** (5.39)	
$\Delta CO_{i,t-1}$						0.421 *** (5.28)
Controls	Y	Y	Y	Y	Y	Y
Industry & Year FE	Y	Y	Y	Y	Y	Y
Obs.	7,680	7,680	7,680	7,680	7,680	7,680
R^2	0.25	0.22	0.22	0.24	0.27	0.25

Table 2 (continued)

Panel B: SES effects on focal firm's fundamentals (industry-adjusted)

	ΔEmployment		ΔRevenue		ΔProfit	
	t	$t+1$	t	$t+1$	t	$t+1$
$SES\_\Delta Employment_t$	0.149*** (8.96)	0.034** (2.37)				
$SES\_\Delta Revenue_t$			0.116*** (9.28)	0.027*** (3.46)		
$SES\_\Delta Profit_t$					0.030*** (9.98)	0.006*** (3.41)
$\Delta Employment_t$		0.076*** (4.23)				
$\Delta Revenue_t$				0.084*** (6.98)		
$\Delta Profit_t$						0.016*** (4.34)
Controls	Y	Y	Y	Y	Y	Y
Obs.	8,640	7,680	8,640	7,680	8,640	7,680
R^2	0.14	0.04	0.12	0.04	0.11	0.03

Table 3: Univariate portfolio tests

This table reports the results of SES firm predictability based on value-weighted (VW) and equally-weighted (EW) univariate sorts of portfolio returns of similar employee satisfaction peer firms. The sample period is from January 2010 to December 2018. The SES predictor is constructed based on the employee satisfaction ranking of [-20, +20] neighbor stocks for each focal firm using equally-weighted peer (EWP) and proximity-weighted peer (PWP) portfolio construction approaches. The portfolio returns of SES peers are sorted into five quintiles. Abnormal returns (in percent) for the focal firm are reported from the lowest quintile Q1 to the highest quintile Q5, and the Q5-Q1 difference portfolio using the excess return, *ret*, the risk-adjusted return from the Fama and French (2018) six-factor model, α_6, and the industry-adjusted return, α_ind. The standard errors are Newey-West adjusted with three lags. The *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

	ret		α_6		α_ind	
VW	EWP	PWP	EWP	PWP	EWP	PWP
Q1 (Low)	-0.20	-0.21	-0.67	-0.79	-0.42	-0.45
Q2	0.02	0.10	-0.42	-0.47	-0.14	-0.12
Q3	0.30	0.32	-0.20	-0.18	0.08	0.06
Q4	0.43	0.54	0.12	0.10	0.24	0.31
Q5 (High)	0.82	0.96	0.49	0.56	0.67	0.80
Q5-Q1	1.02** (2.43)	1.17*** (2.70)	1.16*** (2.69)	1.35*** (3.03)	1.09*** (2.72)	1.25*** (2.98)
EW						
Q1 (Low)	-0.08	-0.07	-0.82	-0.99	-0.17	-0.15
Q2	0.28	0.29	-0.42	-0.48	0.14	0.16
Q3	0.54	0.56	-0.20	-0.27	0.33	0.56
Q4	0.86	0.93	0.15	0.09	0.69	0.81
Q5 (High)	1.27	1.49	0.70	0.80	1.07	1.27
Q5-Q1	1.35*** (2.84)	1.56*** (3.22)	1.53*** (3.17)	1.79*** (3.64)	1.24*** (2.71)	1.42*** (3.03)

Table 4: Univariate portfolio tests for different SES windows and sub-ratings

This table reports the results of SES firm predictability based on value-weighted (VW) and equally-weighted (EW) univariate sorts of portfolio returns of SES peer firms for different sub-ratings and different peer windows using the proximity-weighted neighbor approach. The sample period is from January 2010 to December 2018. Abnormal returns (in percent) for the focal firm are reported for the lowest (Q1) and highest (Q5) quintile sorted on SES portfolios and the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model. In Panel A, univariate portfolio sorts are performed in five sub-ratings from Glassdoor: Culture & Values, Work/Life Balance, Senior Management, Compensation & Benefits, and Career Opportunities. In Panel B, SES peer firm stocks are split into five different distance segments relative to the focal firm. The standard errors are Newey-West adjusted with three lags. The absolute *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Panel A: Different sub-ratings of SES firms

VW	(1) Culture & Values	(2) Work/Life Balance	(3) Senior Management	(4) Compensation & Benefits	(5) Career Opportunities
Q1 (Low)	-0.66	-0.69	-0.73	-0.89	-0.77
Q5 (High)	0.46	0.49	0.52	0.63	0.54
Q5-Q1	1.12***	1.18***	1.26***	1.53***	1.31***
	(2.62)	(2.71)	(2.86)	(3.35)	(2.96)
EW					
Q1 (Low)	-0.81	-0.85	-0.92	-1.12	-0.97
Q5 (High)	0.67	0.70	0.75	0.90	0.79
Q5-Q1	1.48***	1.56***	1.67***	2.02***	1.76***
	(3.08)	(3.22)	(3.42)	(4.06)	(3.59)

Panel B: Different windows of SES firms

VW	(1) [-20,-1], [1,+20]	(2) [-40,-21], [+21,+40]	(3) [-60,-41], [+41,+60]	(4) [-80,-61], [+61,+80]	(5) [-100,-81], [+81,+100]
Q1 (Low)	-0.79	-0.67	-0.55	-0.43	-0.32
Q5 (High)	0.56	0.50	0.39	0.31	0.22
Q5-Q1	1.35***	1.17***	0.95**	0.74*	0.54
	(3.03)	(2.60)	(2.12)	(1.69)	(1.21)
EW					
Q1 (Low)	-0.99	-0.84	-0.69	-0.54	-0.40
Q5 (High)	0.80	0.70	0.56	0.44	0.32
Q5-Q1	1.79***	1.54***	1.25**	0.98**	0.72
	(3.64)	(3.09)	(2.55)	(2.00)	(1.46)

Table 5: Bivariate portfolio tests using the firm's own employee satisfaction score and SES firm predictor

This table presents monthly alphas of value-weighted (VW) and equally-weighted (EW) quintile portfolios sorted on firm's own employee satisfaction score (Panel A) or its change (Panel B) and portfolio returns of SES peer firms. The sample period is from January 2010 to December 2018. The SES predictor is constructed based on the employee satisfaction ranking of [-20, +20] neighbor stocks for each focal firm using proximity-weighted peer (PWP) portfolio construction approaches. Abnormal returns are based on the Fama and French (2018) six-factor model. In Panel A, abnormal returns (in percent) are reported for quintiles of firm's own employee satisfaction score, the lowest (Q1) and highest (Q5) quintiles of SES return portfolios, as well as the Q5-Q1 difference portfolio. In Panel B, firms are sorted on their own changes in the employee satisfaction scores from year $t-2$ to year $t-1$ and grouped into the employee satisfaction decrease and increase groups, "Negative" and "Positive," respectively. In Panel B, abnormal returns (in percent) are reported for "Negative" and "Positive" changes in the firm's own employee satisfaction score, the lowest and highest quintiles of SES return portfolios, as well as the Q5-Q1 difference portfolio. The last column in Panel B, Difference (P-N), shows the difference in monthly alphas between "Positive" and "Negative" groups in employee satisfaction score. The standard errors are Newey-West adjusted with three lags. The t-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Panel A: Firm's own employee satisfaction score

	Firm's own employee satisfaction score				
VW	1 (Low)	2	3	4	5 (High)
Q1 (Low)	-0.63	-0.68	-0.79	-0.84	-0.87
Q5 (High)	0.40	0.50	0.52	0.60	0.66
Q5-Q1	1.03**	1.18***	1.31***	1.44***	1.54***
	(2.28)	(2.65)	(2.93)	(3.22)	(3.47)
EW					
Q1 (Low)	-0.79	-0.80	-0.96	-1.06	-1.17
Q5 (High)	0.62	0.71	0.80	0.85	0.92
Q5-Q1	1.41***	1.51***	1.76***	1.91***	2.09***
	(2.86)	(3.09)	(3.57)	(3.88)	(4.23)

Panel B: Firm's own change in the employee satisfaction score

	Firm's own change in the employee satisfaction score		
VW	Negative	Positive	Difference (P-N)
Q1 (Low)	-0.43	-0.91	
Q5 (High)	0.29	0.59	
Q5-Q1	0.72*	1.50***	0.78**
	(1.75)	(3.44)	(1.99)
EW			
Q1 (Low)	-0.51	-1.21	
Q5 (High)	0.46	0.99	
Q5-Q1	0.97*	2.20***	1.23***
	(1.91)	(4.34)	(2.67)

Table 6: Cross-sectional regressions

This table reports the results of Fama-MacBeth regressions of SES predictability. The sample period is from January 2010 to December 2018. Financial firms (with one-digit SIC code = 6) and stocks with price less than $5 at the end of previous year are excluded. For each focal firm the portfolio of peer firms is constructed based on [-20, +20] neighbor stocks using the proximity-weighted neighbor approach. The dependent variable (multiplied by 100) is the monthly excess return of the focal firm, *ret*, the risk-adjusted return of the focal firm based on the Fama and French (2018) six-factor model, α_6, and the industry-adjusted return of the focal firm, α_ind. The independent variable of interest is $SES_{i,t-1}$, which is the lagged proximity-weighted return of SES peer firms for each focal firm. The control variables are the lagged values of focal firm's size, $Ln(Size)$; book-to-market ratio, $Ln(B/M)$; its own excess return, $ret_{i,t-1}$; medium-term price momentum, Mom; asset growth, AG; gross profitability, GP; best 100 employee satisfaction company indicator, BC; top 100 employee growth company indicator, EG; and its value-weighted industry return, Ind_Mom. All variables are defined in the Appendix Table. All explanatory variables are based on the last non-missing available observation for each month t and are winsorized at 1% and 99% levels. The standard errors are Newey-West adjusted with three lags. The absolute *t*-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	ret	*ret*	α_6	α_ind
$SES_{i,t-1}$	7.28*** (4.63)	6.61*** (4.34)	5.28*** (3.57)	5.92*** (3.92)
$Ln(Size)$		-1.34*** (3.62)	-0.52 (1.44)	-1.28*** (3.22)
$Ln(B/M)$		0.77** (2.30)	0.33 (0.94)	0.75** (2.11)
$ret_{i,t-1}$		-3.95*** (3.23)	-3.15*** (2.64)	-3.47*** (2.84)
Mom		0.46 (1.10)	0.22 (0.58)	0.42 (1.02)
AG		-1.94*** (3.03)	-0.81 (1.29)	-2.18*** (3.40)
GP		1.71* (1.68)	0.74 (0.68)	1.53 (1.44)
BC		2.39*** (2.88)	1.95** (2.27)	2.26*** (2.69)
EG		-1.75*** (2.63)	-1.40** (2.20)	-1.66** (2.50)
Ind_Mom		3.75*** (2.84)	3.04** (2.39)	
Industry FE	Y	Y	Y	N
Obs.	103,680	103,680	103,680	103,680
R^2	0.08	0.11	0.04	0.03

Table 7: Tests with alternative inter-firm momentum links

This table reports the results of Fama-MacBeth regressions of the SES firm predictability in the presence of alternative inter-firm momentum variables. The sample period is from January 2010 to December 2018. The dependent variable (multiplied by 100) is the monthly excess return of the focal firm. The independent variable of interest is $SES_{i,t-1}$, which is the lagged proximity-weighted portfolio return of similar employee satisfaction peer firms. For each focal firm the portfolio of peer firms is constructed based on [-20, +20] neighbor stocks. $Sup\_Ind_{i,t-1}$ and $Cus\_Ind_{i,t-1}$ are the lagged supplier industry momentum and customer industry momentum of the focal firm (Menzly and Ozbas, 2010); $Cus_{i,t-1}$ is the lagged customer momentum of the focal firm (Cohen and Frazzini, 2008); $PC_{i,t-1}$ is the lagged pseudo-conglomerate portfolio return of the focal firm (Cohen and Lou, 2012); $SA_{i,t-1}$ is lagged strategic alliance partners' portfolio return of the focal firm (Cao et al., 2016); $Tech_{i,t-1}$ is the lagged technological partners' portfolio return of the focal firm (Lee et al., 2019); $Geo_{i,t-1}$ is the lagged average return of all other stocks headquartered in the same city of US 20 largest cities (Parsons et al., 2020). $CB_{i,t-1}$ is the lagged weighted-average return of stocks connected through common board members with the focal firm (Burt et al., 2020). $CS_{i,t-1}$ is the lagged weighted-average return of stocks connected through shared analyst coverage with the focal firm (Ali and Hirshleifer, 2020). $CI_{i,t-1}$ is the lagged weighted-average return of stocks connected through common institutional investors with the focal firm (Gao et al., 2017). Control variables are from Table 5, but their coefficients and those of industry fixed effects are not reported. The standard errors are Newey-West adjusted with three lags. The absolute *t*-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$SES_{i,t-1}$	6.61*** (4.34)	5.75*** (3.91)	5.68*** (3.89)	5.56*** (3.80)	6.00*** (3.99)	6.34*** (4.16)	5.33*** (3.56)	5.41*** (3.61)	6.08*** (4.04)	4.81*** (3.45)	5.12*** (3.44)	5.80*** (4.08)
$Sup\_Ind_{i,t-1}$		1.41* (1.90)		1.13 (1.58)								
$Cus\_Ind_{i,t-1}$			1.48** (2.19)	1.01 (1.56)								
$Cus_{i,t-1}$					2.19* (1.89)							
$PC_{i,t-1}$						2.63* (1.94)						
$SA_{i,t-1}$							1.25* (1.69)					
$Tech_{i,t-1}$								3.54** (1.98)				
$Geo_{i,t-1}$									1.22* (2.01)			
$CB_{i,t-1}$										1.19 (1.47)		
$CS_{i,t-1}$											4.46** (2.43)	
$CI_{i,t-1}$												3.94** (2.01)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	103,680	98,169	98,169	98,169	8,147	24,362	14,469	35,579	96,494	43,566	70,097	77,106
R^2	0.11	0.11	0.11	0.11	0.12	0.12	0.11	0.11	0.12	0.10	0.12	0.13

Table 8: International tests

This table reports the results of Fama-MacBeth regressions of SES firm predictability in international markets. The sample period is from January 2010 to December 2018. The international samples include top 1,000 employee satisfaction firms (excluding financial firms) that are both headquartered and primarily listed in Canada, France, Germany, or the United Kingdom. Stocks with price less than \$5 at the end of previous year are excluded. The dependent variable (multiplied by 100) is the monthly excess return of the focal firm, *ret*, the risk-adjusted return of the focal firm based on the Fama and French (2018) six-factor model, α_6, and the industry-adjusted return of the focal firm, α_ind. The independent variable of interest is the country-specific $SES_{i,t-1}$ (country), which is the lagged proximity-weighted portfolio return of similar employee satisfaction peer firms in a given country. For each focal firm in each country the portfolio of peer firms is constructed based on [-20, +20] neighbor stocks. The other explanatory variables are the same as in Table 5, but their coefficients are not reported. The standard errors are Newey-West adjusted with three lags. The absolute *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)
	ret	α_6	α_ind
$SES_{i,t-1}$ (Canada)	3.69***	3.04***	3.33***
	(3.25)	(2.68)	(2.97)
Controls	Y	Y	Y
Industry FE	Y	Y	N
$SES_{i,t-1}$ (France)	-1.42	-1.14	-1.27
	(1.04)	(0.84)	(0.94)
Controls	Y	Y	Y
Industry FE	Y	Y	N
$SES_{i,t-1}$ (Germany)	-0.92	-0.72	-0.74
	(1.12)	(0.82)	(0.93)
Controls	Y	Y	Y
Industry FE	Y	Y	N
$SES_{i,t-1}$ (United Kingdom)	2.83**	2.31**	2.55**
	(2.44)	(2.03)	(2.20)
Controls	Y	Y	Y
Industry FE	Y	Y	N

Table 9: SES firm predictability for earnings announcements and standardized unexpected earnings

This table reports the test results of SES firm predictability for earnings announcements and standardized unexpected earnings (SUEs). The sample period is from January 2010 to December 2018. The dependent variable (multiplied by 100) is the daily return of the focal firm. The SES predictor, $SES_{i,t-1}$, is the proximity-weighted portfolio return of similar employee satisfaction peer firms in the previous month. For each focal firm the portfolio of peer firms is constructed based on [-20, +20] neighbor stocks. Panel A shows the results of panel regressions of SES firm predictability for daily returns within the earnings announcement window. An earnings announcement is defined as the one-day or three-day window centered at the earnings release day, e.g., the one-day window includes day $t-1, t, t+1$. $EDAY$ is a dummy variable, which equals to one if the daily observation is within the announcement window, and zero otherwise. And earnings announcement dates are from the Compustat quarterly database. Earnings announcement day is defined as the day with the highest trading volume scaled by the market trading volume from among the day before, the day of, and the day after the reported earnings announcement date. Control variables include the lagged values for each of the past ten days for stock returns, stock returns squared, and trading volume but their estimates are not reported. Each regression also includes day fixed effects. The standard errors are clustered by time. Panel B shows the results of Fama-MacBeth regressions of SES firm predictability for standardized unexpected earnings, SUEs, for four future fiscal quarters. SUE is defined as the year-over-year change in quarterly earnings before extraordinary items scaled by the standard deviation of unexpected earnings over the eight preceding quarters. The dependent variable is winsorized at 1% and 99% levels in the cross-section, and all the explanatory variables are assigned to deciles and scaled to [0, 1] range. Control variables also include four quarter lags of the firm's own SUEs. The sample is restricted to firms with fiscal quarters ending in March, June, September, and December. The standard errors are calculated using the Newey-West method with three lags. The *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Panel A: Earnings announcements

	1-day window	3-day window
$SES_{i,t-1}$	0.43**	0.54***
	(2.54)	(2.59)
$SES_{i,t-1} \times EDAY$	3.20***	0.21***
	(4.83)	(7.48)
$EDAY$	0.24***	0.23***
	(6.97)	(3.44)
Controls	Y	Y
Day FE	Y	Y
Obs. (days)	3,218,240	3,218,240
R^2	0.13	0.13

Table 9 (continued)

Panel B: Forecasting standardized unexpected earnings

	(1)	(2)	(3)	(4)
	$SUE_{i,t}$	$SUE_{i,t+1}$	$SUE_{i,t+2}$	$SUE_{i,t+3}$
$SES_{i,t-1}$	10.35*** (5.16)	7.26*** (3.62)	4.14** (2.01)	0.93 (0.54)
Lagged SUEs (four quarters)	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Obs. (quarters)	36	36	36	36
R^2	0.23	0.23	0.23	0.23

Table 10: Mechanisms affecting SES firm predictability

This table reports the mechanism tests for the SES firm predictability. The sample period is from January 2010 to December 2018. Each month, all stocks are sorted based on each proxy into two groups by the median, and then independently sorted on peer firms' past returns into the five quintiles. For each focal firm the portfolio of peer firms is constructed based on [-20, +20] neighbor stocks. Abnormal returns (in percent) are reported for the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model. Panel A examines investors' inattention mechanism. The three proxies for investors' inattention are the reciprocals (R) of firm turnover, analyst coverage, and institutional ownership. Turnover is the focal firm's average daily turnover in the prior year. Analyst coverage is the number of analysts covering the focal firm at the end of the previous month. Institutional ownership is the institutional holdings of the focal firm orthogonalized with regard to firm size at the end of December. Panel B examines limits to arbitrage mechanism. The three proxies for the limits to arbitrage are the reciprocal of firm's size, volatility, and illiquidity. Size is the log value of market capitalization of focal firm at the end of the previous month. Idiosyncratic volatility is the standard error of the residuals from a regression of daily stocks returns in the previous month on the Fama and French (1993) three risk factors. Illiquidity is the Amihud (2002) illiquidity measure based on the price impact. Panel C examines information complexity mechanism. The three proxies for information complexity are analysts' dispersion, industry segmentation, and dividend non-payment. Analysts' dispersion is the analyst earnings one-year-ahead forecast dispersion at the end of the previous month. Industry segmentation is the reciprocal of the Herfindahl index, which accounts for different industry segment sales for a given focal firm in the previous year. Dividend non-payment is a binary variable based on the splitting of firms into dividend paying and not paying. The standard errors are Newey-West adjusted with three lags. The absolute *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Panel A: Investors' inattention

VW	Turnover (R)	Analyst coverage (R)	Inst. Ownership (R)
Low (Q5-Q1)	0.54	0.61	0.57
High (Q5-Q1)	2.16	2.09	2.13
High-Low	1.62***	1.49***	1.57***
	(3.42)	(3.17)	(3.32)
EW			
Low (Q5-Q1)	0.62	0.70	0.65
High (Q5-Q1)	2.70	2.62	2.67
High-Low	2.08***	1.92***	2.01***
	(4.24)	(3.95)	(4.13)

Table 10 (continued)

Panel B: Limits to arbitrage

VW	Size (R)	Idiosyncratic Volatility	Illiquidity
Low (Q5-Q1)	0.59	0.80	0.67
High (Q5-Q1)	2.11	1.90	1.98
High-Low	1.51*** (3.22)	1.10** (2.49)	1.31*** (2.91)
EW			
Low (Q5-Q1)	0.68	0.92	0.79
High (Q5-Q1)	2.63	2.38	2.50
High-Low	1.95*** (4.01)	1.46*** (3.13)	1.71*** (3.46)

Panel C: Information complexity

VW	Analysts' dispersion	Industry segmentation	Dividend non-payment
Low (Q5-Q1)	0.72	0.65	0.59
High (Q5-Q1)	1.90	1.71	1.54
High-Low	1.18*** (2.61)	1.06** (2.35)	0.95** (2.12)
EW			
Low (Q5-Q1)	0.82	0.74	0.67
High (Q5-Q1)	2.28	2.05	1.85
High-Low	1.46*** (3.13)	1.31*** (2.82)	1.18** (2.54)

Table 11: The SES firm predictability for firms without decision commonality proxies

This table reports the results of Fama-MacBeth regressions of SES firm predictability on the subsamples of SES firms with no common board members, no common analysts, and no common institutional investors. The sample period is from January 2010 to December 2018. For each focal firm the portfolio of peer firms is constructed based on [-20, +20] neighbor stocks using the proximity-weighted neighbor approach. In Panel A the dependent variable (multiplied by 100) is the monthly excess return of the focal firm, *ret*; the risk-adjusted return of the focal firm based on the Fama and French (2018) six-factor model, α_6; and the industry-adjusted return of the focal firm, α_ind. The independent variable of interest is $SES_{i,t-1}$, which is the lagged proximity-weighted portfolio return of similar employee satisfaction peer firms in a given country. All control variables are the same as in Table 6. All variables are defined in the Appendix Table. The standard errors are Newey-West adjusted with three lags. In Panel B, the variables $\Delta OS_{i,t}$, $\Delta CV_{i,t}$, $\Delta WL_{i,t}$, $\Delta SM_{i,t}$, $\Delta CB_{i,t}$, and $\Delta CO_{i,t}$ are the changes in the focal firm's overall employee satisfaction and its five sub-category ratings, Culture & Values, Work/Life Balance, Senior Management, Compensation & Benefits, and Career Opportunities, respectively. The variable $SES\_\Delta ES_{i,t}$ denotes the change in the specific employment satisfaction rating and stands for one of the six variables, $SES\_\Delta OS_{i,t}$, $SES\_\Delta CV_{i,t}$, $SES\_\Delta WL_{i,t}$, $SES\_\Delta SM_{i,t}$, $SES\_\Delta CB_{i,t}$, and $SES\_\Delta CO_{i,t}$, which are the proximity-weighted changes in the overall employee satisfaction and five sub-category ratings of SES firms, respectively. Control variables are from Table 1-B. The standard errors are clustered by year. The absolute *t*-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The SES firm return predictability

	No common boards			No common analysts			No common investors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ret	α_6	α_ind	*ret*	α_6	α_ind	*ret*	α_6	α_ind
$SES_{i,t-1}$	3.03**	2.38**	2.61**	3.70***	2.97**	3.31***	3.71***	2.69**	3.09**
	(2.22)	(2.08)	(2.29)	(2.99)	(2.32)	(2.74)	(3.01)	(2.17)	(2.41)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ind_Mom and Industry FE	Y	Y	N	Y	Y	N	Y	Y	N
Obs.	39,605	39,605	39,605	98,360	98,360	98,360	94,312	94,312	94,312
R^2	0.08	0.04	0.03	0.09	0.04	0.03	0.09	0.04	0.03

Table 11 (continued)

Panel B: The SES firm employee satisfaction sub-ratings predictability

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta OS_{i,t}$	$\Delta CV_{i,t}$	$\Delta WL_{i,t}$	$\Delta SM_{i,t}$	$\Delta CB_{i,t}$	$\Delta CO_{i,t}$
No common boards						
$SES\_\Delta EC_{i,t-1}$	0.090*	0.079*	0.078	0.085*	0.105**	0.096*
	(1.90)	(1.75)	(1.61)	(1.75)	(2.14)	(1.84)
Controls, Industry & Year FE	Y	Y	Y	Y	Y	Y
No common analysts						
$SES\_\Delta EC_{i,t-1}$	0.107**	0.094**	0.096**	0.104**	0.124***	0.117**
	(2.20)	(2.04)	(1.97)	(1.96)	(2.61)	(2.16)
Controls, Industry & Year FE	Y	Y	Y	Y	Y	Y
No common investors						
$SES\_\Delta EC_{i,t-1}$	0.111**	0.093**	0.101*	0.107**	0.128***	0.115**
	(2.25)	(2.07)	(1.92)	(2.11)	(2.67)	(2.25)
Controls, Industry & Year FE	Y	Y	Y	Y	Y	Y

Table 12: The SES firm predictability across locations with different knowledge spillover potential

This table reports the results of SES firm predictability for focal firms located in US metro areas with different population density and education level. The sample period is from January 2010 to December 2018. Population and education data for metropolitan areas are from the US Census. The SES predictor is constructed based on the employee satisfaction ranking of [-20, +20] neighbor stocks for each focal firm using the proximity-weighted peer portfolio approach. Panel A shows univariate tests using the portfolio returns of SES peer firms to sort stocks into five quintiles. Abnormal returns (in percent) are based on the Fama and French (2018) six-factor model and are reported for the lowest (Q1) and highest (Q5) quintile sorted portfolios and the Q5-Q1 difference portfolio. The sample is split into two subsamples based on focal firm metro area's population density and focal firm's metro area's education level (percent of people with a university degree). The standard errors are calculated using the Newey-West method with three lags. Panel B shows panel regression test results. $H\_Pop_{i,t-1}$ and $H\_Edu_{i,t-1}$ are dummy variables each equal to one if a focal firm is located in the metro area with above median values of population density or education level, respectively. All control variables are the same as in Table 6. All estimations use time and firm fixed effects. Standard errors are clustered by time and firm. The *t*-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Univariate tests

	Population		Education	
	(1)	(2)	(3)	(4)
VW	High	Low	High	Low
Q1 (Low)	-0.86	-0.63	-0.89	-0.58
Q5 (High)	0.61	0.42	0.64	0.42
Q5-Q1	1.47**	1.05*	1.54***	1.00**
	(2.43)	(1.94)	(2.87)	(2.27)
EW				
Q1 (Low)	-1.06	-0.76	-1.12	-0.70
Q5 (High)	0.87	0.64	0.88	0.57
Q5-Q1	1.94***	1.40**	2.00***	1.27***
	(2.98)	(2.24)	(3.40)	(2.64)

Table 12 (continued)

Panel B: Multivariate tests

	ret		α_6		α_ind	
	(1)	(2)	(3)	(4)	(5)	(6)
	Population	Education	Population	Education	Population	Education
$SES_{i,t-1}$	4.87*** (4.44)	4.63*** (4.18)	3.88*** (3.79)	3.39*** (3.25)	4.39*** (3.79)	4.22*** (3.88)
$SES_{i,t-1} \times H\_Pop_{i,t-1}$	2.10** (2.26)		1.73* (1.75)		1.91** (1.96)	
$SES_{i,t-1} \times H\_Edu_{i,t-1}$		2.67** (2.28)		2.07* (1.92)		2.23** (2.00)
Controls, Time and Firm FEs	Y	Y	Y	Y	Y	Y
Obs.	99,172	99,172	99,172	99,172	99,172	99,172
R^2	0.11	0.11	0.04	0.04	0.03	0.03

Figure 1: An example of a focal firm with its SES peers

This figure illustrates one snapshot in 2014 with The Walt Disney Company being a focal firm with its 40 similar employee satisfaction (SES) firms based on the Glassdoor's overall employee satisfaction ratings – 20 SES firms with lower ratings and 20 SES firms with higher ratings.

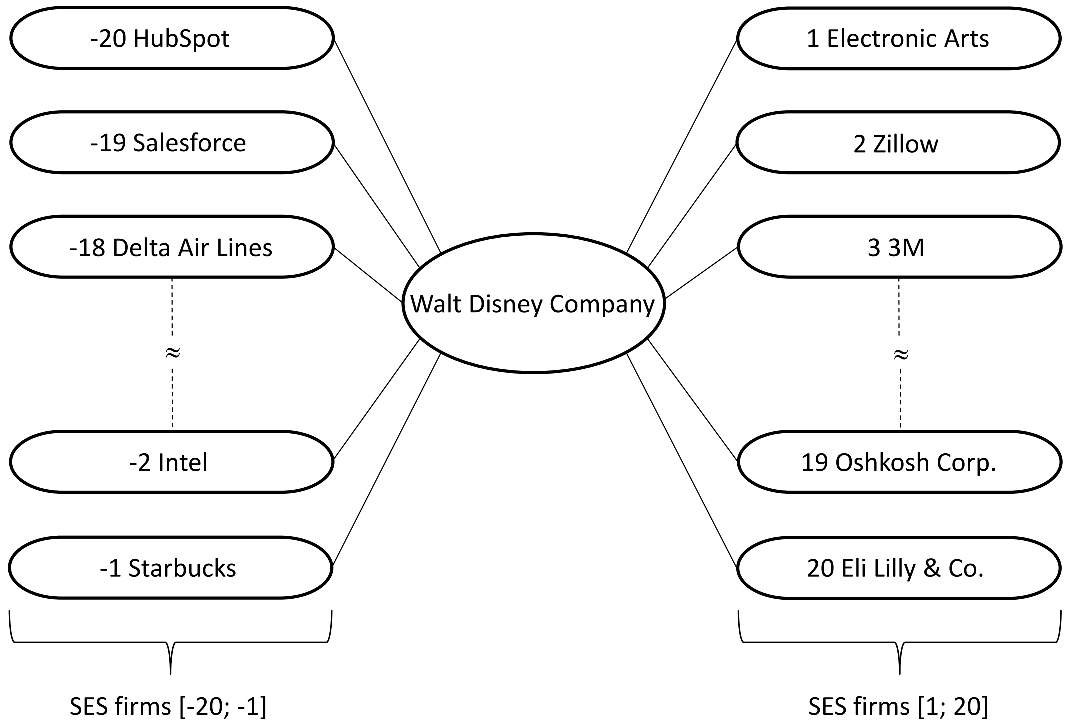


Figure 2: Long-run cumulative excess returns

This figure shows the cumulative excess returns (CERs) of the hedged portfolios based on the portfolio returns of similar employee satisfaction (SES) firms in the twelve months after portfolio formation. The sample period is from January 2010 to December 2018. At the beginning of each month, each focal firm is ranked in the ascending order based on the portfolio return of its peer firms with similar employee satisfaction at the end of the previous month. The portfolio of peer firms is based on [-20, +20] neighbor stocks for each focal firm. The ranked stocks are assigned into the five quintile portfolios. All stocks are value- (equal-) weighted within each portfolio, and the portfolios are rebalanced every month. The solid (dashed) line depicts the value-weighted (equally-weighted) CERs.

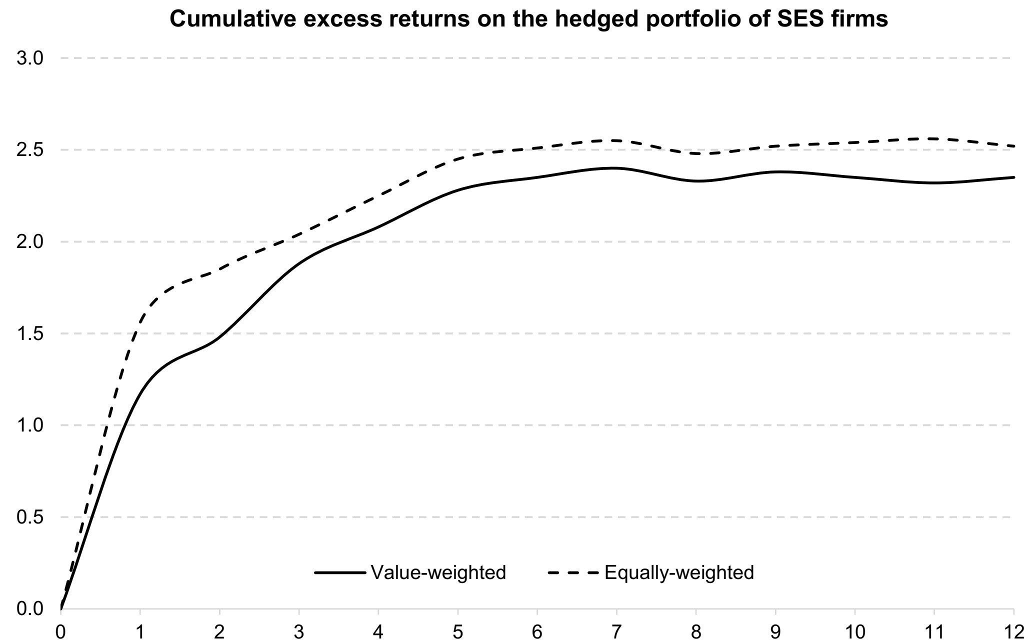
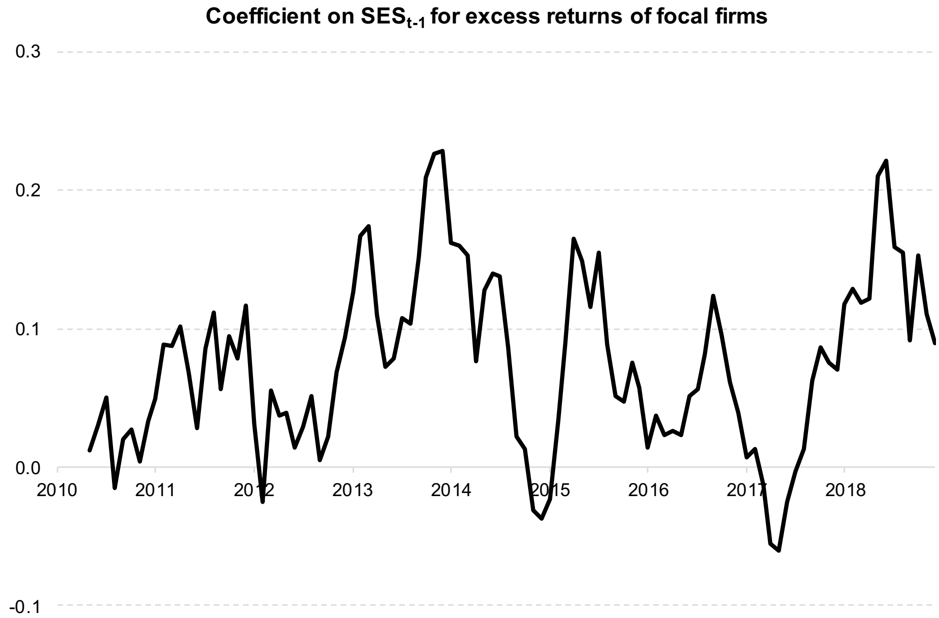


Figure 3: The time-series of estimated SES coefficients from the Fama-MacBeth regressions

This figure shows the time-series of estimated SES predictors from the Fama-MacBeth regressions for excess returns of focal firms. The sample period is from January 2010 to December 2018. At the beginning of each month, each focal firm is ranked in the ascending order based on the portfolio return of its peer firms with similar employee satisfaction at the end of the previous month. The portfolio of peer firms is based on [-20, +20] neighbor stocks for each focal firm. All stocks are value-weighted within each portfolio, and the portfolios are rebalanced every month. The estimated coefficients are obtained from Regression (1) in Table 5 and are averaged over a six-month window.



Appendix

Variable definitions and data sources

Variable	Description	Source	Frequency
SES	Weighted portfolio return of SES peer firms for a focal firm.	Glassdoor, CRSP, Eikon	Monthly
ret	Focal firm's excess return over one-month T-bill.	Glassdoor, CRSP, Eikon	Monthly
Ln(Size)	Log market capitalization.	CRSP, Eikon, Compustat	Monthly
Ln(B/M)	Log book value at the end of December over the market capitalization in month $t-1$.	CRSP, Eikon, Compustat	Monthly
Mom	Focal firm's cumulative return over $t-12$ to $t-2$ months.	CRSP, Eikon	Monthly
Ind_Mom	The industry return of the focal firm.	CRSP, K. French Data	Monthly
AG	Asset growth is a year-over-year growth rate of total asset.	CRSP, Eikon, Compustat	Monthly
GP	Gross profitability is the revenue minus cost of goods sold scaled by assets.	CRSP, Eikon, Compustat	Monthly
BC	Equals one if the focal firm is in the most recent top 100 employee satisfaction firm list.	Glassdoor	Yearly
EG	Equals one if the focal firm is in the top 100 employment growth firms in the past year.	CRSP, Eikon, Compustat	Yearly
Turnover	# of shares traded during a day divided by the # of shares outstanding at the end of the day, averaged over the past 12 months.	CRSP, Eikon	Monthly
Market cap	Market capitalization of the focal firm.	CRSP, Eikon Compustat	Monthly
Analyst coverage	Number of analysts of the focal firm.	CRSP, Eikon Compustat, IBES	Monthly
Institutional ownership	The institutional holdings of the focal firm orthogonalized to firm size at the end of December.	CRSP, Eikon, Thomson-Reuters Holdings (13F)	Monthly
Idiosyncratic volatility	The standard error of the residuals from a regression of daily stock returns in the previous month based on the Fama and French (1993) three-factor model.	CRSP, Eikon, Compustat, K. French Data	Monthly
Illiquidity	Amihud (2002) illiquidity measure based on the price impact.	CRSP	Monthly
Analysts' dispersion	Analyst earnings one-year ahead forecast dispersion at the end of the previous month.	CRSP, Eikon, Compustat, IBES	Monthly
Industry segmentation	Reciprocal of the Herfindahl index, which accounts for different industry segment sales for a given focal firm in the previous year.	CRSP, Compustat	Yearly
Δ*Employment*	$\frac{\#Employees_t - \#Employees_{t-1}}{0.5*(\#Employees_t + \#Employees_{t-1})}$.	CRSP, Eikon, Compustat	Yearly
Δ*Revenue*	$(Revenue\_per\_sh_t / Revenue\_per\_sh_{t-1}) - 1$.	CRSP, Eikon, Compustat	Yearly
Δ*Profit*	$(Profit_t - Profit_{t-1})/Mean(Assets_t, Assets_{t-1})$.	CRSP, Eikon, Compustat	Yearly

Internet appendix

Table A.1 shows the results of SES firm predictability based on the value-weighted and equal-weighted univariate sorts of portfolio returns of SES peer firms for the following three alternative risk-adjustment models: the CAPM, the Daniel et al. (2020) behavioral factor model, and the Hou et al. (2020) q5-factor model. The corresponding abnormal returns are denoted as α_CAPM, α_DHS, and α_q5, respectively. The format of this table is similar to that of Table 3, as the results are reported for both proximity-weighted peer and equally-weighted peer SES portfolio returns, PWP and EWP, respectively. As can be seen in Table A.1, SES firm predictability is robust to all three alternative risk-factor models. The lowest long-short SES portfolio spreads of 110 bps (for EWP), and 128 bps (for PWP) are recorded for the q5 model with value-weighted formation of portfolios based on SES firm return ranking quintiles. However, even in these cases, the statistical significance of the hedge portfolio is still close to the 1% level.

Table A.2 shows the results of testing SES firm return predictability in different sub-samples and sub-periods. First, in the first sub-period (from January 2010 to June 2014), the value- and equal-weighted portfolio alphas are 1.49% and 1.96%, respectively. In the second sub-period (from July 2014 to December 2018), these values are 1.19% and 1.59%, respectively. The four alphas are all statistically significant at 1% level. Second, we test return predictability using a different number of neighbor stocks. We find that the choice of the number of neighbor stocks does not influence return predictability, which eliminates the data mining concerns to peer firms. The obtained alphas are similar to those reported in Table 3. In addition, we also divide peer firms based on industry and state. Both same-industry peer firms and different-industry peer firms generate statistically significant alphas. However, the former firms can generate larger abnormal returns than the latter. Also, peer firms in both within the same state and in different states produce significant alphas. Yet, the same-state peer firms generate larger abnormal returns than different-state peer firms. These results show that information diffusion and cross-learning between firms with SES are not constrained in the same industry and state, but go beyond such boundaries.

An important issue is whether the documented predictability effect would be observed when the same procedure (as the one used for SES firm predictability) is applied to other firm characteristics. In Table A.3 we show the results of firm predictability based on value-weighted univariate sorts of portfolio returns of peer firms similar to the focal firm for each of the following six alternative firm characteristics: size, B/M ratio, momentum, investment, profitability, and total ESG (Environmental, Social, and Governance) score. ESG scores are from Morningstar Sustainalytics – a leading provider of such metric that covers over 10,000 public companies globally from 2009. As in Table 3, the dependent variables are the excess return of the focal firm, the risk-adjusted return of the focal firm based on the Fama and French (2018) six-factor model, or the industry-adjusted return of the focal firm. Focal firm returns are predicted by the proximity-weighted portfolio return of peer firms with a firm characteristic similar to that of the focal firm. Each year, all firms are ranked based on one of their six characteristics, and peer firms are constructed based on the characteristic ranking of [-20, +20] neighbor stocks for each focal firm and sorted into five quintiles. For simplicity, only the Q5-Q1 hedged portfolio's returns are reported. We can see that, unlike strong predictability based on SES among peer firms in Table 3, none of the six alternative characteristics has any predictive power for focal firms.

Furthermore, in Table A.4, we estimate cross-sectional regressions by applying the SES strategy to other six firm characteristics from Table A.3. The dependent variables are the same as in Table 5. The independent variable is the one-month lagged proximity-weighted portfolio return of peer firms with similar characteristic (SC) as that of the focal firm, which we denote as $SC_{i,t-1}$. The SC predictor is constructed based on the characteristic ranking of [-20, +20] neighbor stocks for each focal firm. All controls and fixed effects are identical to those in Table 5. Again, we observe that, similarly to univariate sort test results reported in

Table A.3, none of alternative firm characteristics of similar peer firms has any predictive ability for any next period return measure of the focal firm. Therefore, the results in Tables A.3 and A.4 allow us to conclude that the SES firm predictability strategy is non-replicable to other firm characteristics.

Burt and Hrdlicka (2020) identify the correlation (correlated alphas) between economically linked firms. In Burt and Hrdlicka's correction method, the predicted returns of asset pricing model are subtracted from the sorting return. Following this method, we use the idiosyncratic return (instead of their raw returns) of SES firms to construct predictors. We use the daily returns of firm with SES over the previous 12 months to calculate its alphas and factor loadings to the Fama and French (2018) six-factor model. We then obtain each employee satisfaction-linked firm's idiosyncratic return by using factor coefficient estimates and factor returns.

Table A.5 reports the portfolio returns when we use each firm's idiosyncratic returns (rather than its raw returns) to construct the SES predictor. The results are consistent with those reported Table 3, when we remove the correlated alphas. Therefore, the lagged idiosyncratic returns of employee satisfaction-linked firms can forecast stock returns of focal firms. These results reveal that the information derived from the raw returns of firms with SES is mostly orthogonal to the firms' common exposure to asset pricing factor returns.

In Table A.6, we report the results of SES firm predictability based on value-weighted univariate portfolio sorts by industry using one-digit SIC codes. The portfolio returns of SES peers are proximity-weighted and sorted into five quintiles. Abnormal returns are based on the Fama and French (2018) six-factor model only. The results show that, in terms of magnitude, the largest SES peer firm predictability is observed among the firms in service industries and manufacturing, while the lowest predictability is associated with public administration firms and firms in the unities sector.

References

Burt, A., Hrdlicka, C. M., 2020. Where does the predictability from sorting on returns of economically linked come from? Journal of Financial and Quantitative Analysis, forthcoming.

Daniel, K., Hirshleifer, D., Sun, L., 2020. Short-and long-horizon behavioral factors. Review of Financial Studies 33, 1673-1736.

Fama, E. F., French, K. R., 2018. Choosing factors. Journal of Financial Economics 128, 234-252.

Hou, K., Mo, H., Xue, C., Zhang, L., 2020. An augmented q-factor model with expected growth. Review of Finance, forthcoming.

Table A.1: Alternative risk-adjustment models

This table shows the results of SES firm predictability based on value-weighted and equal-weighted univariate sorts of portfolio returns of SES peer firms for the following three alternative risk-adjustment models: the CAPM, the Daniel et al. (2020) behavioral factor model, and the Hou et al. (2020) q5-factor model. The corresponding abnormal returns are denoted as α_CAPM, α_DHS, and α_q5, respectively. The sample period is form January 2010 to December 2018. The SES predictor is constructed based on the employee satisfaction ranking of [-20, +20] neighbor stocks for each focal firm using equally-weighted peer (EWP) and proximity-weighted peer (PWP) portfolio construction approaches. The portfolio returns of SES peers are sorted into five quintiles. Abnormal returns (in percent) for the focal firm are reported for the lowest (Q1) and highest (Q5) quintile sorted on SES firm portfolio returns and the Q5-Q1 difference. The standard errors are calculated using the Newey-West method with three lags. The *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

	α_CAPM		α_DHS		α_q5	
VW	EWP	PWP	EWP	PWP	EWP	PWP
Q1 (Low)	-0.70	-0.84	-0.67	-0.80	-0.63	-0.75
Q5 (High)	0.55	0.62	0.52	0.59	0.47	0.53
Q5-Q1	1.25*** (2.96)	1.46*** (3.35)	1.19*** (2.64)	1.39*** (3.01)	1.10** (2.55)	1.28*** (2.87)
EW						
Q1 (Low)	-0.88	-1.07	-0.84	-1.02	-0.78	-0.94
Q5 (High)	0.79	0.90	0.76	0.87	0.67	0.76
Q5-Q1	1.67*** (3.55)	1.97*** (4.09)	1.60*** (3.20)	1.89*** (3.72)	1.45*** (3.01)	1.70*** (3.45)

Table A.2: Sub-sample tests

This table reports the results of SES firm predictability based on value-weighted (VW) and equal-weighted (EW) univariate sorts of portfolio returns of similar employee satisfaction peer firms for different sub-samples. The whole sample period is from January 2010 to December 2018. The SES predictor is constructed based on the employee satisfaction ranking of [-20, +20] neighbor stocks for each focal firm using the proximity-weighted peer portfolio approach. The portfolio returns of SES peers are sorted into five quintiles. Abnormal returns (in percent) are reported for the lowest (Q1) and highest (Q5) quintile sorted portfolios and the Q5-Q1 difference portfolio. Abnormal returns are based on the Fama and French (2018) six-factor model, α_6. The sample is split into two subsamples based on period (columns (1-2)), firms with different number of peers (columns (3-4)), whether peers belong to the same industry or not (columns (5-6)), and whether peers are located in the same state or not (columns (7-8)). The standard errors are calculated using the Newey-West method with three lags. The *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample period		Num. peer firms		Industry		US State	
VW	1st half	2nd half	10	30	Same	Different	Same	Different
Q1 (Low)	-0.87	-0.70	-0.77	-0.81	-0.84	-0.73	-0.93	-0.64
Q5 (High)	0.62	0.49	0.54	0.58	0.59	0.52	0.66	0.45
Q5-Q1	1.49***	1.19***	1.31***	1.39***	1.43***	1.26***	1.59***	1.09**
	(3.27)	(2.74)	(2.96)	(3.10)	(3.18)	(2.86)	(3.47)	(2.57)
EW								
Q1 (Low)	-1.09	-0.87	-0.96	-1.02	-1.05	-0.92	-1.17	-0.80
Q5 (High)	0.87	0.72	0.78	0.82	0.84	0.75	0.93	0.67
Q5-Q1	1.96***	1.59***	1.74***	1.84***	1.89***	1.67***	2.10***	1.47***
	(3.94)	(3.27)	(3.55)	(3.73)	(3.82)	(3.42)	(4.18)	(3.06)

Table A.3: Univariate portfolio sorts by applying SES strategy to other firm characteristics

This table reports the return predictability teats based on value-weighted univariate sorts of portfolio returns of peer firms similar to the focal firm through one of the following six characteristics: size, B/M ratio, momentum, investment, profitability, and total ESG (Environmental, Social, and Governance) score. ESG scores are from Morningstar Sustainalytics. The sample period is from January 2010 to December 2018. Abnormal returns (in percent) are the excess return of the focal firm, *ret*, the risk-adjusted return of the focal firm based on the Fama and French (2018) six-factor model, α_6, and the industry-adjusted return of the focal firm, α_ind. Focal firm returns are forecasted by the proximity-weighted portfolio return of peer firms with similar firm characteristic as the focal firm. Each year, all firms are ranked based on their characteristics (e.g., size, B/M, momentum, investment, profitability, and total ESG score) and peer firms are constructed based on the characteristic ranking of [-20, +20] neighbor stocks for each focal firm and sorted into five quintiles. Only the Q5-Q1 quintile hedged portfolio's returns are reported. The standard errors are calculated using Newey-West method with three lags. The absolute *t*-statistics are in parentheses.

Size	*ret*	α_6	α_ind
High-Low (Q5-Q1)	0.48 (1.15)	0.35 (0.84)	0.33 (0.78)
B/M ratio			
High-Low (Q5-Q1)	0.37 (0.89)	0.28 (0.67)	0.26 (0.62)
Momentum			
High-Low (Q5-Q1)	-0.22 (0.53)	-0.17 (0.41)	-0.16 (0.39)
Investment			
High-Low (Q5-Q1)	0.53 (1.27)	0.38 (0.90)	0.35 (0.84)
Profitability			
High-Low (Q5-Q1)	-0.44 (1.07)	-0.35 (0.86)	-0.33 (0.80)
ESG			
High-Low (Q5-Q1)	0.60 (1.51)	0.41 (0.92)	0.47 (1.22)

Table A.4: Cross-sectional regressions by applying SES strategy to other firm characteristics

This table reports the results of Fama-MacBeth regressions with six alternative peer firm characteristics as predictors: size, B/M ratio, momentum, investment, profitability, and total ESG score. ESG scores are from Morningstar Sustainalytics. The sample period is from January 2010 to December 2018. The dependent variables (multiplied by 100) are the excess return of the focal firm, *ret*, the risk-adjusted return of the focal firm based on the Fama and French (2018) six-factor model, α_6, and the industry-adjusted return of the focal firm, α_ind. The independent variable of interest is the one-month lagged proximity-weighted portfolio return of peer firms with similar characteristic as the focal firm, $SC_{i,t-1}$. The SC predictor is constructed based on the characteristic ranking of [-20, +20] neighbor stocks for each focal firm. Other controls are the lagged values of focal firm size, book-to-market ratio, lagged monthly excess return, medium-term price momentum, asset growth, gross profitability, and its value-weighted industry return. All explanatory variables are based on the last non-missing available observation for each month and are winsorized at 1% and 99% levels. Financial firms (with one-digit SIC code = 6) and stocks with price less than $5 at the end of previous year are excluded. The standard errors are calculated using the Newey-West method with three lags. The absolute *t*-statistics are in parentheses.

Table A.4 (continued)

Size	*ret*	α_6	α_ind
$SC_{i,t-1}$	2.17 (1.28)	1.91 (0.99)	2.04 (1.14)
Controls	Y	Y	Y
Ind_Mom & Industry FE	Y	Y	N
B/M ratio			
$SC_{i,t-1}$	1.81 (0.98)	1.69 (0.83)	1.72 (0.87)
Controls	Y	Y	Y
Ind_Mom & Industry FE	Y	Y	N
Momentum			
$SC_{i,t-1}$	-2.71 (0.94)	-2.57 (0.75)	-2.66 (0.87)
Controls	Y	Y	Y
Ind_Mom & Industry FE	Y	Y	N
Investment			
$SC_{i,t-1}$	2.21 (1.26)	2.01 (1.06)	2.14 (1.19)
Controls	Y	Y	Y
Ind_Mom & Industry FE	Y	Y	N
Profitability			
$SC_{i,t-1}$	-3.04 (1.28)	-2.79 (0.98)	-2.92 (1.13)
Controls	Y	Y	Y
Ind_Mom & Industry FE	Y	Y	N
ESG			
$SC_{i,t-1}$	2.90 (1.62)	2.52 (1.39)	2.67 (1.53)
Controls	Y	Y	Y
Ind_Mom & Industry FE	Y	Y	N

Table A.5: Burt and Hrdlicka (2020) adjustment

This table reports the results of SES firm predictability based on value-weighted (VW) and equal-weighted (EW) univariate sorts of portfolio returns of similar employee satisfaction peer firms corrected for Burt and Hrdlicka (2020) adjustment. The sample period is from January 2010 to December 2018. The SES predictor is constructed based on the employee satisfaction ranking of [-20, +20] neighbor stocks for each focal firm. The portfolio returns of SES peers are proximity-weighted and sorted into five quintiles. Abnormal returns (in percent) for the focal firm are reported for the lowest and highest quintile sorted on SES portfolio returns and the Q5-Q1 difference portfolio using excess return, *ret*; the risk-adjusted return from the Fama and French (2018) six-factor model, α_6; and the industry-adjusted return, α_ind. The standard errors are calculated using the Newey-West method with three lags. The *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

VW	*ret*	α_6	α_ind
Q1 (Low)	-0.19	-0.73	-0.40
Q5 (High)	0.88	0.52	0.72
Q5-Q1	1.08**	1.25***	1.12***
	(2.54)	(2.84)	(2.65)
EW			
Q1 (Low)	-0.06	-0.89	-0.13
Q5 (High)	1.35	0.73	1.13
Q5-Q1	1.42***	1.62***	1.26***
	(2.96)	(3.34)	(2.73)

Table A.6: Return predictability among SES firms by industry

This table reports the results of SES firm predictability based on value-weighted univariate portfolio sorts by industry using one-digit SIC codes. The sample period is from January 2010 to December 2018. Each month all firms are divided into nine different industries (except Finance). The SES predictor is constructed based on the employee satisfaction ranking of [-20, +20] neighbor stocks for each focal firm. The portfolio returns of SES peers are proximity-weighted and sorted into five quintiles. Abnormal returns for the focal firm are reported based on the Q5-Q1 difference portfolio using the Fama and French (2018) six-factor model, α_6. The standard errors are calculated using the Newey-West method with three lags. The *t*-statistics are in parentheses. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

SIC Code	Industry	α_6	t-stat
0	Agriculture, Forestry, & Fishing	1.15**	(2.48)
1	Mining & Construction	1.26***	(2.83)
2	Manufacturing (Food, Chemicals, etc.)	1.47***	(3.27)
3	Manufacturing (Leather, Electronic, etc.)	1.62***	(3.54)
4	Transportation, Communications, Electric, Gas, & Sanitary	1.04**	(2.25)
5	Wholesale and Retail Trade	1.17***	(2.62)
6	Finance	N/A	(N/A)
7	Services (Personal, Business, etc.)	1.83***	(3.98)
8	Services (Health, Social, etc.)	1.70***	(3.73)
9	Public Administration	0.93**	(2.02)

Chapter 2

TMT Facial Similarity and Cross-sectional Stock Returns[1]

Inspired by the psychological findings that demographic similarity can promote trust and coordination within a team, we propose that the firm stock performance is positively related to the facial resemblance between top management team (TMT) members due to the higher managerial efficiency. We find the significant predictive power of TMT facial similarity on the firm stock returns. A long-short value-weighted portfolio sorted on the TMT facial similarity yields a significant Fama and French six-factor alpha (Fama and French, 2018) of 40 bps per month. Consistently, we also find evidence that the TMT facial similarity is informative on firm operating performance. In addition, our tests suggest that investors' limited attention and limits of arbitrage are the potential mechanisms behind the documented return predictability.

1. Introduction

The importance of the top management team (TMT) has been extensively studied since the seminal work of Hambrick and Mason (1984). As upper-level managers are entitled to the power of making crucial decisions for the organization, upper echelons theory stresses the influence of TMT on the organizational outcome. However, making firm strategic decisions is a complex and challenging task that requires the integration of diverse judgments, perspectives, and orientations of

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1 This is joint work with Jun Tu and Ran Zhang.

TMT members (Elbanna and Child, 2007; Hambrick, 2007). Associated with various backgrounds, TMT members involve and contribute to strategic decisions by bringing diverse ideas which could conflict with each other (Ancona and Nadler, 1989; Bauman et al., 1997). Therefore, interpersonal trust is required for TMT members to make wise decisions. Trust is crucial to team performance, as work partners are more likely to cooperate and share information in the team with a higher level of trust (Dirks, 1999; Langfred, 2004; Larson and LaFasto 1989; Porter and Lilly, 1996; Zand, 1972). As a determinant of team performance, trust promotes the effectiveness and efficiency of the workgroup (Zand, 1972). Therefore, the firms associated with a higher level of trust within TMT are expected to achieve better performance because of a more effective managerial team.

According to the existing literature, interpersonal trust can be formed based on cognitive foundations and affective foundations (Lewis and Wiegert, 1985). In specific, the affective foundation for trust refers to the emotional bonds linking individuals and providing a basis for trust (Lewis and Wiegert, 1985). “People often use immediately apparent physical features, such as race, sex, and national origin, to categorize others and predict their behavior” (Chatman and Flynn, 2001: 957), and people with demographically similar characteristics are commonly perceived as more honest, trustworthy, and cooperative (Brewer, 1981; McAllister, 1995; Shore et al., 2003; Tsui and O’Reilly, 1989). In particular, psychological research discovers that facial resemblance provides a potential cue of kinship and leads to increased attributions of trustworthiness and cooperation between individuals (DeBruine, 2002; DeBruine, 2005; Krupp et al., 2008). Thus, the trust between TMT members based on the emotional bonds derived from facial resemblance is expected to improve managerial efficiency and effectiveness. And we propose that

TMT facial similarity which measures the facial resemblance between TMT members makes a difference in firm performance.

We start by demonstrating a striking relationship between the stock price and TMT facial similarity. Focal firms associated with higher (lower) TMT facial similarity earn higher (lower) returns. A long-short trading strategy based on the firm TMT facial similarity in the last fiscal year yields a monthly Fama and French six-factor alpha (Fama and French, 2018) of 40 bps per month (value-weighted) and 37 (equal-weighted) basis points. Moreover, we observe a strong return predictability in cross-sectional regressions with control of various firm characteristics, and the results demonstrate that the firm's stock return is positively related to TMT facial similarity. In addition, we test whether TMT facial similarity is informative on firm operating performance. We find that changes in profitability, cash flow, and return on asset (ROA) are all positively related to TMT facial similarity. The significantly positive relationship between TMT facial similarity and firm operating performance provides strong evidences that TMT facial similarity is positively linked to firm performance.

We examine two potential mechanisms behind the return predictability of TMT facial similarity: investors' limited attention (proxied by absolute SUE (Bali et al., 2018) and advertising expenses (Lou, 2014)), and limits to arbitrage (proxied by firm idiosyncratic volatility (Ang et al., 2006) and illiquidity (Amihud, 2002)). Based on the test results, both investors' limited attention and limits to arbitrage are potential mechanisms that help explain the return predictability of TMT facial similarity.

Our research contributes to the literature in the following three aspects. First, we provide innovative empirical evidence on the critical role of interpersonal trust on firm performance. In the field of finance, trust between firms has gradually been acknowledged as an important driver influencing firms' decisions, such as investment (Ang et al., 2015; Bottazzi et al., 2016), cross-border mergers (Ahern et al., 2015), etc. However, the effect of interpersonal trust within the managerial team on firm performance is largely overlooked by the financial scholars. The relevant research is mainly conducted from the psychological or managerial perspectives (Dirks, 1999; Langfred, 2004; Larson and LaFasto 1989; Porter and Lilly, 1996; Zand, 1972), and it focuses on how interpersonal trust affects group performance. Our study aims to fill the gap of literature in this regard by constructing a more objective measure of trust instead of using survey data and we analyze how trust within the managerial team influences the firm stock performance.

Secondly, we contribute to the emerging financial literature related to the importance of facial characteristics of top managers on firm outcomes. Jia et al. (2014) document the relationship between a measure of male CEOs' facial masculinity and financial misreporting. And He et al. (2019) find the association between facial width-to-height ratio (fWHR) and financial analyst's performance. Additionally, hedge funds operated by high-fWHR managers are found to underperform those operated by low- fWHR managers after adjusting for risk (Lu and Teo, 2020). All these studies are based on the finding that the hormone testosterone influences both behavior and the development of the face shape. However, the existing literature related to facial characteristics focuses on self-measures such as an individual's own facial width-to-height ratio. While the TMT facial similarity compares the facial characteristics across individuals within the managerial team. Our study extends the research on how top managers' facial characteristics could affect the firm stock performance.

Lastly, our study adds on the research on upper echelons theory and provides additional empirical evidence on the role of TMT in firm governance and performance. We propose a new measurement to capture TMT efficiency. The TMT facial similarity is informative in firm performance as TMT members tend to trust each other and coordinate more when they share facial resemblance.

The rest of the paper is organized as follows. Section 2 describes the data and variables. Section 3 presents our main empirical results on the return predictability of TMT facial similarity. Section 4 analyses the effects of TMT facial similarity on firm operational performance and earnings surprises. Section 5 explores the underlying mechanisms of SES firm predictability. Conclusions are drawn in Section 6.

2. Data and Variables

We obtain firm TMT information from Boardex, which covers over 15,000 public quoted companies and reports individual profiles on major private entities at the board and executive management level. Our sample focuses on the S&P 1500 firms in the U.S. from 2001 to 2018. We collect the data on stock price, volume, and return of the U.S. firms from the Center for Research in Security Prices (CRSP) and the accounting information from Compustat.

The key independent variable $Similarity$ measures the facial similarity between the TMT members in each firm. To construct this variable, we first search and download pictures of the board of directors and executive managers according to the data available on Boardex. Secondly, based on the collected picture information, we calculate the facial similarity score by using two algorithms: Microsoft Azure Face and Amazon Rekognition Image. The higher score of $Similarity$ indicates the higher facial resemblance among the TMT members. Next, we first briefly introduce the two algorithms of calculating facial similarity: Microsoft Azure Face and Amazon Rekognition Image, then we describe how we construct the variable $Similarity$ in details.

The Azure recognizes faces through face ID. Each detected face corresponds to a face Rectangle field in the response. This set of pixel coordinates for the left, top, width, and height, which mark the located face. Using these coordinates, we get the characteristics of the face and its size. In other words, Face ID represents face landmarks on a face. Face landmarks are a set of easy-to-find points on a face, such as the pupils or the tip of the nose. By default, there are 27 predefined landmark points defined by Microsoft. The details are shown in Figure 1. And the coordinates of the points are returned in units of pixels. Microsoft Azure Face and Amazon Rekognition Image use different deep neural network models to detect and label thousands of objects and scenes in the images, and new labels and facial recognition features are continuously added to the service.

[Insert Figure 1 here.]

To construct the facial similarity measure, we collect the photos of TMT members following the existing literature (He et al., 2019; Jia et al., 2014; Lu and Teo; 2020). We firstly collect the company TMT members' photos from the company website. If the photos are not shown on the company website, we will search for them from the internet. For each TMT member, we use first name, last name, and company name to perform a Google image search for his/her facial picture or pictures. If we find more than one picture, we identify the best photo by the resolution, whether the director is forward-facing in the picture, and whether he has a neutral expression. If we find no picture on the company website or Google image, we use Google video to search for video fragments in which the director is present. We then obtain the picture from the video and include this picture in our database. Then, we use the Microsoft Azure Face and Amazon Rekognition, the facial similarity algorithms provided by the two largest IT companies, to calculate the firm TMT average facial similarity. We calculate the facial similarity score of two different individuals and calculate the average of these two-individual facial similarity scores in TMT. For example, there are 10 TMT members. We can obtain 45(10*9/2) different two-individual facial similarity scores. Then, we calculate the average of the 45 facial similarity scores. Lastly, we calculate the average score of Microsoft facial similarity score and Amazon facial similarity score as $Similarity$, and this measure is used to capture the TMT facial resemblance of each firm. The higher score of $Similarity$ indicates the higher facial similarity between the TMT members. The firm's TMT facial similarity score is normalized from 0 to 1 in the cross-section.

The control variables are the lagged values of focal firm's size, $Ln(Size)$; book-to-market ratio, $Ln(B/M)$; firm's own lagged excess return, $ret_{i,t-1}$; medium-term price momentum defined as the cumulative stock return from month $t-12$ to month $t-2$ as in Jegadeesh and Titman (1993), Mom; asset growth defined as year-over-year growth rate of the total assets, AG; gross profitability defined as the revenue minus the cost of goods sold scaled by the assets, GP; its value-weighted industry return, Ind_Mom; the natural log of the total number of directors in the board, $BoardSize$; the percentage of independent directors in the board, $Independent$; the ratio of female directors in the board, $GenderRatio$; the average number of outside board positions held by the board of directors, $Network$; the directors' average time on board, $Tenure$; and the board member diversity is measured based on directors' demographic characteristics (Finkelstein et al., 2009;

Westphal and Zajac, 2013), $Diversity$. The descriptions of all the variables are shown in Appendix.

Our final sample covers 143,526 firm-month observations spanning from January 2001 to December 2019. The descriptive statistics of firm characteristics are shown in Panel A of Table 1. TMT facial similarity is scaled to range 0 to 1 and the mean value is 0.49 with a standard deviation of 0.29 in our sample. The high variation of TMT facial similarity across firms allows us to test whether it is informative for firm financial performance. Panel B reports the monthly cross-sectional correlations between the TMT facial similarity and other firm characteristics. TMT facial similarity is positively correlated with future return according to both Pearson and Spearman correlations. In addition, both Pearson and Spearman correlations between TMT facial similarity and other firm characteristics are quite low with absolute values all below 0.05. Therefore, TMT facial similarity potentially contains information different from other firm characteristics, and this information is valuable for predicting firm future equity returns.

[Insert Table 1 here.]

3. Empirical Results

3.1 Univariate portfolio sorts

In this section, we design a trading strategy based on the TMT facial similarity score across firms. Based on TMT facial similarity scores, we sort the firms into deciles monthly. Then, we calculate the value and equal-weighted portfolio returns of each decile, as well as the hedged portfolio return of longing Decile 10 and shorting Decile 1, and the corresponding statistical significance level of abnormal returns. We use ten measures of abnormal returns for focal firms: (1) the excess return; (2) the risk-adjusted return from CAPM model, CAPM; (3) the risk-adjusted return from Fama-French three-factor model (Fama and French, 1993), FF3; (4) the risk-adjusted return from a four-factor model (Fama-French three-factor + Momentum Factor (Carhart, 1997)), FFC; (5) the risk-adjusted return from a five-factor model (Fama-French three-factor + Momentum Factor (Carhart, 1997) + Liquidity Factor (Pástor and Stambaugh, 2003)), FFCPS; (6) the risk-adjusted return from Fama and French (2015) five-factor model, FF5; (7) the risk-adjusted return from the Fama and French (2018) six-factor model, FF6; (8) the risk-adjusted return from M4 model (Stambaugh and Yuan, 2016), M4; (9) the risk-adjusted return from q-factor model (Hou et al., 2015), Q4; and (10) the risk-adjusted return from Daniel et al. (2020) behavior factor model, DHS. Excess return is calculated as subtracting the one-month T-bill rate from the focal firm return. CAPM is the abnormal return based on the CAPM model. We compute FF3, FF5, and FF6 based on Fama-French three factors (Fama and French, 1993), Fama-French five factors (Fama and French, 2015), and Fama-French six-factor model (Fama and French, 2018). Following Fama and French (1992) and Cao et al. (2016), we compute the factor loadings for each focal firm by using a time-series regression over the entire sample period. As for FFC and FFCPS, we estimate the abnormal return by adding Momentum Factor (Carhart, 1997) and Liquidity Factor (Pástor and Stambaugh, 2003) to Fama-French three factor model, respectively. We estimate the abnormal return M4, DHS, and Q4 by controlling the risk factors in the mispricing factor model of Stambaugh and Yuan (2016), the behavior factor model of Daniel et al. (2020), and the q-factor model of Hou et al. (2015), respectively. With controls of these well-documented risk factors, the documented excess abnormal returns of our trading strategy can help establish the fact that firm TMT facial similarity provides incremental information on firm stock performance.

The results of the above trading strategy are reported in Table 2. The standard errors are calculated using the Newey-West method (1987). Panel A and Panel B show the monthly excess returns of the value-weighted and equal-weighted portfolios sorting based on firm TMT facial similarity scores, respectively. We observe that, compared to firms with the low TMT facial similarity, firms with the highest TMT facial similarity are associated with a significantly higher excess return. The long-short strategy based on the TMT facial similarity yields monthly excess returns of 37 bps for equal-weighted portfolios and 47 bps for value-weighted portfolios. After controlling various risk factors, our trading strategy still yields a significant abnormal return. For example, the long-short strategy based on the TMT facial similar yields a monthly FF6 abnormal return of 40 bps ($t = 3.11$) for value-weighted and 37 bps ($t = 3.23$) for equal-weighted portfolio, respectively, Q4 abnormal return of 39 bps ($t = 3.51$) for value-weighted portfolio and 40 bps ($t = 3.69$) for equal-weighted portfolio, respectively. Therefore, the results shown in Table 2 provide strong evidence that firm TMT facial similarity can forecast the focal firm's stock returns, and the predictability is still strong after correcting for standard risk factors.

[Insert Table 2 here.]

Next, we test the persistence of the rank of TMT facial similarity and the persistence of the return predictability of TMT facial similarity. If the rank of TMT facial similarity is persistent and the financial market is efficient, investors could learn from the past and we should not observe mispricing over a long sample period. Table 3 presents the probability of keeping in the same TMT facial similarity group or shifting to any of the other nine TMT facial similarity groups in the next year. Specifically, we present the average possibility that a stock in decile i (defined by the rows) in year t will appear in decile j (defined by the columns) in the year $t + 1$. All the possibilities in the matrix should be about 10% (ten decile portfolios) if the change for TMT facial similarity for each firm is random and the relative TMT facial similarity value in one period does not imply the relative magnitude of TMT facial similarity in the next year. Nevertheless, Table 3 presents that approximately 63% of stocks in the lowest TMT facial similarity decile (Port1) in year t continue to be in the same decile in year $t + 1$. Similarly, approximately 74% of the stocks in the highest TMT facial similarity decile (Port10) in year t proceed to be in the same decile in year $t + 1$. These results conclude that TMT facial similarity is a relatively persistent firm characteristic. The previous analyses indicate that investors underprice (overprice) stocks with the highest (lowest) TMT facial similarity in the past. The fact that TMT facial similarity is persistent and it is informative on firm stock performance suggests the possibility that investors do not fully capture the information contained in TMT facial similarity due to the limited attention. And we explore this possible mechanism in section 5.

[Insert Table 3 here.]

We further study the long-term predictive performance of TMT facial similarity by calculating the Fama and French (2018) six-factor alphas of the TMT facial similarity deciles from two to twelve months after the portfolio formation. The results are shown in Table 4. In the second month after the portfolio formation, the decile portfolio of stocks with the highest (lowest) TMT facial similarity yields a monthly value-weighted return of 13 (-25) basis points. The difference between the two extreme portfolios equals to 38 basis points and with a t-statistic of 2.70. And the long-short strategy based on TMT facial similarity yields a monthly value-weighted return of 37 basis points with a t-statistic of 2.49 in the third month after the portfolio formation. The predictive power of TMT facial similarity on future returns decreases as one moves further away from the portfolio formation month and becomes insignificant after ten months. These results indicate that the positive cross-sectional relation between TMT facial similarity and future returns is not just a one-month event and the underreaction to the information contained in TMT facial similarity persists several months into the future, supported by the continuing theoretical evidence by Hong and Stein (1999) as an outcome of the gradual information dissemination.

[Insert Table 4 here.]

Furthermore, we examine the yearly profits of the long-short portfolio sorting on facial similarity by showing the value-weighted yearly returns from 2001 to 2019. In Figure 2, we depict the annual value-weighted returns of the long-short portfolio sorted on TMT facial similarity. It is shown that the portfolio returns are above 5% in 9 out 19 years, the value-weighted returns in 2001, 2003, 2004, and 2014 are above 10%, and none of the portfolios yields return below -5% in 19 years. These results imply that the trading strategy based on the information contained in TMT facial similarity earns relatively stable profit across years.

[Insert Figure 2 here.]

3.2 Multivariate regressions

In this section, we use Fama and MacBeth (1973)'s two-step procedure to further examine the predictability of TMT facial similarity on future stock return with controlling for various firm characteristics and industry momentum. The stock level's Fama-Macbeth regression consists of two steps. We use the following cross-sectional regression in each month:

$$RET_{i,t} = \alpha + \beta_1 Similarity_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where the dependent variable $RET_{i,t}$ is the excess return; $Similarity_{i,t-1}$ is firm TMT facial similarity measured based on TMT members reported at the end of the previous year; $X_{i,t-1}$ is a vector of firm-level controls that include both financial and board-level characteristics as shown in Table 1. In these estimations, firm size is captured as the natural log of market capitalization measured in million US dollars (Banz, 1981). Likewise, we use the natural log of book-to-market equity ratio (Basu, 1983). The control set includes the lagged focal firm's excess return to account for short-term reversal, $ret_{i,t-1}$ (Jegadeesh, 1990; Lo and MacKinlay, 1990); medium-term price momentum, Mom; asset growth, AG; gross profitability, GP; Ind_Mom to account for industry momentum (Moskowitz and Grinblatt, 1999). In terms of the board-level characteristics, we include the natural log of the total number of directors sitting on firm board of directors, $BoardSize$; the percentage of independent directors in the board, $Independent$; the ratio of female directors in the board, $GenderRatio$; the average number of outside board positions held by the board of directors, $Network$; the average directors' tenure in the board, $Tenure$; and the board member diversity, $Diversity$. And variable γ_i stands for the industry dummies.

[Insert Table 5 here.]

In Table 5, Panel A presents results estimated for one-month-ahead returns using the ordinary least squares (OLS) methodology, and Panel B presents results estimated for one-month-ahead returns using the weighted least squares (WLS) methodology following Asparouhova et al. (2013), in which each observed return is weighted by one plus the observed prior return on the stock. Column (1) reports the results without control variables, but with industry-fixed effects controlled. We find that the TMT facial similarity can predict returns of focal firms in all the specifications: the coefficient on $Similarity$ is positive and significant at 1% level. From Column (2) to Column (14), it is shown that the predictive power of TMT facial similarity still appears after controlling various financial variables and board characteristics for both OLS and WLS estimations.

In addition, we report the average portfolio characteristics for portfolios formed based on the TMT facial similarity scores. Table 6 shows the time-series averages of the monthly averages for TMT facial similarity and various firm-specific characteristics for each decile sorted on TMT facial similarity scores.

[Insert Table 6 here.]

4. TMT Facial Similarity and Firm Operating Performance

The predictive power of TMT facial similarity on firm stock return is strongly supported by the above compelling evidence. The results indicate that investors are unaware of the non-public information implied by the TMT facial similarity. In this section, we further explore if TMT facial similarity is positively related to the firm performance by showing the predictability of TMT facial similarity on firm operating performance and future earnings surprises.

4.1 Operating performance

As shown by the psychological literature, the facial resemblance of team members promotes team trust and cooperation. In a firm, the TMT makes critical decisions for the firm. According to the upper echelon theory, the effectiveness of a firm board could be crucial for firm operating performance. Therefore, we conjecture that the TMT facial similarity among directors could be informative for firm performance. We test this hypothesis by using the following three measures of firm operating performance: change in profitability, cash flow, and ROA. Profitability is defined as revenue minus cost of goods sold, scaled by total asset; cash flow is measured as the total cash flow scaled by the total asset; ROA is measured as net income scaled by the total asset. And the regression specification for changes in operating performance is as follows:

$$\Delta\, OperatingPerformance_{i,t} = \alpha + \beta_1 Similarity_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t}, \quad (2)$$

where the dependent variable is $\Delta Profitability$, $\Delta CashFlow,$ or $\Delta ROA.$ And X stands for control variables including firm basic characteristics: firm size, book-to-market ratio, asset growth, gross profitability, asset growth; and board-level characteristics: board size, the percentage of independent directors on the board, the ratio of female directors in the board, the average number of outside board positions held by the board of directors, the average number of outside board positions held by the board of directors, and board diversity. For each dependent variable, we report the estimations with control of only firm basic characteristics, and those with both firm and board-level characteristics controlled, respectively. In all the specifications, both firm and year fixed effects are controlled. As shown in Table 7, the estimated coefficients on *Similarity* are significantly positive in all the specifications. The results provide strong evidence that TMT facial similarity could partially capture the information related to firm operating performance including the change of profitability, cash flow, and ROA.

[Insert Table 7 here.]

4.2 Earnings surprise

As shown in the above discussions, we find compelling evidence that TMT member facial resemblance is informative in terms of firm operating performance. However, if this information is not incorporated by the market, we conjecture that the earnings surprises could be predicated by TMT facial similarity. To explore this hypothesis, we use returns around earnings announcement window as the proxy for earnings surprises. And the regression specification is as follows:

$$CAR_{i,t+1} = \alpha + \beta_1 Similarity_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where CAR is measured as the three-day cumulative abnormal returns around the earnings announcement date. And X stands for control variables including firm basic characteristics and board-level characteristics: firm size, book-to-market ratio, asset growth, gross profitability, asset growth, board size, the percentage of independent directors on the board, the ratio of female directors in the board, the average number of outside board positions held by the board of directors, the average number of outside board positions held by the board of directors, and board diversity. In addition, we add industry fixed effects in all the specifications.

In model 1, the cumulative abnormal return is computed as the sum of a three-day stock return around an earnings announcement. In model 2, the cumulative abnormal return is computed as the sum of three-day stock return around earnings announcement minus the corresponding return of the CRSP value-weighted portfolio. The estimation results are reported in Table 8. The coefficient of the variable of interest $Similarity$ remains significantly positive in all the specifications, suggesting that the future earnings surprises are positively related to TMT member facial similarity, and the information of TMT facial similarity on firm performance is not fully incorporated by the market.

[Insert Table 8 here.]

5. Mechanisms

In this section, we further explore to understand the potential mechanisms that explain the cross-sectional predictive pattern of our main results. Following the existing literature, the possible behavioral explanations could be investors' limited attention and limits to arbitrage. We perform double-sort analysis on the TMT facial similarity and the proxies for investor attention or arbitrage cost, respectively. Specifically, at the end of the previous year, we sort all stocks into terciles based on each proxy, then we independently sort stocks into quintiles based on the TMT facial similarity and construct the value-weighted portfolios.

[Insert Table 9 here.]

5.1 Investors' limited attention

One possible explanation is that investors pay limited attention to TMT facial similarity which is positively related to the trust and cooperation between TMT members. If investors fully realize the TMT facial similarity-relevant information, the firm stock price would quickly incorporate it. However, Barber and Odean (2008) propose that individual investors can only handle limited investment choices due to the restriction of limited time and resources. Following the literature, we use two prevalent proxies of investors' inattention: the absolute SUE (Bali et al., 2018) and the changes in advertising expenses (Lou, 2014). Intuitively, firms with lower absolute SUE and less advertising expenses compared with last year receive less attention from investors and, therefore, should show more slow-moving stock price reactions to the information related to the firm and greater stock return predictability of TMT facial similarity. For the absolute SUE, we use the last non-missing SUE value that is released before the portfolio sorting during the past 12 months. The changes in advertising expenses are measured as the changes in advertising expenditures from year $t-1$ to year t. If the change in advertising expenses is missing, we set it to zero. Panel A of Table 9 reports the Fama and French (2018) six-factor alphas of zero-cost TMT facial similarity quintile portfolios in each of the attention tercile groups. Consistent with our expectation, the results indicate that the return predictability of the TMT facial similarity is strongest among stocks with lower investor attention, and the statistical significance of the abnormal return becomes much weaker in the high investor attention group. Overall, the results support our hypothesis that the return predictability is partly driven by investors' limited attention to the information contained in TMT facial similarity.

5.2 Limits to arbitrage

In this section, we further seek the role of limits to arbitrage in explaining our documented return predictability. If the predictive power of TMT facial similarity is driven by mispricing to some extent, then we would expect the return predictability to be more pronounced for stocks with large costs of arbitrage. Therefore, we use two proxies of limits to arbitrage that are common in the literature to test this hypothesis. The first proxy is idiosyncratic volatility. We follow Ang et al. (2006) and measure the monthly IVOL as the standard deviation of the daily residuals from the regression of daily excess stock returns on the three factors of Fama and French (1993) over the past one month. And the other proxy is illiquidity. Following Amihud (2002), we calculate the illiquidity measure based on daily returns and daily volumes during the past year. Panel B of Table 9 reports the double-sort results. Consistent with limits to arbitrage argument, the Fama and French (2018) six-factor alphas of zero-cost TMT facial similarity portfolio are higher in high idiosyncratic volatility group and high illiquidity group. Thus, limits to arbitrage may be another driver to the return predictability of TMT facial similarity trading strategy. In sum, the return predictability of the TMT facial similarity can be explained by the slow diffusion of facial similarity-relevant information resulted from investors' limited attention and limits to arbitrage.

6. Conclusion

In this study, we report the evidence of return predictability of facial similarity between firm TMT members. The information contained in TMT facial similarity is largely overlooked by investors, although the facial resemblance is documented to promote trust and cooperation within a group and the firm performance is highly related to the efficiency of the managerial team according to the upper echelons theory. Furthermore, we show that TMT facial similarity is a relatively persistent firm characteristic and the positive cross-sectional relationship between TMT facial similarity and future stock returns is not just a one-month event and the underreaction to the information contained in TMT facial similarity persists several months. In addition, we find that facial similarity between TMT members could partially capture the information related to firm operating performance and have predictive power on earnings surprises. Lastly, we identify that the potential mechanisms behind our documented return predictability are investors' limited attention and limits to arbitrage.

References

Ahern, K. R., Daminelli, D., Fracassi, C.. 2015. Lost in translation? The effect of cultural values on mergers around the world. Journal of Financial Economics 117, 165-189.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31-56.

Ancona, D. G., Nadler, D. A., 1989. Top hats and executive tales: Designing the senior team. MIT Sloan Management Review 31, 19.

Ang, J. S., Cheng, Y., Wu, C., 2015. Trust, investment, and business contracting. Journal of Financial and Quantitative Analysis 50, 569-595.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X., 2006. The cross-section of volatility and expected returns. The Journal of Finance 61, 259-299.

Asparouhova, E., Bessembinder, H., Kalcheva, I., 2013. Noisy prices and inference regarding returns. The Journal of Finance 68, 665-714.

Bali, T. G., Hirshleifer, D. A., Peng, L., Tang, Y., 2018. Attention, social interaction, and investor attraction to lottery stocks. In 9th Miami Behavioral Finance Conference.

Banz, R. W., 1981. The relationship between return and market value of common stocks. Journal of financial economics 9, 3-18.

Barber, B. M., & Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. The review of financial studies 21, 785-818.

Bauman, R., Jackson, P., Lawrence, J., 1997. From Promise to Performance: A Journey of Transformation at SmithKline Beecham. Boston, MA: HBS Press.

Basu, S., 1983. The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. Journal of financial economics 12, 129-156.

Bottazzi, L., Da Rin, M., Hellmann, T., 2016. The importance of trust for investment: Evidence from venture capital. The Review of Financial Studies 29, 2283-2318.

Brewer, M. B., 1981. Ethnocentrism and its role in interpersonal trust. In M. B. Brewer, B. E. Collins (Eds.), Scientific inquiry and the social sciences (pp. 345–359). New York: Jossey-Bass.

Cao, J., Tarun, C., Chen, L., 2016. Alliances and return predictability. Journal of Financial and Quantitative Analysis 51, 1689-1717.

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

Chatman, J., Flynn, F., 2001. The influence of demographic heterogeneity on the emergence and consequences of cooperative norms in work teams. Academy of Management Journal 44, 956–974.

DeBruine, L. M., 2002. Facial resemblance enhances trust. Proceedings of the Royal Society B: Biological Sciences 269, 1307–1312.

DeBruine, L. M., 2005. Trustworthy but not lust-worthy: Context-specific effects of facial resemblance. Proceedings of the Royal Society B: Biological Sciences 272, 919–922.

Dirks, K. T., 1999. The effects of interpersonal trust on work group performance. Journal of Applied Psychology 84, 445.

Elbanna, S., Child, J., 2007. The Influence of Decision, Environmental and Firm Characteristics on the Rationality of Strategic Decision-Making. Journal of Management Studies 44, 561–91.

Fama, E. F., & French, K. R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427-465.

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

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, E. F., French, K. R., 2018. Choosing factors. Journal of Financial Economics 128, 234-252.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.

Finkelstein, S., Hambrick, D.C., & Cannella, A.A., 2009. Strategic leadership: Theory and research on executives, top management teams, and boards. Oxford: Oxford University Press.

Hambrick, D. C., 2007. Editor Forum: Upper Echelons Theory: An Update. Academy of Management Review 32, 334–43.

Hambrick, D. C., Mason, P. A., 1984. Upper echelons: The organization as a reflection of its top managers. Academy of Management Review 9, 193-206.

He, X., Yin, H., Zeng, Y., Zhang, H., Zhao, H., 2019. Facial structure and achievement drive: evidence from financial analysts. Journal of Accounting Research 57, 1013-1057.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of finance 54, 2143-2184.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. The Review of Financial Studies 28, 650–705.

Langfred, C. W., 2004. Too much of a good thing? Negative effects of high trust and individual autonomy in self-managing teams. Academy of management journal 47, 385-399.

Larson, C., F. LaFasto, 1989. Teamwork. Sage, Newbury Park, CA.

Lewis, J. D., Weigert, A., 1985. Trust as a social reality. Social Forces, 63: 967-985.

Lo, A. W., MacKinlay, A. C., 1990. Data-snooping biases in tests of financial asset pricing models. The Review of Financial Studies 3, 431-467.

Lou, D., 2014. Attracting investor attention through advertising. The Review of Financial Studies 27, 1797-1829.

Lu, Y., Teo M., 2018. Facial structure and delegated portfolio management. Available at SSRN 3100645.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. The Journal of finance 45, 881-898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance 48, 65–91.

Jia, Y., Lent, L. V., Zeng, Y., 2014. Masculinity, testosterone, and financial misreporting. Journal of Accounting Research 52, 1195-1246.

Moskowitz, T. J., Grinblatt, M., 1999. Do industries explain momentum?. The Journal of finance 54, 1249-1290.

Krupp, D. B., DeBruine, L. M., Barclay, P., 2008. A cue of kinship promotes cooperation for the public good. Evolution & Human Behavior 29, 49–55.

McAllister, D. J., 1995. Affect- and cognition-based trust as foundations for interpersonal cooperation in organizations. Academy of Management Journal 38, 24–59.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Pástor, Ľ., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political economy 111, 642-685.

Porter, T. W., Lilly, B. S., 1996. The effects of conflict, trust, and task commitment on project team performance. International Journal of Conflict Management 7, 361-376

Shore, L. M., Cleveland, J. N., Goldberg, C. B., 2003. Work attitudes and decisions as a function of manager age and employee age. Journal of Applied Psychology 88, 529–537.

Stambaugh, R. F., Yuan, Y., 2016. Mispricing factors. The Review of Financial Studies 30, 1270–1315.

Tsui, A. S., O'Reilly, III, C. A., 1989. Beyond simple demographic effects: The importance of relational demography in superior-subordinate dyads. Academy of Management Journal 32, 402–423.

Westphal, J. D., Zajac, E. J., 2013. A behavioral theory of corporate governance: Explicating the mechanisms of socially situated and socially constituted agency. Academy of Management Annals 7, 607-661.

Zand, D. E., 1972. Trust and managerial problem solving. Administrative Science Quarterly 17, 229-239.

Table 1: Summary statistics

Panel A: Firm characteristics

	Mean	SD	Min	Med	Max
$Similarity_{i,t-1}$	0.49	0.29	0.00	0.49	1.00
$Ln(Size)$	7.53	1.35	2.48	7.46	11.76
$Ln(B/M)$	-0.80	0.76	-7.50	-0.74	3.63
ret_{t-1}	1.38	12.29	-87.76	1.18	1349.51
Mom	1.39	3.68	-24.63	1.31	127.74
AG	0.12	0.34	-0.85	0.06	8.28
GP	0.35	0.25	-2.58	0.30	3.00
$BoardSize$	2.29	0.39	1.39	2.20	5.70
$Independent$	0.78	0.16	0.02	0.83	1.00
$GenderRatio$	0.12	0.10	0.00	0.11	0.75
$Network$	1.19	2.50	0.00	0.75	67.59
$Tenure$	8.98	4.13	0.10	8.53	31.86
$Diversity$	2.90	0.68	0.73	2.86	5.72

Table 1 (continued)

Panel B: Pearson (Spearman) correlations below (above) the diagonal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ret		0.001	-0.008	-0.010	-0.027	-0.006	0.049	0.015	-0.006	-0.006	-0.008	-0.005	0.000	-0.005
$Similarity_{i,t-1}$	0.008		-0.021	0.028	0.001	0.014	0.006	-0.027	-0.037	-0.014	-0.039	-0.056	-0.042	-0.004
$Ln(Size)$	-0.034	-0.014		-0.273	-0.004	0.017	0.020	-0.111	0.562	-0.077	0.267	0.512	-0.038	-0.103
$Ln(B/M)$	-0.002	0.016	-0.287		-0.018	-0.173	-0.165	-0.450	0.010	0.083	-0.017	-0.125	0.060	0.036
ret_{t-1}	-0.006	0.008	-0.030	-0.009		-0.012	0.054	0.016	-0.008	-0.007	-0.010	-0.006	-0.001	-0.005
Mom	-0.024	0.024	-0.011	-0.144	-0.025		0.242	0.087	-0.049	-0.027	-0.050	-0.030	-0.010	-0.006
AG	0.039	0.020	0.000	-0.045	0.039	0.175		0.053	-0.090	-0.090	-0.128	-0.073	0.012	-0.024
GP	0.016	-0.016	-0.066	-0.362	0.017	0.074	-0.043		-0.091	-0.130	-0.001	-0.048	0.074	0.088
$BoardSize$	-0.014	-0.036	0.508	-0.038	-0.016	-0.046	-0.033	-0.020		-0.108	0.250	0.535	-0.013	0.047
$Independent$	-0.003	-0.005	-0.193	0.067	-0.003	-0.011	-0.037	-0.082	-0.583		0.186	-0.157	-0.080	-0.008
$GenderRatio$	-0.014	-0.048	0.260	-0.034	-0.017	-0.054	-0.084	0.057	0.168	0.111		0.148	-0.089	0.206
$Network$	-0.001	-0.020	0.250	-0.102	-0.002	-0.008	0.005	0.016	0.577	-0.480	-0.002		-0.182	-0.174
$Tenure$	-0.005	-0.047	-0.062	0.084	-0.006	-0.017	-0.055	0.036	-0.033	-0.098	-0.096	-0.043		0.100
$Diversity$	0.000	-0.009	-0.115	0.056	0.000	-0.006	-0.007	0.086	0.001	0.003	0.197	-0.147	0.116	

Table 2: Univariate portfolio tests

Panel A, the portfolios are sorted into ten deciles based on TMT facial similarity. Abnormal returns (in percent) for the focal firm are reported for each decile sorted on TMT facial similarity and the difference portfolio (P10-P1) are reported, using the excess return; the risk-adjusted return from CAPM model, CAPM; the risk-adjusted return from Fama-French three-factor model (Fama and French,1993), FF3; the risk-adjusted return from a four-factor model (Fama-French three-factor + Momentum Factor (Carhart, 1997)), FFC; the risk-adjusted return from a five-factor model (Fama-French three-factor + Momentum Factor (Carhart, 1997) + Liquidity Factor (Pástor and Stambaugh, 2003)), FFCPS; the risk-adjusted return from Fama and French (2015) five-factor model, FF5; the risk-adjusted return from the Fama and French (2018) six-factor model, FF6; the risk-adjusted return from the mispricing model (Stambaugh and Yuan (2016)), M4; the risk-adjusted return from q-factor model (Hou et al. (2015)), Q4; and the risk-adjusted return from the Daniel et al. (2020) behavioral factor model, DHS. The sample periods of all factor models are from July 2001 to December 2019 except the factor model DHS which stops at December 2018. The standard errors are calculated using the Newey-West (1987) method and the *t*-statistics are in parentheses.

Table 2 (continued)

Panel A: Value Weighted

	Excess Return	CAPM	FF3	FFC	FFCPS	FF5	FF6	M4	Q4	DHS
Short	0.47	-0.13	-0.17	-0.15	-0.13	-0.26	-0.26	-0.12	-0.15	-0.04
	(1.04)	(-1.02)	(-1.47)	(-1.21)	(-1.11)	(-2.19)	(-2.31)	(-0.99)	(-1.26)	(-0.32)
P2	0.67	-0.01	-0.06	-0.06	-0.08	-0.24	-0.24	-0.19	-0.10	0.06
	(1.66)	(-0.05)	(-0.29)	(-0.28)	(-0.36)	(-1.06)	(-1.08)	(-0.85)	(-0.45)	(0.26)
P3	0.59	-0.17	-0.24	-0.21	-0.22	-0.17	-0.18	-0.12	-0.10	0.09
	(1.33)	(-0.99)	(-1.53)	(-1.29)	(-1.42)	(-1.14)	(-1.18)	(-0.71)	(-0.59)	(0.48)
P4	0.48	-0.14	-0.19	-0.17	-0.18	-0.10	-0.10	-0.15	-0.09	-0.03
	(1.29)	(-0.81)	(-1.13)	(-1.02)	(-1.03)	(-0.60)	(-0.61)	(-0.85)	(-0.46)	(-0.14)
P5	0.98	0.35	0.27	0.31	0.31	0.16	0.15	0.27	0.34	0.39
	(2.67)	(2.00)	(1.86)	(2.09)	(2.01)	(1.03)	(1.04)	(1.77)	(2.14)	(2.15)
P6	0.71	0.14	0.08	0.07	0.07	-0.10	-0.10	-0.03	0.04	0.11
	(2.21)	(0.98)	(0.64)	(0.51)	(0.51)	(-0.79)	(-0.79)	(-0.23)	(0.31)	(0.70)
P7	0.68	0.03	-0.03	-0.02	-0.04	-0.18	-0.18	-0.05	-0.03	0.05
	(1.82)	(0.21)	(-0.18)	(-0.14)	(-0.27)	(-1.21)	(-1.21)	(-0.30)	(-0.22)	(0.28)
P8	0.66	-0.02	-0.06	-0.01	-0.02	-0.07	-0.08	0.15	0.04	0.19
	(1.57)	(-0.08)	(-0.30)	(-0.05)	(-0.08)	(-0.30)	(-0.34)	(0.50)	(0.14)	(0.52)
P9	0.62	0.05	0.02	0.01	0.02	-0.05	-0.04	-0.06	-0.01	0.07
	(1.88)	(0.36)	(0.16)	(0.05)	(0.16)	(-0.29)	(-0.28)	(-0.39)	(-0.07)	(0.39)
Long	0.94	0.26	0.19	0.18	0.19	0.14	0.14	0.21	0.23	0.39
	(3.05)	(1.88)	(1.52)	(1.45)	(1.47)	(1.54)	(1.60)	(0.10)	(1.11)	(1.36)
Long - Short	0.47	0.39	0.36	0.33	0.32	0.39	0.40	0.33	0.39	0.43
	(2.86)	(2.82)	(2.80)	(2.48)	(2.46)	(3.07)	(3.11)	(2.28)	(3.51)	(3.06)

Table 2 (continued)

Panel B: Equal Weighted

	Excess Return	CAPM	FF3	FFC	FFCPS	FF5	FF6	M4	Q4	DHS
Short	1.07	0.38	0.26	0.27	0.27	0.11	0.11	0.18	0.25	0.43
	(2.02)	(1.72)	(1.68)	(1.86)	(1.76)	(0.78)	(0.73)	(1.15)	(1.65)	(2.04)
P2	1.15	0.48	0.36	0.38	0.39	0.21	0.21	0.26	0.36	0.52
	(3.03)	(2.94)	(3.22)	(3.14)	(3.14)	(1.85)	(1.78)	(1.88)	(3.07)	(3.20)
P3	1.19	0.51	0.38	0.42	0.41	0.30	0.29	0.37	0.46	0.65
	(3.08)	(3.21)	(3.72)	(3.94)	(3.77)	(2.89)	(2.84)	(3.17)	(4.28)	(4.00)
P4	1.10	0.44	0.31	0.34	0.34	0.24	0.24	0.24	0.36	0.50
	(2.91)	(2.58)	(2.76)	(2.85)	(2.90)	(1.92)	(1.94)	(1.73)	(2.93)	(3.05)
P5	1.29	0.61	0.48	0.51	0.52	0.35	0.34	0.46	0.51	0.64
	(3.36)	(3.44)	(4.23)	(4.42)	(4.41)	(3.07)	(3.20)	(3.70)	(4.05)	(3.64)
P6	1.22	0.54	0.41	0.42	0.42	0.23	0.23	0.30	0.43	0.55
	(3.18)	(3.00)	(3.47)	(3.50)	(3.37)	(2.14)	(2.09)	(2.49)	(3.84)	(3.14)
P7	1.40	0.68	0.53	0.57	0.56	0.39	0.38	0.54	0.59	0.71
	(3.29)	(3.29)	(4.30)	(4.28)	(4.12)	(3.18)	(3.09)	(3.44)	(4.26)	(3.55)
P8	1.32	0.59	0.46	0.52	0.51	0.39	0.38	0.52	0.57	0.73
	(3.02)	(3.01)	(3.12)	(3.08)	(3.09)	(2.47)	(2.48)	(2.36)	(3.41)	(3.04)
P9	1.37	0.68	0.55	0.61	0.63	0.66	0.65	0.65	0.73	0.88
	(3.40)	(3.89)	(5.00)	(5.81)	(5.96)	(5.68)	(6.33)	(5.10)	(6.13)	(4.84)
Long	1.45	0.70	0.55	0.62	0.63	0.49	0.48	0.56	0.65	0.83
	(4.10)	(4.17)	(4.77)	(5.45)	(5.37)	(3.82)	(4.01)	(4.05)	(5.15)	(4.90)
Long - Short	0.37	0.32	0.30	0.35	0.36	0.38	0.37	0.39	0.40	0.40
	(3.35)	(3.02)	(3.05)	(3.54)	(3.62)	(3.16)	(3.23)	(3.14)	(3.69)	(3.63)

Table 3: Transition matrix

This table reports the transition probabilities for TMT facial similarity in next year from 2001 to 2019. For each TMT facial similarity decile in year t, the percentage of stocks that fall into each of the TMT facial similarity decile at year $t + 1$ is calculated, and the time-series averages of these transition probabilities are presented.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P1	63%	18%	8%	4%	3%	1%	1%	1%	1%	0%
P2	12%	52%	17%	9%	5%	2%	1%	1%	1%	0%
P3	7%	13%	57%	11%	6%	3%	1%	1%	1%	0%
P4	4%	6%	11%	56%	10%	9%	2%	1%	1%	0%
P5	4%	5%	8%	12%	50%	11%	6%	3%	1%	0%
P6	2%	3%	5%	6%	11%	55%	10%	7%	1%	0%
P7	1%	2%	2%	2%	4%	17%	53%	13%	6%	0%
P8	0%	1%	1%	2%	3%	3%	18%	59%	11%	2%
P9	0%	1%	1%	2%	2%	2%	2%	16%	56%	18%
P10	0%	1%	1%	1%	1%	2%	4%	7%	9%	74%

Table 4: Long-term performance

This table presents long-term return comparisons of value-weighted decile formed monthly based on TMT facial similarity from 2001 to 2019. Port1 is the value-weighted portfolio of stocks with the lowest TMT facial similarity and Port10 is the value-weighted portfolio of stocks with the highest TMT facial similarity. The table reports the six-factor alphas for each decile from two to twelve months after the portfolio formation. The last column in each panel shows the differences of monthly Fama and French (2018) six-factor alphas between deciles 10 and 1. Newey and West (1987) adjusted t-statistics are presented in parentheses.

	Port1	Port2	Port3	Port4	Port5	Port6	Port7	Port8	Port9	Port10	High-Low
m+2	-0.25	-0.14	-0.17	-0.09	0.16	-0.06	-0.17	0.06	-0.02	0.13	0.38
	(-2.08)	(-0.63)	(-1.06)	(-0.52)	(1.08)	(-0.53)	(-1.13)	(0.28)	(-0.12)	(1.22)	(2.70)
m+3	-0.25	-0.16	-0.13	-0.13	0.15	-0.06	-0.18	0.06	-0.03	0.12	0.37
	(-2.30)	(-0.73)	(-0.86)	(-0.71)	(1.04)	(-0.49)	(-1.22)	(0.25)	(-0.20)	(1.20)	(2.49)
m+4	-0.24	-0.20	-0.09	-0.13	0.14	-0.08	-0.19	0.09	-0.03	0.12	0.36
	(-2.05)	(-0.87)	(-0.56)	(-0.73)	(1.02)	(-0.65)	(-1.26)	(0.36)	(-0.19)	(1.22)	(2.42)
m+5	-0.23	-0.15	-0.07	-0.07	0.13	-0.04	-0.17	0.12	-0.05	0.12	0.35
	(-1.94)	(-0.67)	(-0.43)	(-0.41)	(0.96)	(-0.33)	(-1.06)	(0.50)	(-0.30)	(1.21)	(2.25)
m+6	-0.23	-0.16	-0.08	-0.09	0.13	-0.06	-0.15	0.09	-0.03	0.11	0.34
	(-2.01)	(-0.73)	(-0.53)	(-0.49)	(0.95)	(-0.54)	(-0.94)	(0.36)	(-0.19)	(1.21)	(2.07)
m+7	-0.22	-0.17	-0.06	-0.12	0.13	-0.06	-0.16	0.11	0.00	0.11	0.33

	(-1.94)	(-0.75)	(-0.38)	(-0.64)	(0.94)	(-0.48)	(-1.00)	(0.44)	(-0.01)	(1.21)	(1.93)
m+8	-0.21	-0.16	0.00	-0.16	0.12	-0.06	-0.16	0.17	-0.01	0.12	0.33
	(-2.25)	(-0.74)	(-0.01)	(-0.82)	(0.85)	(-0.49)	(-1.04)	(0.66)	(-0.10)	(1.22)	(1.74)
m+9	-0.18	-0.17	0.06	-0.08	0.17	-0.07	-0.16	0.22	-0.03	0.14	0.32
	(-2.03)	(-0.80)	(0.39)	(-0.42)	(1.23)	(-0.59)	(-1.03)	(0.88)	(-0.18)	(1.24)	(1.78)
m+10	-0.21	-0.09	0.05	-0.09	0.17	-0.02	-0.19	0.22	-0.02	0.11	0.32
	(-1.98)	(-0.47)	(0.29)	(-0.47)	(1.23)	(-0.21)	(-1.26)	(0.88)	(-0.16)	(1.18)	(1.67)
m+11	-0.19	-0.05	0.00	-0.05	0.17	-0.01	-0.22	0.08	-0.01	0.11	0.30
	(-1.62)	(-0.29)	(0.01)	(-0.23)	(1.23)	(-0.07)	(-1.42)	(0.48)	(-0.09)	(1.18)	(1.60)
m+12	-0.19	-0.14	0.17	0.17	0.13	0.02	-0.21	0.22	-0.02	0.11	0.30
	(-1.64)	(-0.81)	(0.83)	(0.52)	(1.00)	(0.20)	(-1.39)	(1.06)	(-0.10)	(1.17)	(1.60)

Table 5: Cross-sectional regressions

This table reports the results of Fama-MacBeth regressions of TMT facial similarity predictability. The sample period is from January 2001 to December 2019. Financial firms are excluded. The independent variable is TMT facial similarity constructed based on the pictures of TMT members. The control variables are the lagged values of focal firm's size, $Ln(Size)$; book-to-market ratio, $Ln(B/M)$; lagged excess return, $ret_{i,t-1}$; medium-term price momentum, Mom; asset growth, AG; gross profitability, GP; industry's value-weighted return, Ind_Mom; the natural log of the total number of directors sitting in the firm board, $BoardSize$; the percentage of independent directors in the board, $Independent$; the ratio of female directors in the board, $GenderRatio$; the average number of outside board positions held by the board of directors, $Network$; the directors' average tenure in the firm board, $Tenure$; and the board member diversity, $Diversity$. Panel A presents results estimated for one-month-ahead returns using the ordinary least squares (OLS) methodology. Panel B presents results estimated for one-month-ahead returns using the weighted least squares (WLS) methodology of Asparouhova et al (2013), where each observed return is weighted by one plus the observed prior return on the stock. All explanatory variables are based on last non-missing available observation for each month t. The standard errors are calculated using the Newey-West (1987) method. The t-statistics are in parentheses.

Panel A: OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$Similarity_{i,t-1}$	0.33	0.30	0.31	0.32	0.29	0.26	0.25	0.28	0.24	0.24	0.23	0.24	0.24	0.24
	(2.75)	(2.55)	(2.65)	(2.77)	(2.56)	(2.39)	(2.28)	(2.59)	(2.21)	(2.17)	(2.09)	(2.16)	(2.14)	(2.13)
$Ln(Size)$		-0.24	-0.31	-0.30	-0.30	-0.29	-0.27	-0.28	-0.34	-0.34	-0.32	-0.33	-0.32	-0.32
		(-3.59)	(-4.94)	(-4.87)	(-4.71)	(-4.62)	(-4.20)	(-4.27)	(-4.90)	(-4.72)	(-4.48)	(-4.48)	(-4.47)	(-4.48)
$Ln(B/M)$			-0.36	-0.36	-0.43	-0.40	-0.30	-0.33	-0.30	-0.29	-0.29	-0.28	-0.28	-0.28
			(-3.75)	(-3.77)	(-4.74)	(-4.94)	(-3.44)	(-3.81)	(-3.38)	(-3.36)	(-3.31)	(-3.27)	(-3.26)	(-3.28)
$ret_{i,t-1}$				-0.02	-0.02	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
				(-2.86)	(-3.35)	(-3.65)	(-3.76)	(-3.97)	(-3.53)	(-3.54)	(-3.51)	(-3.53)	(-3.58)	(-3.63)
Mom					-0.05	-0.08	-0.08	-0.08	-0.06	-0.06	-0.07	-0.07	-0.07	-0.07
					(-1.33)	(-1.99)	(-2.05)	(-2.11)	(-1.55)	(-1.57)	(-1.59)	(-1.61)	(-1.63)	(-1.64)
AG						1.78	1.80	1.82	1.95	1.93	1.93	1.93	1.92	1.92

Table 5 Panel A (continued)

						(2.55)	(2.59)	(2.60)	(2.51)	(2.47)	(2.46)	(2.46)	(2.45)	(2.45)
GP							0.83	0.79	0.68	0.66	0.70	0.72	0.72	0.72
							(3.22)	(3.11)	(2.53)	(2.45)	(2.59)	(2.66)	(2.71)	(2.70)
Ind_Mom								0.03	0.03	0.03	0.03	0.03	0.03	0.03
								(1.52)	(1.53)	(1.59)	(1.55)	(1.53)	(1.55)	(1.52)
$BoardSize$									0.14	0.02	0.07	0.01	-0.01	-0.01
									(1.45)	(0.13)	(0.51)	(0.04)	(-0.07)	(-0.07)
$Independent$										-0.54	-0.40	-0.33	-0.37	-0.37
										(-1.80)	(-1.37)	(-1.12)	(-1.21)	(-1.20)
$GenderRatio$											-1.02	-1.01	-1.04	-1.03
											(-2.44)	(-2.42)	(-2.47)	(-2.37)
$Network$												0.03	0.03	0.03
												(1.62)	(1.62)	(1.51)
$Tenure$													-0.01	-0.01
													(-0.58)	(-0.59)
$Diversity$														0.01
														(0.22)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	143,526	143,484	140,417	140,417	140,417	140,402	140,389	139,893	123,598	123,598	123,578	123,577	123,598	123,575
R^2	0.23	0.24	0.25	0.26	0.28	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32

Table 5 (continued)

Panel B: WLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$Similarity_{i,t-1}$	0.40	0.36	0.37	0.36	0.33	0.30	0.28	0.29	0.26	0.26	0.25	0.26	0.25	0.25
	(3.07)	(2.90)	(2.91)	(3.00)	(2.78)	(2.61)	(2.52)	(2.61)	(2.22)	(2.18)	(2.10)	(2.15)	(2.11)	(2.11)
$Ln(Size)$		-0.24	-0.31	-0.31	-0.30	-0.30	-0.28	-0.28	-0.34	-0.34	-0.33	-0.33	-0.33	-0.32
		(-3.41)	(-4.72)	(-4.74)	(-4.58)	(-4.49)	(-4.11)	(-4.13)	(-4.74)	(-4.59)	(-4.37)	(-4.39)	(-4.37)	(-4.37)
$Ln(B/M)$			-0.39	-0.38	-0.45	-0.41	-0.31	-0.32	-0.29	-0.29	-0.28	-0.28	-0.27	-0.27
			(-3.90)	(-3.76)	(-4.69)	(-5.01)	(-3.55)	(-3.62)	(-3.18)	(-3.18)	(-3.13)	(-3.09)	(-3.03)	(-3.06)
$ret_{i,t-1}$				-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
				(-0.64)	(-1.09)	(-1.35)	(-1.44)	(-1.60)	(-1.10)	(-1.10)	(-1.07)	(-1.08)	(-1.11)	(-1.16)
Mom					-0.05	-0.08	-0.08	-0.08	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07
					(-1.28)	(-1.93)	(-1.98)	(-2.02)	(-1.52)	(-1.53)	(-1.56)	(-1.57)	(-1.59)	(-1.60)
AG						1.90	1.91	1.92	2.06	2.04	2.03	2.04	2.02	2.03
						(2.41)	(2.45)	(2.45)	(2.36)	(2.33)	(2.32)	(2.32)	(2.31)	(2.31)
GP							0.84	0.83	0.69	0.67	0.70	0.72	0.73	0.72
							(3.29)	(3.32)	(2.57)	(2.50)	(2.62)	(2.68)	(2.76)	(2.73)
Ind_Mom								0.03	0.03	0.03	0.03	0.03	0.03	0.03
								(1.40)	(1.53)	(1.59)	(1.55)	(1.53)	(1.56)	(1.52)
$BoardSize$									0.13	0.01	0.06	-0.01	-0.03	-0.03
									(1.23)	(0.08)	(0.45)	(-0.05)	(-0.18)	(-0.22)
$Independent$										-0.51	-0.37	-0.29	-0.35	-0.33
										(-1.68)	(-1.25)	(-0.97)	(-1.11)	(-1.08)
$GenderRatio$											-0.97	-0.96	-1.01	-1.04

Table 5 Panel B (continued)

											(-2.34)	(-2.31)	(-2.42)	(-2.44)
Network												0.03	0.03	0.03
												(1.78)	(1.79)	(1.75)
Tenure													-0.01	-0.01
													(-0.93)	(-0.99)
Diversity														0.03
														(0.69)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	142,806	142,764	139,722	139,722	139,722	139,707	139,710	139,710	123,398	123,398	123,398	123,398	123,376	123,375
R^2	0.21	0.22	0.23	0.25	0.27	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32

Table 6: Average portfolio characteristics

This table presents the average portfolio characteristics for portfolios formed based on the TMT facial similarity scores. Portfolio 1 is the portfolio of stocks with the lowest TMT facial similarity score and Portfolio 10 is the portfolio of stocks with the highest TMT facial similarity score. The table reports the time-series averages of the monthly averages for TMT facial similarity and various firmcharacteristics for each decile. The last columns show the differences for the firm-specific characteristics between Portfolio 1 and Portfolio 10. TMT facial similarity score and other firm-specific characteristics are defined as in Table 5. The overall sample period is from July 2001 to December 2019.

Variables	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$Similarity$	0.04	0.14	0.25	0.34	0.44	0.54	0.64	0.75	0.84	0.95	0.91
$Ln(Size)$	7.59	7.53	7.62	7.59	7.47	7.60	7.74	7.51	7.35	7.61	0.02
$Ln(B/M)$	-0.86	-0.73	-0.80	-0.86	-0.88	-0.77	-0.73	-0.81	-0.88	-0.74	0.12
$ret_{i,t-1}$	1.14	1.22	1.25	1.19	1.37	1.32	1.34	1.39	1.40	1.50	0.36
Mom	1.20	1.29	1.33	1.26	1.38	1.37	1.40	1.44	1.47	1.52	0.32
AG	0.10	0.12	0.11	0.09	0.12	0.13	0.10	0.11	0.14	0.12	0.02
GP	0.34	0.32	0.33	0.40	0.38	0.35	0.32	0.34	0.34	0.34	0.00
Ind_Mom	1.03	1.03	1.00	1.04	1.02	1.04	1.00	1.00	1.00	1.05	0.02
$BoardSize$	2.29	2.30	2.31	2.32	2.27	2.29	2.35	2.26	2.21	2.29	0.00
$Independent$	0.79	0.78	0.79	0.77	0.78	0.79	0.76	0.80	0.79	0.77	-0.02
$GenderRatio$	0.12	0.13	0.12	0.13	0.11	0.12	0.12	0.13	0.11	0.10	-0.02
$Network$	0.97	1.39	1.36	1.30	1.28	1.04	1.47	1.02	0.99	1.12	0.15
$Tenure$	9.43	9.40	9.29	9.18	8.85	8.63	8.97	8.16	8.72	9.40	-0.03
$Diversity$	2.96	2.98	2.86	2.86	2.87	2.85	2.89	2.85	3.00	2.89	-0.07

Table 7: TMT facial similarity and firm operating performance

This table reports the regressions of firm operating performance change on firm TMT facial similarity and other firm characteristics. The dependent variables Δ*Profitability*, where *Profitability* is defined as the revenue minus the cost of goods sold, scaled by the total asset and Δ*Profitability* is the change of firm profitability compared with previous year; Δ*CashFlow,* where *CashFlow* is measured as the total cash flow scaled by total asset and Δ*CashFlow* is the change of *CashFlow* compared with previous year; and Δ*ROA*, where *ROA* is measured as the net income scaled by the total asset and Δ*ROA* is the change of *ROA* compared with previous year. The key independent variable is TMT facial similarity, which is constructed based on the pictures of TMT members. Control variables are defined` as in Table 5. And t-statistics are reported in parentheses. We winsorize all variables at the 1% and 99% levels and standardize all independent variables to zero mean and one standard deviation.

	$\Delta Profitability$	$\Delta Profitability$	$\Delta CashFlow$	$\Delta CashFlow$	ΔROA	ΔROA
$Similarity_{i,t-1}$	0.578	0.608	1.702	1.549	1.043	0.984
	(3.70)	(3.71)	(3.02)	(2.61)	(1.90)	(1.73)
$Ln(Size)$	0.029	0.044	-0.162	-0.155	-0.074	-0.090
	(3.51)	(4.61)	(-5.14)	(-4.27)	(-2.68)	(-2.77)
$Ln(B/M)$	-0.006	0.003	0.041	0.062	-0.026	-0.006
	(-1.04)	(0.44)	(1.91)	(2.57)	(-1.38)	(-0.30)
AG	-0.126	-0.122	0.174	0.190	0.075	0.091
	(-42.53)	(-37.95)	(15.62)	(15.54)	(7.49)	(8.29)
GP	-0.686	-0.660	0.398	0.426	0.479	0.528
	(-93.02)	(-81.71)	(14.34)	(13.97)	(19.29)	(19.19)
$BoardSize$		-0.012		-0.015		-0.027
		(-2.09)		(-0.70)		(-1.42)
$Independent$		-0.007		0.006		0.015
		(-1.58)		(0.36)		(0.97)
$GenderRatio$		-0.015		-0.010		-0.010
		(-2.68)		(-0.46)		(-0.51)
$Network$		-0.001		0.029		0.003
		(-0.18)		(1.46)		(0.16)
$Tenure$		-0.015		-0.037		-0.045
		(-2.65)		(-1.80)		(-2.38)
$Diversity$		0.006		0.030		0.020
		(1.41)		(1.81)		(1.31)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs.	11,743	10,338	11,156	9,783	12,281	10,551
R^2	0.93	0.93	0.07	0.07	0.10	0.11

Table 8: Return predictablity around the earnings announcement window

This table reports the results from the OLS regressions where dependent variable is the three-day cumulative abnormal returns around the earnings announcement date. The independent variable is TMT facial similarity constructed based on the pictures of TMT members. All control variables are based on last non-missing observations prior to each quarter. In model 1, the cumulative abnormal return is computed as the sum of the daily stock return around the earnings announcement window [-1, +1]. In model 2, the cumulative abnormal return is computed as the sum of the daily stock return minus return on the CRSP value-weighted portfolio return. TMT facial similarity and other firm-specific characteristics are defined in Table 5. And t-statistics are reported below the coefficient estimates.

	Model 1		*Model 2*	
	$CAR_{t-1,t+1}$	$CAR_{t-1,t+1}$	$CAR_{t-1,t+1}$	$CAR_{t-1,t+1}$
$Similarity_{i,t-1}$	0.002	0.002	0.002	0.002
	(2.89)	(2.44)	(2.86)	(2.35)
$Ln(Size)$	-0.011	-0.011	-0.011	-0.011
	(-5.71)	(-5.28)	(-6.12)	(-5.72)
$Ln(B/M)$	0.005	0.005	0.005	0.005
	(1.56)	(1.32)	(1.66)	(1.37)
MOM	-0.005	-0.006	-0.003	-0.004
	(-0.70)	(-0.76)	(-0.48)	(-0.55)
AG	-0.005	-0.005	-0.004	-0.004
	(-0.99)	(-0.97)	(-0.75)	(-0.75)
GP	0.02	0.013	0.018	0.013
	(3.98)	(2.21)	(3.80)	(2.17)
$BoardSize$	0.004	0.006	0.004	0.006
	(1.02)	(1.73)	(1.04)	(1.76)
$Independent$	-0.003	-0.001	-0.002	-0.001
	(-1.68)	(-0.75)	(-1.49)	(-0.56)
$GenderRatio$	-0.005	-0.004	-0.004	-0.004
	(-2.92)	(-2.29)	(-2.77)	(-2.19)
$Network$	-0.004	-0.005	-0.002	-0.004
	(-0.55)	(-0.80)	(-0.34)	(-0.60)
$Tenure$	-0.002	-0.001	-0.002	-0.002
	(-1.17)	(-0.87)	(-1.32)	(-0.96)
$Diversity$	0.000	-0.001	0.000	-0.001
	(0.01)	(-0.54)	(-0.09)	(-0.65)
Industry FE	N	Y	N	Y
Obs.	41,128	41,128	41,128	41,128
R^2	0.003	0.01	0.003	0.01

Table 9: Limited attention and limits to arbitrage

This table presents results from the value-weighted portfolios based on bivariate sorts of various firm-specific attributes and facial similarity. First, tercile portfolios are formed every month based on a firm-specific attribute (proxy for limited attention/limits to arbitrage). Next, quintile portfolios are formed based on facial similarity within each firm-specific attribute tercile. The table reports one-month-ahead Fama and French (2018) six-factor alphas for each quintile. The last row in each panel shows the differences of monthly alphas between TMT facial similarity quintiles 5 and 1 for each firm-specific attribute tercile. Panel A reports double-sort results with proxies of investor attention including the *absolute SUE* following Bali et al. (2018) and the Δ*Advertising expenses* following Lou (2014). The absolute SUE is defined as the absolute value of SUE based on the last non-missing SUE during the past year. The Δ*Advertising expenses* are changes in advertising expenditures from year $t-1$ to year t. Panel B reports double-sort results with proxies of limits to arbitrage including idiosyncratic volatility and illiquidity. *Idiosyncratic volatility* is constructed following Ang et al. (2006). *Illiquidity* is the Amihud (2002) illiquidity measure based on the price impact. Newey-West (1987) adjusted t-statistics are presented in parentheses.

Panel A: Investor limited attention

Absolute SUE	|SUE| L	|SUE| M	|SUE| H
Port1	-0.30	-0.20	-0.14
	(-1.30)	(-0.94)	(-0.61)
Port2	-0.12	-0.08	-0.06
	(-0.74)	(-0.49)	(-0.31)
Port 3	-0.13	-0.08	-0.06
	(-0.98)	(-0.66)	(-0.46)
Port 4	-0.10	-0.07	-0.05
	(-0.41)	(-0.30)	(-0.18)
Port5	0.18	0.12	0.08
	(1.61)	(1.07)	(0.68)
High-Low	0.48	0.32	0.22
	(3.51)	(2.40)	(1.57)
Δ*Advertising expenses*	Adv L	Adv M	Adv H
Port1	-0.12	-0.08	-0.05
	(-0.55)	(-0.39)	(-0.24)
Port2	-0.11	-0.07	-0.05
	(-0.58)	(-0.38)	(-0.23)
Port 3	0.05	0.04	0.02
	(0.39)	(0.27)	(0.16)
Port 4	0.04	0.03	0.02
	(0.31)	(0.21)	(0.13)
Port5	0.28	0.21	0.14
	(1.67)	(1.08)	(0.71)
High-Low	0.40	0.29	0.19
	(2.66)	(1.82)	(1.12)

Table 9 (continued)

Panel B: Limits to arbitrage

Idiosyncratic volatility	Ivo L	Ivo M	Ivo H
Port1	-0.07	-0.11	-0.28
	(-0.27)	(-0.58)	(-1.20)
Port2	-0.05	-0.09	-0.22
	(-0.28)	(-0.54)	(-1.03)
Port 3	-0.01	-0.02	-0.04
	(-0.09)	(-0.17)	(-0.34)
Port 4	0.05	0.12	0.21
	(0.18)	(0.39)	(0.73)
Port5	0.08	0.17	0.30
	(0.28)	(0.62)	(1.11)
High-Low	0.14	0.28	0.58
	(0.77)	(1.50)	(2.87)
Illiquidity	Ill L	Ill M	Ill H
Port1	-0.01	-0.02	-0.04
	(-0.06)	(-0.10)	(-0.19)
Port2	0.03	0.04	0.08
	(0.12)	(0.20)	(0.35)
Port 3	0.05	0.08	0.15
	(0.26)	(0.38)	(0.68)
Port 4	0.09	0.14	0.26
	(0.32)	(0.55)	(0.94)
Port5	0.17	0.29	0.52
	(0.45)	(0.80)	(1.85)
High-Low	0.18	0.32	0.56
	(0.84)	(1.36)	(2.57)

Figure 1:

This figure depicts the 27 landmark points defined by Microsoft. The figure is downloaded from https://docs.microsoft.com/en-us/azure/cognitive-services/face/concepts/face-detection.

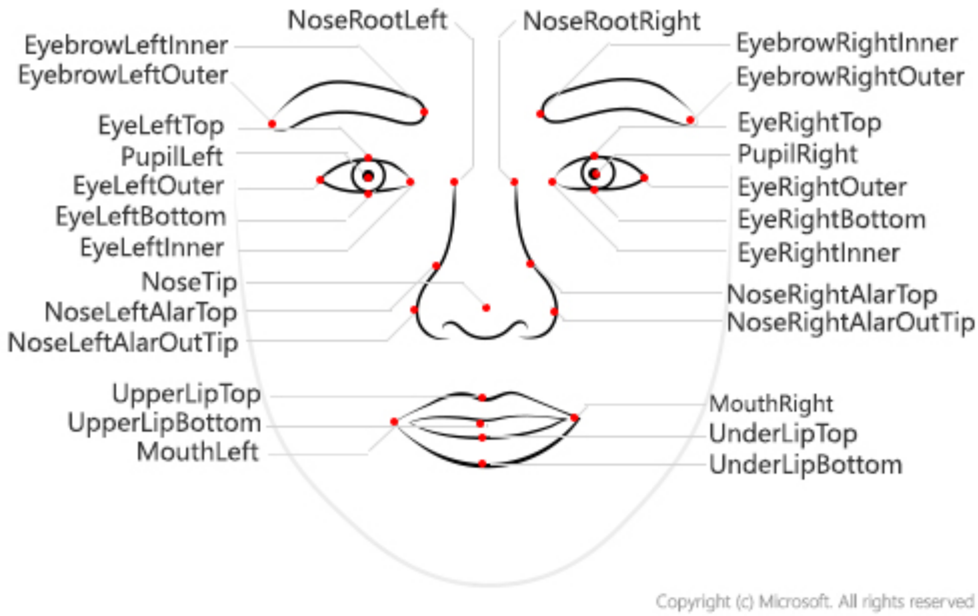
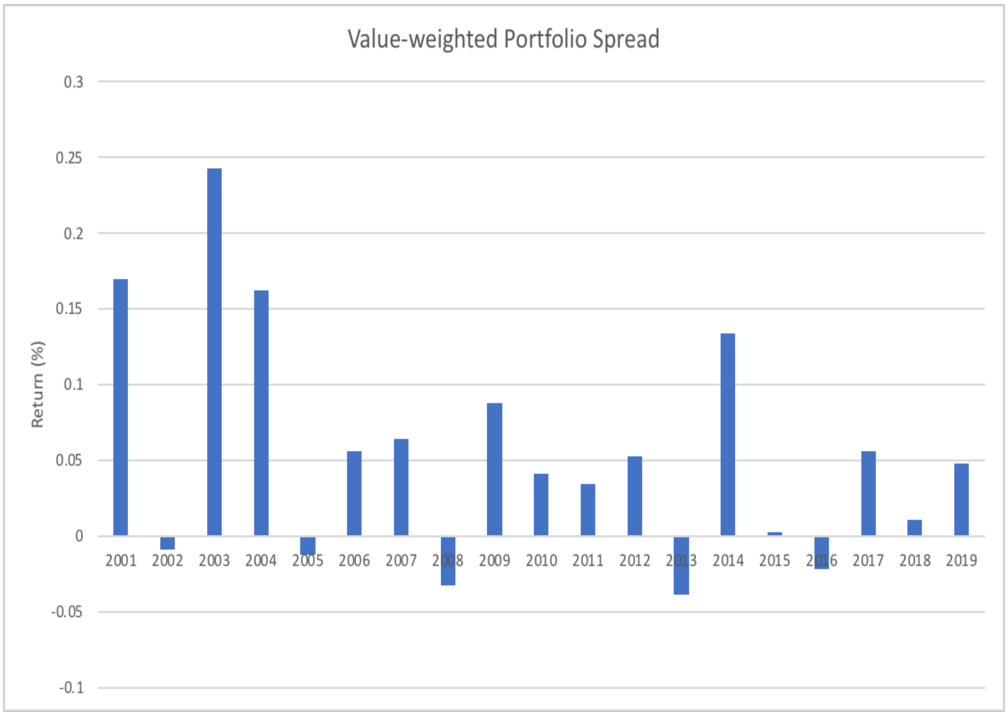


Figure 2: Annual value-weighted return of the long-short portfolio

This figure shows the annual value-weighted returns of the long-short portfolio sorted on TMT facial similarity. From 2001 to 2019, the portfolios are sorted into deciles based on TMT facial similarity at the end of year t-1 from 2000 to 2018. The long-short portfolio buys the top decile of stocks with the highest TMT facial similarity and sells the bottom decile of stocks with the lowest TMT facial similarity.



Appendix

Variable definitions and data sources

Variable	Description	Source	Frequency
$Simlarity$	*Similarity* measures the facial resemblance between TMT members.	Boardex	Yearly
ret	Focal firm's excess return over one-month T-bill.	CRSP	Monthly
Ln(Size)	Log market capitalization.	CRSP, Compustat	Monthly
Ln(B/M)	Log book value at the end of December over the market capitalization in month $t-1$.	CRSP, Compustat	Monthly
Mom	Focal firm's cumulative return over $t-12$ to $t-2$ months.	CRSP	Monthly
Ind_Mom	The focal firm industry's value-weighted average return.	CRSP, K. French Data	Monthly
AG	Asset growth is a year-over-year growth rate of the total asset.	CRSP, Compustat	Monthly
GP	Gross profitability is the revenue minus the cost of goods sold scaled by the total asset.	CRSP, Compustat	Monthly
BoardSize	The natural log of the total number of directors sitting in firm board.	Boardex	Monthly
Independent	The percentage of independent directors in the board.	Boardex	Monthly
GenderRatio	The ratio of female directors in the board.	Boardex	Monthly
Network	The average number of outside board positions held by the board of directors.	Boardex	Monthly
Tenure	The directors' average tenure in the firm board.	Boardex	Monthly
Diversity	The board member diversity is measured along directors' demographic characteristics.	Boardex	Monthly
Δ*Profit*	*Profitability* is measured as the revenue minus the cost of goods sold, scaled by the total asset and Δ*Profitability* is the change of *Profitability* compared with previous year.	CRSP, Compustat	Yearly
Δ*CashFlow*	*CashFlow* is measured as the total cash flow scaled by the total asset and Δ*CashFlow* is the change of *CashFlow* compared with previous year.	CRSP, Compustat	Yearly
Δ*ROA*	*ROA* is measures as net income scaled by total asset. Δ*ROA* is the change of *ROA* compared with previous year.	CRSP, Compustat	Yearly

Chapter 3

Tweet More or Less: How does CEO Tweeting Skill Impact Firm Stock Return?[1]

This paper studies the effects of CEO tweeting on firm stock performance based on the U.S. public firms from 2012 to 2018. By creating a measure of CEO tweeting skill, we show that how well and how often CEOs tweet together can make a difference in firm market value. If CEOs are good at communicating on Twitter, firms benefit from CEO's high exposure. In contrast, if CEOs' tweeting skill is low, firms are better off when their CEOs tweet less. And the results hold across different countries (such as France, Germany, and the United Kingdom). The possible mechanisms behind our documented findings are shown to be investor's limited attention and limits to arbitrage. Moreover, our documented effects are more likely to be explained by the behavioral bias other than risk explanations.

1. Introduction

Twitter has been widely used as a social communication platform, not only by the general population to share their daily life but also by firm managers to advertise products, highlight the firm image and boost their firm performance. Jung et al. (2018) report that in 2015 almost half of S&P 1500 firms have firm-managed Twitter accounts, which are used to draw investors' attention to press releases. There is emerging literature that focuses on the special effect of Twitter, providing

[1] This is joint work with Ran Zhang.

a platform for both information disclosure and interaction among participants, on the financial market. However, the effects can be two-fold. On the one hand, tweets attract investors' attention to the firm ("any publicity is good publicity"), raise firm popularity as well as diminish information asymmetry. Thus, firms could make use of Twitter to strategically disclose information to help mitigate negative reports or magnify positive news. On the other hand, the quick spread of bad news or a "wear-out" effect created by the repeated exposure could be harmful to a firm instead. The effects of tweets on the financial market differ with the information contained in the tweeters, the specific timeslot of posting tweeters, even the Twitter accounts via which the tweets are posted. As the impacts of Twitter could be complicated and mixed, researchers try to untangle them and explore how the firms strategically utilize Twitter to build the firm image. So far, most of the existing literature studies the impacts of tweets posted by the firm's official account, but the specific effect of tweets posted by CEOs has not been paid attention yet.

Since the first tweet posted by CEO appeared in 2008, CEOs posting tweets via personal accounts instead of the firm's official accounts gradually becomes a common phenomenon. For example, Elon Musk has posted thousands of tweets since his first one and now there are more than 51 million followers on his personal account. Most of his tweets are related to SpaceX or Tesla, which may cause both positive and negative fluctuations in the firm stock price. Elon Musk is not the only one who prefers using Twitter to broadcast information, there is a trend that companies are developing social media as a platform to make some official statement or sending the latest news to investors. In our sample, about 12 percent of all S&P 1500 firms' CEOs have opened their own account to further connect with investors, and it is foreseeable that more and more senior executives will embrace social media. Thus, exploring how the CEOs behave on Twitter and the potential effects on their firms is a field of interest. The effect of a CEO's tweets is uncertain, and it depends on how well the CEO communicates and interacts with stakeholders on social media. In an interview with Yahoo Finance Warren, Buffett once commented that Musk would benefit from being more selective about what he posts on Twitter.

Different from the firm's official Twitter account, the tweets posted on CEO's personal Twitter account not only release information related to firm but also could improve investors' trust in the firm (Elliott et al., 2018). According to social identity theory, the social bonds related to individuals tend to be stronger than those related to the whole organization. As a result, the information posted on CEO's individual social media account could influence investors' perception of management and build the social bond between investors and the manager more than the ones posted via the company's official account. In this way, not only the information contained in the tweets matters but also the frequency and the way how CEOs express and communicate on Twitter could play a crucial role in investors' valuation of a firm.

In this paper, we show that CEO tweeting skill and the number of posted tweets jointly affect the firm's future stock returns and this impact is predictable. CEOs post tweets to advertise products, disseminate good news, explain negative events, and so on. In other words, CEOs take use of Twitter as a new platform to improve the firm image and promote the firm performance. However, not every tweet posted by CEO can positively affect firm performance. Intuitively, if a CEO discloses the information strategically and interacts well with stakeholders on social media, the firm could benefit from CEO's active participation on social media in general. In contrast, if a CEO is "bad" at communicating on Twitter, the high frequency of tweeting harms the firm's valuation instead. As a result, we expect tweets posted by different CEOs could play different roles in how the market value the firm, and the various effects are predictable. Based on the simple assumption that the tweeting skill of a particular CEO does not change significantly over time, the effects of tweets posted by the CEO previously give us insight into the potential outcome of future tweets.

To predict the effects of CEO tweeting on firm stock performance, we first identify the tweeting skill of each CEO. Based on the assumption that the tweeting skill of a CEO tends to be persistent, we estimate the skill by using the CEO's past ability of affecting firm value (e.g., market valuation) by posting tweets in the preceding months. The idea behind this method is to isolate the extent to which a given CEO could successfully use social media to increase investors' valuation in the firm. We then interact CEO tweeting skill with the number of tweeters posted by the CEOs to examine the effects of CEO tweeting on firm performance. It is shown that the effect of CEO posting tweets is predictable and relatively stable, and the information embedded in the previous effects of CEO tweeting is largely ignored by the market.

In each month t, we sort the sample firms based on their CEO tweeting skill into three CEO tweeting skill groups (top 30%, middle 40%, and bottom 30%). We then sort the firms independently on the numbers of tweets posted by their CEOs in the previous month $t-1$ into three groups (top 30%, middle 40%, and bottom 30%). The monthly return is then calculated for each double-sorted portfolio in month t. Conditional on high CEO tweeting skill, the excess returns on the double-sorted portfolios, both value and equal-weighted, are broadly significantly positive, suggesting that CEO tweeting, in general, is beneficial for firms if the CEO can effectively convey information and interact well with stakeholders via Twitter. If CEOs are associated with high communication skills on social media, the tweets posted by CEOs could promote the spread of good news. In terms of bad news, the information released from the personal channel could mitigate the negative effects when the CEOs are good at explaining events and effectively interact with investors online (Elliott et al., 2018). Conditional on low CEO tweeting skill, the portfolio excess/abnormal return decreases as the number of CEO tweets increases, with a spread of more than 1% per month between the tweet few and more portfolios regardless of the measures for the excess return. Intuitively, when a CEO is bad at communicating on Twitter, it is better to speak less. In contrast, if CEO is associated with high tweeting skill, he/she may take advantage of Twitter to advertise and boost firm performance. The results also show that the magnitude of abnormal return between the tweet few and more portfolios conditional on CEO high tweeting skill is smaller and less significant than that conditional on CEO low tweeting skill. This asymmetry is consistent with the saying that “it is easier to do harm than good”. Furthermore, conditional on tweeting more, the portfolio excess/abnormal return increases with the CEO tweeting skill, with a spread of around 1% between the tweet few and more portfolios. Conditional on tweeting less, however, the portfolio excess/abnormal return decreases with the CEO tweeting skill, but the difference is less significant. This suggests that the benefit (cost) of high (low) CEO tweeting skill is more significant when CEO posts more tweets as the firm receives more attention. And CEOs need to be more cautious if they are active on social media. The results of Fama-MacBeth regressions (1973) regressing monthly stock returns on the intersection between CEO tweeting skill and the number of CEO tweets are also in support of the argument that the CEO tweeting skill and the number of tweets posted by CEOs together could affect investors' valuation on the firm. To show the robustness of our results, we use alternative CEO tweeting skill measures estimated based on firm operating performance such as sales, revenues, and profits instead of market valuation. The estimated effects of CEO tweeting on stock returns based on these alternative measures are consistent with our main results.

To study whether the effect of CEO tweeting exists across countries, we extend our Fama-MacBeth regressions with United Kingdom, France, Germany, and Japan samples. The overall effect of CEO tweeting is similar to those found in the U.S. sample. When CEO tweeting skill is low, the monthly abnormal return of longing tweeting less and shorting tweeting more is 0.44 ($t = 2.09$) in France and 0.56 ($t = 2.36$) in the United Kingdom. Moreover, we observe relatively weaker effects of CEO tweeting in Japan and German, and this may be explained by the potential language barrier for international investors who do not understand German and/or Japanese. In contrast, both official languages in the US and the UK are English, which is widely understood around the world and thus the tweets in these countries are easier to grab attention from investors around the world and eventually create larger effects on the stock returns.

We also test how CEO tweeting affects firm operating performance. It is shown that the combination of high tweeting skill and more tweets has a positive effect on firm operating performance (measured by ROA, Sales, Revenues, and Profits), and this provides possible explanations for why CEO tweeting could affect firm market valuation. We further test the possible mechanisms (i.e., investor limited attention, limits to arbitrage, risk channels) of our documented effects by analyzing the returns of portfolios that are triple sorted on CEO tweeting skill, the number of CEO tweets, and a proxy for the mechanism in question. We find that the effect of CEO tweeting is strengthened by both the extent of investor limited attention and the extent of limits to arbitrage. Besides, the effect of CEO tweeting is stronger during the period of earnings announcements and the firm's future earnings surprises (as measured by the standardized unexpected earnings, SUE) could be partly explained by the CEO tweeting skill and the number of tweets. This implies that our documented results are more likely due to the mispricing explanations instead of risk factors.

Our study contributes to several burgeoning research streams. Firstly, we contribute to the literature investigating the impact of social media on the financial market (Sprenger et al., 2014; Blankespoor et al., 2014; Chen et al., 2014; Elliott et al., 2018; Chen et al., 2017; Bartov et al., 2017) and how firm managers take advantage of the social media to strategically disclose information and improve firm valuation (Jung et al., 2018; Lee et al., 2015; Crowley et al., 2018). In terms of the effects of Twitter, most studies focus on the tweets posted by firms or investors. Our paper adds to the research by exploring the specific effects of tweets posted by CEOs, who serve as managerial executives in firms. Our results show that the number of tweets posted by CEOs and how CEOs communicate with stakeholders via Twitter make differences in firm valuation.

We also add evidence on the literature related to the managerial effects on firm market value. One research stream examines how the specific relationship between CEO and firm, such as compensation, ownership, or tenure, influences the firm performance and strategy (Gormley et al., 2013; Lilienfeld-Toal and Ruenzi, 2014; Brochet et al., 2019). Another stream focuses on how the managers' personal characteristics, such as education background, gender, and experience, affect how investors value the firm (Cohen and Dean, 2005; Bigelow et al, 2014; Higgins and Gulati, 2006). In our paper, we discover a specific impact of CEO on firm stock performance and document that the skill and frequency of CEO tweeting together affect firm valuation via investors' perception on firms' management.

The rest of the paper proceeds as follows: Section 2 shows the literature review. In Section 3, we discuss the data sample, the construction of CEO tweeting skill measure, and the summary statistics. In Section 4, we present the results of our empirical analysis. In Section 5, we study the possible mechanism behind our documented return predictability. Section 6 studies whether the return predictability can be explained by risk factors or mispricing explanations. In section 7, we conclude.

2. Literature Review

As social media is commonly used by the market participants, a burgeoning academic literature begins to pay attention to the special role of Twitter in the capital market. Bartov et al. (2017) show that the aggregate opinion posted by the public on Twitter, especially those tweets directly related to earnings, firm fundamentals, and stock trading, helps predict quarterly earnings. Chawla et al. (2016) find that the intraday retail trading pattern is highly related to the diffusion speed of tweets, but the effect is completely reversed the next day. Jung et al. (2018) show that firms are strategic in disseminating earning news on social media. For example, bad news with worse magnitude is less likely to be posted on Twitter. Furthermore, Crowley et al. (2018) find that firms make discretionary choices on timing and presentation format when disseminating information on social media, and the feedback from Twitter users is also incorporated into their dissemination strategies. Lee et al. (2015) show that firms use social media channels, such as

Twitter, to interact with investors in order to attenuate the negative price reactions to consumer product recalls. Crowley et al. (2019) also document that the firms with poor CSR performance use Twitter to play a greenwashing strategy, but this strategy is not effective in leading to capital market consequences. Mao et al. (2012) find that the levels, changes, and absolute changes in the S&P 500 Index are significantly associated with the daily number of tweets mentioning S&P 500 stocks.

CEOs, as the top managerial executives, possess the most immediate and comprehensive information about a firm. Thus, the CEO's social media activities become an important channel for the investors to unearth the inside information about the firm to make trading decisions. Due to the special importance of CEO, recent studies start to focus on the specific role of CEOs' social media activities on firm valuation. Blankespoor et al. (2014) document that the nonverbal visual and auditory signals of CEO presentations at IPO road shows are important for investors' perceptions of firm management which is seriously taken into consideration to value firms. As for Twitter, the news disclosed from the CEO's personal account and the firm's account play different roles on how investors value the firm. According to Elliott et al. (2018), the communication via the CEO's personal Twitter account helps develop a stronger social bond between investors and the firm. Thus, CEOs could utilize social media to improve investors' trust and mitigate the effects of negative information. In the study of Chen et al. (2017), they systematically study the "social executives" which is defined as the top executives making use of social media to connect with investors directly, personally, and in real-time. And they show that top executives' tweets are shown to contain novel and valuable information for investors.

Our paper examines the importance of the CEO on firm stock performance from a different perspective. We focus on how the tweets posted by CEOs affect firm stock performance based on the tweeting skill of CEOs and the frequency of tweeting. We find that the trading strategy based on CEO tweeting skill and tweet amount could deliver a significant abnormal return.

3. Data and Measure

3.1 Data

Twitter was founded in 2006 and has become the most popular microblogging site in the U.S. It is an important social media platform allowing users to post short messages to their followers and the public. The first tweet posted by the CEO appeared in 2008, and CEO tweeting gradually becomes a common phenomenon three years later. Therefore, we test the effect of CEO tweeting on financial market reactions based on the sample from 2012 to 2018. To obtain the CEOs' personal Twitter account information (including account identifier, tweet identifier, date, time, the content, and the number of re-tweets), we use web crawler technique to download Twitter account information of CEOs who serve in firms listed on the NYSE, NASDAQ, or NYSE MKT with share codes are 10 or 11, and can be merged with the CRSP/COMPUSTAT data file. We also obtain the information of CEOs from the Execucomp database, which contains CEO characteristics (e.g., compensation data and ownership data) for all CEOs of S&P 1500 companies as well as companies that were once part of the S&P 1500 index and those are still trading. There is one thing that is worth noticing. Some CEOs post their tweets at a rather high frequency, such as Elon Musk and Tim Cook who post tweets almost on daily basis. Even though our paper mainly focuses on portfolio management at a monthly basis, daily portfolios can also be constructed based on CEO's tweets.

One issue with using the data related to Twitter is that there are many fake accounts that post misleading messages. To obtain accurate estimated results, we identify the true accounts in the first step. To do so, we start with the complete list of all CEOs and locate users with active Twitter accounts that have the exact same first and last names as the CEOs that we are interested in. In addition, we also cross-check the CEOs' middle names, gender, and company information with user characteristics to make sure that the Twitter accounts we use in this research indeed belong to the CEOs. We acknowledge the possibility that a CEO's personal Twitter account may be managed by a CEO's assistant or the firm's social media team. For example, Warren Buffet acknowledged that his tweets were posted by his assistant, and he himself even does not know how to post a tweet. Since we do not have inside information on who actually posts the tweets or managing the account for a CEO, we assume that the tweets posted on CEO's personal account should be approved by CEO and the impact of CEO tweeting does not depend on who post it as the public have no inside information.

The financial data and the accounting information of U.S. firms is collected from the Center for Research in Security Prices (CRSP) and Compustat. Institutional ownership data and analyst coverage for all firms in the sample are obtained from Thomson Reuters Institutional Holdings (13F) and Thomson Reuters IBES, respectively. And we use the one-month U.S. T-bill rate to calculate monthly excess returns.

3.2 Measure of CEO tweeting skill

Following Cohen et al. (2013)'s method of assessing the efficiency of a company's R&D investment, we try to capture CEO tweeting skill by isolating how the tweets posted by CEOs could effectively change the firm market valuation. Intuitively, if a CEO is good at tweeting (i.e. she/he masters the skill of how to announce inspiring news and how to defend company) when facing harsh criticism or big shocks, tweets posted by CEOs help improve investors' trust and thus mitigate negative effects. On the other hand, if a CEO does not know how to appropriately communicate on social media (i.e., she/he makes the public feels like showing off when the company is doing well and cannot explain properly when the company faces doubts, what she/he posts may be harmful to the firm's value. On social media, the impact of CEO language skill can be intensified, as information is accessible to more individual investors and the information could be spread at a much higher speed. And we assume the tweeting skill of a CEO keeps persistent, so we measure the skill by tracking back the past effect of tweets posted by the same CEO on the firm value. Empirically, we estimate how much the change of firm valuation depends on the tweets posted by CEO in the last period for each firm (as shown in Equation 1), and the coefficient β_i, which measures the average effect of CEO tweeting on firm value change, is defined as a proxy for CEO tweeting skill.

$$log\left(\frac{MktCap_{i,t}}{MktCap_{i,t-1}}\right) = \alpha_i + \beta_i \, log\left(1 + Tweets_{i,t-1}\right) + \epsilon_{i,t} \qquad (1)$$

where $MktCap_{i,t}$ and $MktCap_{i,t-1}$ are the market capitalization of firm i at the end of month t and at the end of month $t-1$ respectively, and $Tweets_{i,t-1}$ is the number of tweets posted by the CEO of firm i during month $t-1$.[2] For each firm, β_i is estimated on a rolling window of 36 preceding months before the subsequent stock return is calculated. For example, we run the above regression on firm i for the 36 months from January 2009 to December 2011, and the estimated β_i is our measure for CEO tweeting skill (*Skill*) for firm i in December 2011.

[2] For robustness, we also calculate this measure at a quarterly frequency and obtain similar results. See discussions in Section 4.2 for more details.

The sample coverage and firm characteristics of our data sample are shown in Table 1. Panel A reports the coverage of our sample as a fraction of the CRSP universe. The firms in our sample cover 12% of the total number of firms and 20% of the CRSP common stock universe in terms of market capitalization. This implies that CEO from a company with a high market valuation is more likely to have an official Twitter account. The average monthly number of tweets posted by CEOs in our sample is around 11 and the standard deviation is 12.29. And the mean value of the estimated CEO tweeting skill is 0.38 with a standard deviation 1.19. It shows that the two key variables that we are interested in are associated with high variation. Panel B reports the main statistics of the following five firm characteristics: market capitalization (in billion U.S. dollars), book-to-market ratio (B/M), asset growth (AG), gross profitability (GP), and momentum. Asset growth is measured as the year-over-year growth rate of the total asset; gross profitability is defined as the revenue minus cost of goods sold scaled by assets; momentum is defined as the cumulative stock return from month $t-12$ to month $t-2$ as in Jegadeesh and Titman (1993). Panel C reports CEOs' basic characteristics, and the summary statistics are consistent with our impression about CEOs, such as the median value of age is 56 and the median value of CEO tenure is 7. Thus, we can conclude that our CEO sample is representative.

4. Empirical Results

In this section, we report and discuss our main tests about the effects of CEO tweeting on firm stock performance. To show the robustness of our results, we test the main specifications with alternative measures of CEO tweeting skill. In addition, the documented results also exist the international samples, including sample firms in France, Germany, the United Kingdom, and Japan.

4.1 Main results on portfolio returns

In this section, we present the effects of CEO tweeting on firm stock returns by analyzing the returns on double-sorted portfolios and the corresponding Fama-MacBeth regressions. In each month t, we sort the sample firms based on their CEO tweeting skill β_i estimated from (1) in the preceding 36 months ($[t-36, t-1]$) into three CEO tweeting skill groups (top 30%, middle 40%, and bottom 30%). We then independently sort the firms according to the numbers of tweets posted by their CEOs in the previous month $t-1$ into three groups (top 30%, middle 40%, and bottom 30%). The monthly return is then calculated for each double-sorted portfolio (i.e., the intersection of each pair of groups from the previous sorting procedure) in the following month t.

In Table 2, we report the excess returns, the six-factor alphas (Fama and French, 2018), and the q5-factor alphas (Daniel et al., 2020) of the double-sorted value-weighted and equal-weighted portfolios, and the spread between the extreme portfolios. Conditional on high CEO tweeting skill, the excess returns on the double-sorted portfolios, value-weighted or equal-weighted, are broadly significantly positive, suggesting that CEO tweeting, in general, is beneficial for firms when CEO is good at communication on social media. CEOs' tweets intrigue publicity or a pure short-term effect of attention catching.[3] In addition, based on the social identity theory, the CEO's tweets help improve investors' trust on the firm through the social bond (Elliott et al., 2018). While conditional on low CEO tweeting skill, the portfolio excess/abnormal return decreases as the number of CEO tweets increases, and the difference in monthly return between the two extreme portfolios is above 1% regardless of the measures for the excess return. Intuitively,

[3] We will explore the potential mechanisms in later Section 5.

when a CEO is not good at communication on Twitter, he/she can prevent from the negative effects by speaking less. As discussed earlier, firms can benefit from CEO's higher exposure on social media when a CEO holds a high tweeting skill. However, the benefit of tweeting more when the CEO holds a high tweeting skill is less significant than the harm caused by the CEO who is associated with relatively low tweeting skill. This asymmetry is consistent with the saying that "it is easier to do harm than good".

Furthermore, we analyze how the firm stock performance changes with CEO tweeting skills conditional on different amounts of tweets posted by CEOs. For both the tweets-more and tweets-few groups, the portfolio excess/abnormal return increases with the CEO tweeting skill. However, the portfolio spread of longing high tweeting skill and shorting low tweeting skill conditional on few tweets posted by CEOs, is less significant than that conditional on high CEO tweeting frequency. This suggests that when CEO is active on social media, the benefit (cost) of high (low) CEO tweeting skill is more evident due to the high attention from stakeholders.

Noticeably, we further control more risk factors by switching from CAPM model to six-factor model (Fama and French, 2018) or DHS-factor model (Daniel et al., 2020), and the documented effects of CEO tweeting on firm stock performance still hold. The alpha value of high skill and more tweets group is 0.81% ($t = 2.18$) for equal-weighted portfolio and 0.62% ($t = 1.75$) for value-weighted portfolio with control of the risk factors in Fama and French (2018) six-factor model. When the excess return is based on the DHS-factor model, the abnormal return of high skill and more tweets group is 0.62% ($t = 1.78$) for equal-weighted portfolio and 0.48% ($t = 1.42$) for value-weighted portfolio. For low skill and more tweets group, the three alphas based on the three different asset pricing models of both value and equal-weight portfolio are all significantly negative. Similar to findings based on the CAPM model, the trading portfolio based on the number of tweets and CEO tweeting skill still yield significant abnormal returns after controlling the well-known risk factors. All the above results indicate that we find an alpha that cannot be explained by current well-known risk-factors.

In Table 3, we report the results of Fama-MacBeth regressions of monthly stock returns (excess returns in Panel A, six-factor alphas in Panel B, and q5-factor alphas in Panel C) on CEO tweeting skill and numbers of tweets. The regression is based on the following model,

$$RET_{i,t} = \alpha + \beta\, Skill_{i,t-1} * Tweets_{i,t-1} + \lambda\, X_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

where the dependent variable is one of the three measures of excess return. The variable of interest is the interaction between the dummy for CEO tweeting skill and the dummy for the number of tweets. We regress the excess returns on the four different interactions (high/low skill *more/less tweets) respectively in different specifications. We further control firm characteristics which are related to the firm stock performance. Firm control variables include firm size ($Ln(Size)$), book-to-market ratio ($Ln(B/M)$), focal firm's own lagged monthly return ($RET_{i,t-1}$), medium-term price momentum (Mom), asset growth (AG), gross profitability (GP), and stock turnover (*Turnover*). To control for the potential return spillover effects, we add the average lagged return from period $t-1$ to $t-36$ ($RET_{i,t-36:\,t-1}$) and the interaction term between it and the tweeter amount. CEO level control variables include a dummy variable that equals one if the CEO serves in a Fortune 500 firm ($Fortune\ 500\ CEO$), the age of the CEO in years ($CEO\ age$), a dummy variable which equals to one if the CEO is female ($CEO\ gender$), number of years that the

CEO has served as the firm's CEO ($CEO\ tenure$), the total compensation obtained by the CEO ($CEO\ compensation$), a dummy variable that equals one if the firm's CEO is also the chairman and/or the president ($CEO - Chairman/President$), and the percentage of shares outstanding held by the CEO ($CEO\ ownership$). And industry-fixed effect is controlled in all the specifications.

For each specification, we report the estimated results without firm or CEO level controls, with the firm level controls, and with both firm and CEO level controls in Table 3, respectively. We find that the coefficient of the interaction between the dummy for low tweeting skill ($Skill_{low}$) and the dummy for few tweets ($Tweets_{few}$) is significantly positive, so is the coefficient of the interaction between the dummy for high tweeting skill ($Skill_{high}$) and the dummy for more tweets ($Tweets_{more}$). These results further confirm that if CEOs are associated with low tweeting skills, firms are better off when CEOs speak less. Oppositely, the firm valuation is positively related to the number of tweets posted by CEOs, if the CEO is adept at delivering information on social media. The magnitude of coefficient on the interaction term between the dummy for high tweeting skill ($Skill_{high}$) and the dummy for more tweets ($Tweets_{more}$) is smaller than that on the interaction term between the dummy for low tweeting skill ($Skill_{low}$) and the dummy for more tweets ($Tweets_{more}$). Again, this is in support of the argument that it is easier to do badly than good. In sum, these results are consistent with the findings of portfolio sorting based on CEO tweeting information.

4.2 Robustness tests: alternative measures for CEO tweeting skill

In this section, we further exam the impacts of tweets posted by CEOs with alternative tweeting skill measurements. In specific, we estimate the CEO tweeting skill based on Equation (2), but the firm performance measures are sales, revenues, or profits. Since these firm performance variables are reported quarterly in our dataset, our regression is now based on the rolling windows of the preceding 12 quarters. The measure based on quarterly $MktCap$ is also analyzed for comparison purpose. In each quarter t, we run the quarterly time-series regression to estimate the CEO tweeting skill β_i of firm i.

$$log\left(\frac{Performance_{i,t}}{Performance_{i,t-1}}\right) = \alpha_i + \beta_i\, log\left(1 + Tweets_{i,t-1}\right) + \epsilon_{i,t} \qquad (3)$$

where $Performance_{i,t}$ is the quarterly $MktCap$, $Sales$, $Revenues$, or $Profits$ of firm i at the end of quarter t, and $Tweets_{i,t-1}$ is the number of tweets posted by the CEO of firm i during quarter $t-1$.

To obtain the returns of double-sorted portfolios, in each month t, we sort the sample firms based on their CEO tweeting skill β_i estimated from (3) into three CEO tweeting skill groups (top 30%, middle 40%, and bottom 30%). We also sort the firms independently on the numbers of tweets posted by their CEOs in the previous quarter $t-1$ into three groups (top 30%, middle 40%, and bottom 30%). The quarterly return is then calculated for each double-sorted portfolio in the following quarter $t+1$. We report the Fama and French (2018) six-factor abnormal returns of the equal-weighted portfolios from double sorting. Results are presented in Table 4. Generally speaking, alphas of trading portfolios based on the CEO tweeting skill measured by the firm performance are not as significant as those using β_i estimated by market value. This may be explained by the noise in the fundamental data. Using current accounting principles, companies are able to manipulate their financial statements by either deferring some costs or recognizing profits in advance. Currently, there is no general procedure that works for all company's financial statement to eliminate potential noise in financial data, and we use the raw data without further data cleaning. Also, these fundamental variables reflect the information of multiple factors such as company strategy, seasonal fluctuation, and new projects, which could directly affect sales, revenues, and profits. All these could help explain why the effect of CEO tweeting is not as strong as those discussed in the previous section.

Despite the potential noise of the alternative CEO tweeting skill measurements, the results still provide supportive evidence on our main assumptions. Consistent with our main results, when CEO tweeting skill is low, the portfolio return for the more tweets subgroup is more than 1% lower than that for the few-tweets subgroup at a significance level of less than 5%. Conditional on tweeting more, the portfolio return for the high-skill subgroup is significantly higher than that for the low-skill subgroup. The results are unanimous across all the four different CEO tweeting skill measures. The difference between extreme portfolios is still significant despite the potential noises in the data we use. In sum, our method of capturing CEO tweeting skill is shown to be reasonable, and we can effectively differentiate stocks based on our proxies. Moreover, the correlation between CEO tweets and stock return is robust to the alternative CEO tweeting skill measures.

4.3 Extension: international sample

To further investigate the robustness of results, we also test our main hypothesis based on the firm samples in other countries. Twitter is a globally popular social media that is also well accepted in Europe and Latin America. And we test whether the documented results hold across nations. We extend our analysis to firms in other developed countries such as France, Germany, and the United Kingdom. These countries are chosen because they have relatively developed financial markets and are influential worldwide. In Table 5, we present the results of Fama-MacBeth regressions regressing monthly stock returns on the CEO tweeting skill (measured as in Section 4.1) and the number of CEO tweets. The dependent variable is abnormal stock return adjusted by CAPM model or Fama and French (2018) six-factor model. Stocks with prices less than \$5 at the end of the previous year are excluded. In Panel A, the combined effect of low CEO tweeting skill together with tweeting less is reported; in Panel B, the combined effect of high CEO tweeting skill together with tweeting more is reported. Consistent with the results found in the U.S. sample, when the CEO tweeting skill is low, CEO tweeting less could be beneficial for the firm. In contrast, more tweets posted by CEOs who are good at communicating on social media could help boost firm market valuation. These two effects are also broadly observed among the international sample firms in France, Germany, United Kingdom, and Japan. The specification is based on Equation (2), and the coefficients on interaction term $Skill_{low} * Tweets_{more}$ are all significantly negative across countries (except for Japan) as what we expected. In general, the effects of CEO tweeting on firm stock performance are less significant in Germany and Japan. One possible explanation is that the tweets in Germany and Japan are more likely to be posted in their own native language (i.e., German for Germany, and Japanese for Japan), and there exist language barriers for international investors from other countries. As a result, the effects of the CEO tweets (positive or negative) from non-English-speaking countries are in general weaker than those in English-speaking countries such as the U.S. and the U.K. In conclusion, the documented effects of CEO tweeting skill in the financial market exist in general but may differ across countries.

4.4 Effects of CEO tweeting on firm operating performance

So far, we show that the CEO tweeting on social media could have a crucial influence on firms' stock market performance. The tweets posted by CEOs who are good at communicating could gain trust from stakeholders (including investors, consumers, suppliers et al.), and further result in changes in firm operating performance. For example, when a CEO is good at advertising the products of his/her firm, the tweets posted by CEO help intrigue higher sales, higher revenue, and consequently improve firm performance. Also, tweets posted by CEO potentially influence the company's overall image, and further strengthen/worsen employee's loyalty or customers' confidence. Firm's operating ability could be impacted because of high/ low employee morale/consumer identity. Employees are inspired to work for CEO who has strong managerial ability as the company is more likely to have a promising future. In contrast, if a CEO cannot handle tweets well, stakeholders may doubt the managerial team and question the firm's current strategy. All these could result in stakeholders losing trust and hurt firm performance. To test if CEO tweeting can have real effects on firm operating performance, we regress the changes in firm operating performance on the interaction term of CEO tweeting skill and the number of tweets with the following specification,

$$OP_{i,t} - OP_{i,t-1} = \alpha + \beta\, Skill_{i,t-1} * Tweets_{i,t-1} + \lambda\, X_{i,t-1} + \varepsilon_{i,t} \quad (4)$$

where the dependent variable OP is one of the quarterly growth measures on firm operating performance: ROA, $Sales$, $Revenues$, and $Profits$. The independent variable of interest ($Skill \times Tweets$) is either $Skill_{low} \times Tweets_{few}$ or $Skill_{high} \times Tweets_{more}$. We also include industry dummy, firm characteristics control variables, and CEO-level control variables which are the same as those described in Table 3.

Consistent with our arguments, the results in Table 6 demonstrate both the significant negative effect of the combination of low CEO tweeting skill and a large amount of CEO tweets (in Panel A) and the significant positive effect of more CEO tweets associated with high CEO tweeting skill (in Panel B). For all the four operating performance measures, the estimated coefficients on the interaction term of tweeting skill and tweet amount are all statistically significant. The estimation results also tell us that sales are most sensitive to CEO tweets among the four firm operating performance measures, with a coefficient around 0.36 which is much greater than the estimated coefficients of other operating performance variables (around 0.1). This can be explained by the fact that sales are most highly related to advertising strategy. Tweets posted by CEO can somehow be viewed as a new type of ad and the CEO is undoubtedly the most influential salesman of a firm, and the quality of "ad" will greatly improve/worsen sales performance. In sum, the results in Table 6 show the effects of tweets posted by CEOs on the firm's operating performance, and this is one of the channels that the CEO tweeting affects firm stock performance.

5. Behavioral Mechanisms

In this section, we further explore the potential mechanisms that help explain the effects of CEO tweeting on firm stock performance. Following the existing literature (e.g., Cohen and Lou, 2012; Lee et al., 2019; Ali and Hirshleifer, 2020), we test the two well-known mechanisms: investors' limited attention and limits to arbitrage.

5.1 Investor limited attention

Limited attention is widely documented as an important behavioral explanation on return predictability. As argued by Barber and Odean (2008), investors are prevented from taking all the possible equity investments into consideration by their limited time, resource, and attention. To test whether investor's limited attention is a mechanism helps explain the documented return predictability of CEO tweeting, we use three proxies for limited attention: advertising expenses ($Advertising$), analyst coverage ($Analyst\ Coverage$), and residual institutional ownership ($Res\ Inst\ Own$). $Advertising$ is the focal firm's advertising expenses in the previous year. $Analyst\ Coverage$ is the number of analysts covering the focal firm at the end of the previous month. $Res\ Inst\ Own$ is the institutional ownership orthogonalized to firm size at the end of the December of the prior year. Usually, firms with high expenses on advertising are more likely to be known by the public and thus attract more attention. For analysts, they focus on firms that investors are interested in, so they can potentially serve more clients. And in turn, higher analyst coverage will lead more investors to pay attention to the stocks. Institutional ownership is also a good proxy of investor attention. The companies invested by institutional investors are deeply studied and analyzed by professional institutions. For the firms that received high attention, information is covered and analyzed by more parties, and investors pay more attention and update their beliefs more efficiently. While for those firms associated with less attention, there exists more information asymmetry and market inefficiency.

To test whether limited attention is the potential mechanism of our documented results, we further sort sample firms according to the attention measure in addition to the double sorting as described above (CEO tweeting skill and the number of CEO tweets). Each sorting procedure halves the sample firms. The return spread between the few tweet subgroup and the more tweets subgroup conditional on low CEO tweeting skill, and the return spread between high and low CEO tweeting skill conditional on more tweets for both low and high attention groups are presented in Panel A of Table 7. Conditional on low CEO tweeting skill, the return spread of the few-tweets subgroup over the more-tweets subgroup decreases with the level of investor attention, and the estimated difference is significant at 1% level for all the three attention measures. And conditional on CEO tweeting frequently, the return spread between high and low CEO tweeting skill is larger when the firm is associated with less attention. This again suggests that when investors pay less attention, the effect of CEO tweeting is stronger on firm stock performance. The firms associated with less attention experience a higher level of asymmetric information problem and the market reacts less effectively. In addition, if a company is heavily investigated and analyzed, investors may rely less on the information posted on social media.

5.2 Limits to arbitrage

According to the existing literature (Hirshleifer et al., 2011; Beneish et al., 2015), we expect stronger effects of CEO tweeting for the stocks associated with firms with higher arbitrage costs, due to the barriers for investors to fully update stock prices. To analyze the mechanism of limits to arbitrage, we do a similar triple-sorting procedure based on each of the proxies of limits to arbitrage ($StVol$, $IdioVol$, or $Funding\ illiquidity$), CEO tweeting skill, and the number of CEO tweets. $StVol$ is the stock volatility in the previous quarter; $IdioVol$ is the standard error of the residuals from a regression of daily stocks returns on the Fama and French (1993) three-factor model in the previous month; $Funding\ illiquidity$ is the broker-dealer's quarterly leverage as defined by and obtained from Federal Reverse. Firms associated with high stock price volatility are commonly deemed as with high illiquidity. Similarly, higher $IdioVol$ stands for higher illiquidity. Broker-dealer's quarterly leverage is used as a proxy for illiquidity as the higher the ratio, the harder it is to buy/sell a stock. When the stock's liquidity is low, the efficient markets hypothesis cannot hold anymore. Thus, we expect stronger effects of CEO tweeting skill on the financial market when the firm is associated with a higher cost of arbitrage. As shown in Panel B of Table 7, conditional on low CEO tweeting skill, the return spread of the few tweets subgroup over the more tweets subgroup increases with the level of limits to arbitrage. Conditional on more tweets, the return spread between high and low CEO tweeting skill groups also follows a similar trend. The results confirm that the estimated effects of CEO tweets are magnified for those firms associated with higher limits to arbitrage, implying limits to arbitrage can be a potential underlying mechanism of our documented results.

In addition, we run the horse-race tests among these two competing mechanisms to tell which one plays a more important role. We add interaction terms between the dummy value of the CEO tweeting skill (low/high), the number of CEO tweets (more/few) ($Skill_{i,t-1} * Tweets_{i,t-1}$), and the dummy variable for attention and limits to arbitrage proxies (D_x, D_y) as shown in Equation (4).

$$RET_{i,t} = \alpha + \beta_1\, Skill_{i,t-1} * Tweets_{i,t-1} + \beta_2\, D_x + \beta_3\, Skill_{i,t-1} * Tweets_{i,t-1} * D_x + \beta_4\, D_y + \beta_5\, Skill_{i,t-1} * Tweets_{i,t-1} * D_y + \lambda\, X_{i,t-1} + \varepsilon_{i,t} \quad (4)$$

where the independent variable ($Skill_{i,t-1} * Tweets_{i,t-1}$) equals $Skill_{low} * Tweets_{more}$ in Panel A of Table 8 and $Skill_{high} * Tweets_{more}$ in Panel B of Table 8. D_1 (limited attention) equals one if the limited attention characteristic ($Advertising$, $Analyst\ Coverage$, or $Res\ Inst\ Own$) is above the median and zero otherwise. D_2 (limits to arbitrage) equals one if the limits to arbitrage characteristic ($StVol$, $IdVol$, or $Illiquidity$) is above the median and zero otherwise. The control variables are the same as those in Table 3. Panel A of Table 8 compares the two mechanisms underlying the effect of CEO low tweeting skill and tweets more. The estimated coefficients of the interaction term between the CEO tweeting effect and high attention dummy are significantly positive, and the estimated coefficients of the interaction term between the CEO tweeting effect and high limits to arbitrage dummy are negative for different measures. The results are consistent with the statement that both limited attention and limits to arbitrage are the potential mechanisms underlying our documented effects. However, compared with the estimated coefficients of the interaction term for the limits to arbitrage, the corresponding estimated coefficients for the limited attention are both statistically and economically more significant. Similarly, the limited attention is also the relatively more important mechanism underlying the effect of CEO high tweeting skill and tweets more as shown Panel B of Table 8.

In a nutshell, with limited investor's attention or high limits to arbitrage, the spread between the extreme portfolios (either sorting on tweeting skill or the number of tweets) are stronger and statistically more significant, indicating both limited attention and limits to arbitrage are possible mechanisms that explain the documented effects of CEO tweeting on the financial market. Based on the horse-race tests, limited attention tends to be the more influential mechanism behind our documented effects.

6. Risk versus Mispricing

In this section, we analyze whether the effect of CEO tweeting is explained by mispricing channels or risk factors, by testing how the stock returns react around earnings announcement window, and whether the future standardized unexpected earnings can be predicted by CEO tweeting skill and the number of tweets posted by CEO.

To tell whether the documented return predictability is resulted from mispricing or risk factors, a commonly adopted method is to test the return predictability around the earning announcement days. If the mispricing explanations are the key factors to the documented effects of CEO tweeting, the effects tend to be magnified around the earning announcement days as the market updates and incorporate new information during this period. In contrast, if our results are explained by the risk factors, we should expect no magnified effects during the earning announcement window. To test if there exist enhanced effects of CEO tweeting during the earning announcements window, we add the interaction terms of CEO tweeting skill, tweets amount, and dummy variables regarding the earnings announcing window to the previous Fama-Macbeth regression,

$$Daily\_RET_{i,t} = \alpha + \beta_1\, Skill_{i,t-1} * Tweets_{i,t-1} + \beta_2\, EDAY_{i,t} + \beta_3\, Skill_{i,t-1} * Tweets_{i,t-1} * EDAY_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $Daily\_RET_{i,t}$ is the daily stock return for firm i at day t; $EDAY_{i,t}$ is a dummy variable that equals 1 if day t is within the three-day window [-1,1] around an earnings announcement of the firm i and zero otherwise. Following Engelberg et al. (2018), we collect earnings announcement dates from the Compustat quarterly database, calculate the trading volume of the firm stock scaled by market trading volume on the day before, the day of, and the day after the reported earnings announcement date, and then define the day with the highest volume as the earnings announcement day. Industry dummy is included in all regressions. Control variables are the lagged values of stock return, stock return squared, and trading volume up to ten days before day t. For brevity, the coefficients on control variables are not reported.

As shown in Table 9, the estimated results of the two interesting coefficients are both consistent with our expectations. $Skill_{low} * Tweets_{more} * EDAY$ is negatively significant both statistically and economically (in Panel A), and the estimated coefficient of $Skill_{high} * Tweets_{more} * EDAY$ is significantly positive (in Panel B). The results imply the effects of CEO tweeting are significantly stronger around earnings announcement days. Noticeably, on average the magnitude of the estimated coefficient on $Skill * Tweet * EDAY$ (around 0.04) is much greater than that coefficient of $Skill * Tweet$ (around 0.01), indicating the effect of CEO tweeting around announcing days is 4 times more influential. It provides strong evidence that the effects of CEO tweeting could be ascribed to mispricing explanations.

To further examine whether the documented effects are resulted from risk factors or not, we also test whether CEO tweeting can help explain the future standardized unexpected earnings (SUE) changes using Fama-Macbeth regressions. SUE is defined as the unexpected earnings (year-over-year change in quarterly earnings before extraordinary items) scaled by the standard deviation of unexpected earnings over the eight preceding quarters. The sample is restricted to the firms with fiscal quarters ending in March, June, September, and December. Lagged SUEs up to four quarters prior are included as control variables since analysts misevaluate the earning sometimes and the mistake could last for several periods before analysts finally correct them. Across all four quarters, the combined effect of low CEO tweeting skill and more CEO tweets is negative on SUE, while the effect of high CEO tweeting skill and more CEO tweets is positive. A possible explanation is that analysts make predictions depending on financial statement data and business strategy, and CEO tweeting has not been taken into consideration or this information is undervalued during the assessment. As a result, part of the unexpected earnings could be originated from the effects of CEO tweeting. As shown by our previous results, tweets posted by CEOs could have a positive/negative impact on the firm's operation performance which will then lead to positive/negative unexpected earnings. We find that the effects within the first and second quarters of the year are statistically more significant. A potential explanation is that as it approaches the end of the year, especially the fourth quarter which includes the holiday season, there are other more salient ways (e.g., holiday discounts, commercials) to affect earnings other than CEO tweeting. Taking Apple as an example, in the first two quarters there are no major updates of their products, while in the third quarter (September) Apple will release their most important, also most conspicuous product, such as the new generation of iPhone. Tim Cook's tweeting may have a huge impact on earnings in the first two quarters, while in the last two quarters it's more likely to let the product speak for itself, and earnings depend more on the latest iPhone's performance rather than the CEO's tweets.

To conclude, CEO tweeting has an enhanced impact on stock returns during earnings announcement period and tweets do have an impact on SUEs. Both results are in support the hypothesis that our documented result is more likely to be explained by the mispricing rather than risk factors.

7. Conclusion

The dramatic increase in the use of social media among CEOs in the past few years has a significant impact on the capital market. CEOs use their Twitter accounts as a new platform to disclose information and communicate with stakeholders more directly and easily. This paper studies the effects of CEO tweeting on the firm stock performance based on the sample firms from 2012 to 2018 in the U.S. By creating a measure of CEO tweeting skill, we show that if CEO tweeting skill is high, firms can benefit from the CEO's active participation on Twitter. While conditional on CEO tweeting frequently, it is significantly harmful to the firm values when the tweeting skill of the CEO is low. The documented results are not restricted to U.S firms, but also can be observed among firms in France, Germany, and the United Kingdom. We show that limited attention and limits to arbitrage are the potential mechanisms behind our documented results. The magnified effect of CEO tweeting during earnings announcement windows and the predictive power of CEO tweeting on future standardized unexpected earnings suggest that behavioral biases rather than risk factors are more likely to explain our findings.

The contributions of this paper are twofold. First, our results indicate that CEO tweeting skill combined with CEO tweeting frequency can be informative on firm stock performance. And the excess return of the constructed portfolio based on CEO tweeting information cannot be explained by the well-known risk factors. Second, CEOs could examine their tweeting skills following our paper and disclose information strategically on Twitter. In addition, CEOs may hire professional assistants to help improve the quality of their tweets to avoid the unnecessary stock price shocks.

References

Ali, U., Hirshleifer, D., 2020. Shared analyst coverage: Unifying momentum spillover effects. Journal of Financial Economics 136, 649-675.

Barber, B. M., & Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. The review of financial studies 21, 785-818.

Bartov, E., Faurel, L., Mohanram, P. S. , 2017. Can Twitter help predict firm-level earnings and stock returns?. The Accounting Review 93, 25-57.

Beneish, M. D., Lee, C. M., Nichols, D. C., 2015. In short supply: Short-sellers and stock returns. Journal of accounting and economics 60, 33-57.

Bigelow, L., Lundmark, L., McLean Parks, J., Wuebker, R., 2014. Skirting the issues: Experimental evidence of gender bias in IPO prospectus evaluations. Journal of Management 40, 1732-1759.

Blankespoor, E., Miller, G. S., White, H. D., 2014. The role of dissemination in market liquidity: Evidence from firms' use of Twitter™. The Accounting Review 89, 79-112.

Brochet, F., Limbach, P., Schmid, M., Scholz-Daneshgari, M., 2019. CEO tenure and firm value. In Paris December 2015 Finance Meeting EUROFIDAI-AFFI.

Chawla, N., Da, Z., Xu, J., Ye, M., 2016. Information Diffusion on Social Media: Does It Affect Trading, Return, and Liquidity?. Return, and Liquidity.

Chen, H., De, P., Hu, Y. J., Hwang, B. H., 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. The Review of Financial Studies 27, 1367-1403.

Chen, H., Hwang, B. H., Liu, B., 2017. Economic consequences of social media adoption by CEOs and CFOs. Unpublished working paper. Cornell University, Ithaca, NY.

Cohen, B. D., Dean, T. J., 2005. Information asymmetry and investor valuation of IPOs: Top management team legitimacy as a capital market signal. Strategic Management Journal 26, 683-690.

Cohen, L., Diether, K., Malloy, C., 2013. Misvaluing innovation. The Review of Financial Studies 26, 635-666.

Cohen, L., Lou, D., 2012. Complicated firms. Journal of Financial Economics 104, 383-400.

Crowley, R. M., Huang, W., Lu, H., 2018. Discretionary dissemination on Twitter. Rotman School of Management Working Paper, (3105847).

Crowley, R. M., Huang, W., Lu, H., Luo, W., 2019. Do Firms Manage Their CSR Reputation? Evidence from Twitter. Evidence from Twitter. Unpublished working paper.

Daniel, K., Hirshleifer, D., Sun, L., 2020. Short-and long-horizon behavioral factors. Review of Financial Studies 33, 1673-1736.

Elliott, W. B., Grant, S. M., Hodge, F. D., 2018. Negative news and investor trust: The role of $ Firm and# CEO Twitter use. Journal of Accounting Research 56, 1483-1519.

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

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.

Fama, E. F., French, K. R., 2018. Choosing factors. Journal of Financial Economics 128, 234-252.

Gormley, T. A., Matsa, D. A., Milbourn, T., 2013. CEO compensation and corporate risk: Evidence from a natural experiment. Journal of Accounting and Economics 56, 79-101.

Higgins, M. C., Gulati, R., 2006. Stacking the deck: The effects of top management backgrounds on investor decisions. Strategic Management Journal 27, 1-25.

Hirshleifer, D., Teoh, S.H., Yu, J., 2011. Short arbitrage, return asymmetry, and the accrual anomaly. Review of Financial Studies 24, 2429–2461.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance 48, 65–91.

Jung, M. J., Naughton, J. P., Tahoun, A., Wang, C., 2018. Do firms strategically disseminate? Evidence from corporate use of social media. The Accounting Review 93, 225-252.

Lee, L. F., Hutton, A. P., Shu, S., 2015. The role of social media in the capital market: Evidence from consumer product recalls. Journal of Accounting Research 53, 367-404.

Lee, C. M., Sun, S. T., Wang, R., Zhang, R., 2019. Technological links and predictable returns. Journal of Financial Economics 132, 76-96.

Lilienfeld-Total, U. V., Ruenzi, S., 2014. CEO ownership, stock market performance, and managerial discretion. The Journal of Finance 69, 1013-1050.

Mao, Y., Wei, W., Wang, B., Liu, B., 2012. Correlating S&P 500 stocks with Twitter data. In Proceedings of the first ACM international workshop on hot topics on interdisciplinary social networks research (pp. 69-72).

Sprenger, T. O., Tumasjan, A., Sandner, P. G., Welpe, I. M., 2014. Tweets and trades: The information content of stock microblogs. European Financial Management 20, 926-957.

Table 1: Summary statistics

This table presents the summary statistics for the sample coverage and firm characteristics. The sample includes S&P 1500 firms with CEO Twitter account and share codes are 10 or 11. Stocks with price less than $5 at the end of the previous year and financial firms (one-digit SIC code = 6) are excluded. The sample period for the rolling-window estimation of CEO tweeting skill starts from January 2009 and ends at December 2015, while the sample period for the subsequent monthly stock returns is from January 2012 to December 2018. All variables' definitions are in the Appendix Table. Panel A reports the sample coverage statistics as a fraction of the CRSP universe in terms of the total number of firms and total market capitalization. This panel also provides the statistics for the monthly number of CEO's tweets and CEO tweeting skill. Panel B reports the statistics of five firm characteristics: market capitalization ($bln), book-to-market ratio, asset growth, gross profitability, and momentum. Panel C reports the statistics of seven CEO characteristics in S&P 1500 firms: Fortune 500 CEO (dummy), CEO age, CEO gender (dummy), CEO tenure, CEO compensation ($mln), CEO ownership, and CEO-Chairman/President (dummy).

Panel A: Sample coverage

	Mean	StD	25th	Med	75th
% of total number of stocks covered in S&P 1500	0.12	0.03	0.10	0.12	0.14
% of total market capitalization covered in S&P 1500	0.20	0.04	0.19	0.20	0.21
The monthly number of tweets per CEO	11.62	12.29	6.93	10.08	13.77
CEO tweeting skill	0.38	1.19	-0.69	0.33	1.32

Panel B: Firm characteristics

	Mean	StD	25th	Med	75th
Market capitalization ($ bln)	5.87	10.44	1.48	4.74	14.09
B/M	0.87	1.29	0.28	0.57	1.15
Asset growth	0.17	0.28	-0.05	0.14	0.32
Gross profitability	0.32	0.26	0.19	0.28	0.38
Momentum	0.16	0.38	-0.07	0.12	0.32

Panel C: CEO characteristics

	Mean	StD	25th	Med	75th
Fortune 500 CEO (dummy)	0.31	0.38	0.00	0.00	1.00
CEO age	56.77	7.49	52.00	56.00	60.00
CEO gender (dummy)	0.03	0.19	0.00	0.00	0.00
CEO tenure	7.78	8.13	3.00	7.00	11.00
CEO compensation ($ mln)	5.98	7.97	1.59	3.14	10.88
CEO ownership	0.03	0.07	0.00	0.02	0.04
CEO-Chairman/President (dummy)	0.63	0.52	0.00	1.00	1.00

Table 2: Portfolio returns: double sorts based on the CEO tweeting skill and the number of tweets

This table reports the monthly returns on the value-weighted and equal-weighted portfolios which are double-sorted on the CEO tweeting skill and the number of CEO tweets. The CEO tweeting skill is estimated from the time-series regression with a rolling window of 36 months; i.e. in each month t, we run the monthly time-series regression $log\left(\frac{MktCap_{i,t}}{MktCap_{i,t-1}}\right) = \alpha_i + \beta_i \, log(1 + Tweets_{i,t-1}) + \epsilon_{i,t}$ for the previous 36 months to estimate the CEO tweeting skill β_i, based on the monthly number of tweets by the CEO of firm i and the change of market capitalization. A firm is included in the rolling-window sample only if the corresponding CEO has tweeted in at least 18 months among the 36 months of the rolling window and the CEO does not change within the same 36 months as well as in the subsequent month when portfolio returns are calculated. In each month t, based on the estimated β_i, firms are sorted into three CEO tweeting skill groups (top 30%, middle 40%, and bottom 30%), and also independently sorted on the number of CEO tweets of the previous month into three groups (top 30%, middle 40%, and bottom 30%). The monthly portfolio return is calculated for the intersection of each pair of groups from the two sorts in the following month $t + 1$. Panel A presents the portfolio CAPM alphas. Panel B presents the abnormal portfolio returns using the Fama and French (2018) six-factor model. Panel C reports abnormal portfolio returns using the Daniel et al. (2020) DHS-factor model. Stocks with price less than $5 at the end of the previous year are excluded. The sample period for the rolling-window estimation of CEO tweeting skill starts from January 2009 and ends at December 2015, while the sample period for the subsequent monthly stock returns is from January 2012 to December 2018. *T*-statistics are calculated using the Newey-West (1987) method with six lags and shown in parentheses. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: CAPM alphas

Equal Weights	Few tweets (30%)	More tweets (30%)	Spread (More-Few)
High Skill (30%)	0.66*	0.93**	0.27
	(1.73)	(2.36)	(0.82)
Low Skill (30%)	0.53	-1.05***	-1.58***
	(1.44)	(-2.64)	(-3.89)
Spread (High-Low)	0.13	1.98***	
	(0.50)	(4.81)	
Value Weights	**Few tweets (30%)**	**More tweets (30%)**	**Spread (More-Few)**
High Skill (30%)	0.51	0.72*	0.21
	(1.38)	(1.89)	(0.66)
Low Skill (30%)	0.41	-0.81**	-1.22***
	(1.15)	(-2.11)	(-3.11)
Spread (High-Low)	0.10	1.53***	
	(0.40)	(3.84)	

Table 2 (continued)

Panel B: six-factor alphas

Equal Weights	Few tweets (30%)	More tweets (30%)	Spread (More-Few)
High Skill (30%)	0.55	0.81**	0.26
	(1.52)	(2.18)	(0.75)
Low Skill (30%)	0.44	-0.91**	-1.35***
	(1.27)	(-2.44)	(-3.50)
Spread (High-Low)	0.11	1.72***	
	(0.44)	(4.43)	

Value Weights	Few tweets (30%)	More tweets (30%)	Spread (More-Few)
High Skill (30%)	0.42	0.62*	0.20
	(1.23)	(1.75)	(0.59)
Low Skill (30%)	0.34	-0.70*	-1.04**
	(1.01)	(-1.95)	(-2.81)
Spread (High-Low)	0.08	1.32***	
	(0.35)	(3.53)	

Panel C: DHS-factor alphas

Equal Weights	Few tweets (30%)	More tweets (30%)	Spread (More-Few)
High Skill (30%)	0.40	0.62*	0.22
	(1.19)	(1.78)	(0.59)
Low Skill (30%)	0.32	-0.70**	-1.02***
	(0.99)	(-1.97)	(-2.80)
Spread (High-Low)	0.08	1.32***	
	(0.34)	(3.65)	

Value Weights	Few tweets (30%)	More tweets (30%)	Spread (More-Few)
High Skill (30%)	0.31	0.48	0.17
	(0.95)	(1.42)	(0.48)
Low Skill (30%)	0.25	-0.54	-0.79**
	(0.79)	(-1.59)	(-2.24)
Spread (High-Low)	0.06	1.02***	
	(0.27)	(2.90)	

Table 3: Fama-MacBeth regressions

This table presents the results from Fama-MacBeth (1973) regressions of monthly stock returns on the number of CEO tweets and the CEO tweeting skill. The CEO tweeting skill is estimated from the time-series regression with a rolling window of 36 months. In each month *t*, we run the monthly time-series regression $log\left(\frac{MktCap_{i,t}}{MktCap_{i,t-1}}\right) = \alpha_i + \beta_i\, log\left(1\ + Tweets_{i,t-1}\right) + \epsilon_{i,t}$ for the previous 36 months to estimate the CEO tweeting skill β_i, based on the monthly number of tweets posted by the CEO of firm *i* and the change of market capitalization. A firm is included in the rolling-window sample only if the corresponding CEO has tweeted in at least 18 months among the 36 months of the rolling window and the CEO does not change within the same 36 months as well as in the subsequent month when portfolio returns are calculated. $Skill_{high}$ ($Skill_{low}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% group based on CEO tweeting skill during the past 36 months and zero otherwise. $Tweets_{more}$ ($Tweets_{few}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% of the number group based on the number of CEO tweets in month $t-1$. Industry dummy is included in all regressions. Firm control variables include firm size ($Ln(Size)$), book-to-market ratio ($Ln(B/M)$), focal firm's own lagged monthly return ($RET_{i,t-1}$), medium-term price momentum (Mom), asset growth (AG), gross profitability (GP), stock turnover (*Turnover*), and focal firm's value-weighted industry return (Ind_mom). CEO control variables include a dummy variable that equals one if the CEO serves in a Fortune 500 firm (Fortune 500 CEO), the age of CEO in year t (CEO age), a dummy variable equals one if the CEO is female (CEO gender), number of years the CEO has served as the firm's CEO (CEO tenure), the total compensation obtained by the CEO (CEO compensation), a dummy variable that equals one if the firm's CEO is also the chairman and/or the president (CEO-Chairman/President), and the percentage of shares outstanding held by the CEO (CEO ownership). All variables are defined in Appendix. Panel A presents the results on abnormal stock returns using CAPM. Panel B presents the results on abnormal stock returns using the Fama and French (2018) six-factor model. Panel C reports the results on abnormal portfolio returns using the Daniel et al. (2020) DHS-factor model. Stocks with price less than \$5 at the end of previous year are excluded. The sample period for the rolling-window estimation of CEO tweeting skill starts from January 2009 and ends at December 2015, while the sample period for the subsequent monthly stock returns is from January 2012 to December 2018. *T*-statistics are calculated using the Newey-West (1987) method with six-period lag and shown in parentheses. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3 (continued)

Panel A: RET_mkt

	(1)	(2)	(2)	(4)	(5)	(6)	(7)	(8)	(8)	(10)	(11)	(11)
$Skill_{low} * Tweets_{few}$	0.43	0.38	0.33									
	(1.48)	(1.26)	(1.07)									
$Skill_{low} * Tweets_{more}$				-0.84***	-0.75**	-0.71**						
				(-2.71)	(-2.38)	(-2.27)						
$Skill_{high} * Tweets_{more}$							0.79***	0.72**	0.65**			
							(2.60)	(2.25)	(2.06)			
$Skill_{high} * Tweets_{few}$										0.55*	0.47	0.41
										(1.78)	(1.54)	(1.35)
$RET_{i,t-36:t-1} * Tweets_{few}$	0.11	0.12	0.08							0.16	0.14	0.09
	(0.65)	(0.65)	(0.55)							(0.95)	(0.76)	(0.68)
$RET_{i,t-36:t-1} * Tweets_{more}$				-0.20	-0.18	-0.18	-0.19	-0.15	-0.19			
				(-1.32)	(-1.04)	(-1.19)	(-1.30)	(-0.95)	(-1.24)			
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Characteristics Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
CEO Characteristics Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Number of months	84	84	84	84	84	84	84	84	84	84	84	84
R^2	0.04	0.06	0.07	0.07	0.09	0.10	0.06	0.08	0.09	0.05	0.07	0.08

Table 3 (continued)

Panel B: RET_FF6

	(1)	(2)	(2)	(4)	(5)	(5)	(7)	(8)	(8)	(10)	(11)	(11)
$Skill_{low} * Tweets_{few}$	0.36	0.32	0.27									
	(1.30)	(1.18)	(0.99)									
$Skill_{low} * Tweets_{more}$				-0.77**	-0.67**	-0.62**						
				(-2.56)	(-2.18)	(-2.04)						
$Skill_{high} * Tweets_{more}$							0.70**	0.61**	0.58**			
							(2.33)	(2.11)	(1.97)			
$Skill_{high} * Tweets_{few}$										0.46	0.39	0.33
										(1.60)	(1.33)	(1.16)
$RET_{i,t-36:t-1} * Tweets_{few}$	0.09	0.09	0.08							0.11	0.09	0.10
	(0.59)	(0.59)	(0.48)							(0.84)	(0.71)	(0.51)
$RET_{i,t-36:t-1} * Tweets_{more}$				-0.21	-0.19	-0.16	-0.17	-0.15	-0.16			
				(-1.21)	(-1.04)	(-0.91)	(-1.11)	(-1.00)	(-1.06)			
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Characteristics Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
CEO Characteristics Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Number of months	84	84	84	84	84	84	84	84	84	84	84	84
R^2	0.03	0.05	0.06	0.06	0.08	0.09	0.05	0.07	0.08	0.04	0.06	0.07

Table 3 (continued)

Panel B: RET_DHS

Panel C	(1)	(2)	(2)	(4)	(5)	(5)	(7)	(8)	(8)	(10)	(11)	(11)
$Skill_{low} * Tweets_{few}$	0.26	0.24	0.19									
	(0.99)	(0.90)	(0.77)									
$Skill_{low} * Tweets_{more}$				-0.57**	-0.49*	-0.48*						
				(-2.07)	(-1.84)	(-1.76)						
$Skill_{high} * Tweets_{more}$							0.56**	0.50*	0.48*			
							(1.93)	(1.76)	(1.66)			
$Skill_{high} * Tweets_{few}$										0.32	0.29	0.24
										(1.21)	(1.06)	(0.84)
$RET_{i,t-36:t-1} * Tweets_{few}$	0.07	0.07	0.05							0.09	0.07	0.07
	(0.54)	(0.42)	(0.33)							(0.53)	(0.55)	(0.44)
$RET_{i,t-36:t-1} * Tweets_{more}$				-0.16	-0.12	-0.14	-0.15	-0.12	-0.10			
				(-0.93)	(-0.98)	(-0.84)	(-0.90)	(-0.79)	(-0.70)			
Industry Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Characteristics Controls	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
CEO Characteristics Controls	N	N	Y	N	N	Y	N	N	Y	N	N	Y
Number of months	84	84	84	84	84	84	84	84	84	84	84	84
R^2	0.03	0.05	0.06	0.06	0.08	0.09	0.05	0.07	0.08	0.04	0.06	0.07

Table 4: Robustness tests: alternative measures for CEO tweeting skill

This table reports the quarterly abnormal returns on the equal-weighted portfolios double-sorted on the CEO tweeting skill (estimated using alternative firm performance measures (*MktCap*, *Sales*, *Revenues*, or *Profits*)), and the number of CEO tweets. The CEO tweeting skill is estimated from the time-series regression with a rolling window of 12 quarters. In each quarter *t*, we run the quarterly time-series regression $log\left(\frac{Variable_{i,t}}{Variable_{i,t-1}}\right) = \alpha_i + \beta_i\, log\left(1 + Tweets_{i,t-1}\right) + \epsilon_{i,t}$ for the previous 12 quarters to estimate the CEO tweeting skill β_i, based on the quarterly number of tweets by the CEO of firm i and the quarterly change of market capitalization or a quarterly firm operating performance measure. $Variable$ is quarterly MktCap, Sales, Revenues, or Profits. In each quarter *t*, based on the estimated β_i, firms are sorted into three CEO tweeting skill groups (top 30%, middle 40%, and bottom 30%), and also independently sorted on the number of CEO tweets of the previous quarter into three groups (top 30%, middle 40%, and bottom 30%). A firm is included in the rolling-window sample only if the corresponding CEO has tweeted in at least 6 quarters among the 12 quarters of the rolling window and the CEO does not change within the same 12 quarters as well as in the subsequent quarter when portfolio returns are calculated. We report the Fama and French (2018) six-factor abnormal returns of the equal-weighted portfolios from double sorting. The sample period for the rolling-window estimation of CEO tweeting skill starts from January 2009 and ends at December 2015, while the sample period for the subsequent monthly stock returns is from January 2012 to December 2018. T-statistics are calculated using the Newey-West (1987) method with six-period lag and shown in parentheses. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Using quarterly MktCap to measure the CEO tweeting skill

Equal Weights	Few tweets (30%)	More tweets (30%)	Spread (More-Few)
Low skill (30%)	0.40	-0.82**	-1.22***
	(1.08)	(-2.07)	(-2.98)
Equal Weights	Low skill (30%)	High skill (30%)	Spread (High-Low)
More tweets (30%)	-0.82**	0.77**	1.59***
	(-2.07)	(1.96)	(3.99)

Panel B: Using quarterly sales to measure the CEO tweeting skill

Equal Weights	Few tweets (30%)	More tweets (30%)	Spread (More-Few)
Low skill (30%)	0.36	-0.75*	-1.12***
	(0.94)	(-1.80)	(-2.59)
Equal Weights	Low skill (30%)	High skill (30%)	Spread (High-Low)
More tweets (30%)	-0.75*	0.75*	1.50***
	(-1.80)	(1.81)	(3.67)

Table 4 (continued)

Panel C: Using quarterly revenues to measure the CEO tweeting skill

Equal Weights	Few tweets (30%)	More tweets (30%)	Spread (More-Few)
Low skill (30%)	0.34	-0.69	-1.03**
	(0.82)	(-1.57)	(-2.25)
Equal Weights	**Low skill (30%)**	**High skill (30%)**	**Spread (High-Low)**
More tweets (30%)	-0.69	0.72*	1.42***
	(-1.57)	(1.66)	(3.37)

Panel D: Using quarterly profits to measure the CEO tweeting skill

Equal Weights	Few tweets (30%)	More tweets (30%)	Spread (More-Few)
Low skill (30%)	0.31	-0.64	-0.95**
	(0.71)	(-1.37)	(-1.98)
Equal Weights	**Low skill (30%)**	**High skill (30%)**	**Spread (High-Low)**
More tweets (30%)	-0.64	0.70	1.34***
	(-1.37)	(1.53)	(3.10)

Table 5: Fama-MacBeth regressions: international samples

This table presents the results from monthly Fama-MacBeth (1973) regressions of stock returns on the CEO tweeting skill and the number of CEO tweets for various groups in an international sample (*France*, *Germany*, *UK*, *JP*, and *All four & US*). The CEO tweeting skill is estimated from the time-series regression with a rolling window of 36 months. In each month *t*, we run the monthly time-series regression $log\left(\frac{MktCap_{i,t}}{MktCap_{i,t-1}}\right) = \alpha_i + \beta_i\, log\left(1 + Tweets_{i,t-1}\right) + \epsilon_{i,t}$ for the previous 36 months to estimate the CEO tweeting skill β_i, based on the monthly number of tweets posted by the CEO of firm i and the change of market capitalization. A firm is included in the rolling-window sample only if the corresponding CEO has tweeted in at least 18 months among the 36 months of the rolling window and the CEO does not change within the same 36 months as well as in the subsequent month when portfolio returns are calculated. $Skill_{high}$ ($Skill_{low}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% group based on CEO tweeting skill during the past 36 months and zero otherwise. $Tweets_{more}$ ($Tweets_{few}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% of the number group based on the number of CEO tweets in month $t-1$. Industry dummy is included in all regressions. Firm control variables include firm size ($Ln(Size)$), book-to-market ratio ($Ln(B/M)$), focal firm's own lagged monthly return ($RET_{i,t-1}$), medium-term price momentum (Mom), asset growth (AG), gross profitability (GP), stock turnover (*Turnover*), and focal firm's value-weighted industry return (Ind_mom). CEO control variables include a dummy variable that equals one if the CEO serves in a Fortune 500 firm (Fortune 500 CEO), the age of CEO in year t (CEO age), a dummy variable equals one if the CEO is female (CEO gender), number of years the CEO has served as the firm's CEO (CEO tenure), the total compensation obtained by the CEO (CEO compensation), a dummy variable that equals one if the firm's CEO is also the chairman and/or the president (CEO-Chairman/President), and the percentage of shares outstanding held by the CEO (CEO ownership). All variables are defined in Appendix. We present the results on abnormal stock returns using the CAPM model and the dependent variable in the Fama-MacBeth regressions is the excess return with control of Fama and French (2018) six-factors.Stocks with price less than $5 at the end of previous year are excluded. The sample period for the rolling-window estimation of CEO tweeting skill starts from January 2009 and ends in December 2015, while the sample period for the subsequent monthly stock returns is from January 2012 to December 2018. *T*-statistics are calculated using the Newey-West (1987) method with six-period lag and shown in parentheses. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5 (continued)

Panel A: $Skill_{low} * Tweets_{more}$

	France	Germany	UK	JP	All four & US
	RET_mkt	RET_mkt	RET_mkt	RET_mkt	RET_mkt
$Skill_{low} * Tweets_{more}$	-0.44**	-0.33	-0.56**	-0.24	-0.52**
	(-2.09)	(-1.59)	(-2.36)	(-1.23)	(-2.30)
	$RET_{i,t}^{FF6}$	$RET_{i,t}^{FF6}$	$RET_{i,t}^{FF6}$	$RET_{i,t}^{FF6}$	$RET_{i,t}^{FF6}$
$Skill_{low} * Tweets_{more}$	-0.39*	-0.29	-0.48**	-0.19	-0.45**
	(-1.75)	(-1.42)	(-2.14)	(-1.11)	(-1.99)
Industry Fixed Effects	Y	Y	Y	Y	Y
Firm Characteristics Controls	Y	Y	Y	Y	Y

Panel B: $Skill_{high} * Tweets_{more}$

	France	Germany	UK	JP	All four & US
	RET_mkt	RET_mkt	RET_mkt	RET_mkt	RET_mkt
$Skill_{high} * Tweets_{more}$	0.48**	0.36	0.58**	0.26	0.53**
	(2.04)	(1.62)	(2.34)	(1.32)	(2.20)
	$RET_{i,t}^{FF6}$	$RET_{i,t}^{FF6}$	$RET_{i,t}^{FF6}$	$RET_{i,t}^{FF6}$	$RET_{i,t}^{FF6}$
$Skill_{high} * Tweets_{more}$	0.40*	0.31	0.49**	0.20	0.46**
	(1.83)	(1.50)	(2.11)	(1.14)	(2.03)
Industry Fixed Effects	Y	Y	Y	Y	Y
Firm Characteristics Controls	Y	Y	Y	Y	Y

Table 6: Firm operating performance

This table presents the results from quarterly Fama-MacBeth (1973) regressions of firm operating performance on the number of CEO tweets and the CEO tweeting skill,

$$OP_{i,t} - OP_{i,t-1} = \alpha + \beta\, Skill_{i,t-1} * Tweets_{i,t-1} + \lambda\, X_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable (OP) is the quarterly growth of a measure for firm operating performance (*ROA*, *Sales*, *Revenues*, or *Profits*). The independent variable of interest ($Skill * Tweets_{i,t-1}$) is either $Skill_{low} * Tweets_{more}$ (Panel A) or $Skill_{high} * Tweets_{more}$ (Panel B). $Skill_{high}$ ($Skill_{low}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% group based on CEO tweeting skill in the past 12 quarters and zero otherwise. $Tweets_{more}$ ($Tweets_{few}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% of the number group based on the number of CEO tweets for month $t-1$. The CEO tweeting skill is estimated from the time-series regression with a rolling window of 36 months. In each month *t*, we run the monthly time-series regression $log\left(\frac{MktCap_{i,t}}{MktCap_{i,t-1}}\right) = \alpha_i + \beta_i\, log\left(1 + Tweets_{i,t-1}\right) + \epsilon_{i,t}$ for the previous 36 months to estimate the CEO tweeting skill β_i, based on the monthly number of tweets posted by the CEO of firm i and the change of market capitalization. A firm is included in the rolling-window sample only if the corresponding CEO has tweeted in at least 18 months among the 36 months of the rolling window and the CEO does not change within the same 36 months as well as in the subsequent month when portfolio returns are calculated. $Skill_{high}$ ($Skill_{low}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% group based on CEO tweeting skill during the past 36 months and zero otherwise. $Tweets_{more}$ ($Tweets_{few}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% of the number group based on the number of CEO tweets in month $t-1$. Industry dummy is included in all regressions. Firm control variables include firm size ($Ln(Size)$), book-to-market ratio ($Ln(B/M)$), focal firm's own lagged monthly return ($RET_{i,t-1}$), medium-term price momentum (Mom), asset growth (AG), gross profitability (GP), stock turnover (*Turnover*), and focal firm's value-weighted industry return (Ind_mom). CEO control variables include a dummy variable that equals one if the CEO serves in a Fortune 500 firm (Fortune 500 CEO), the age of CEO in year t (CEO age), a dummy variable equals one if the CEO is female (CEO gender), number of years the CEO has served as the firm's CEO (CEO tenure), the total compensation obtained by the CEO (CEO compensation), a dummy variable that equals one if the firm's CEO is also the chairman and/or the president (CEO-Chairman/President), and the percentage of shares outstanding held by the CEO (CEO ownership). All variables are defined in Appendix. Stocks with price less than $5 at the end of the previous year are excluded. The sample period for the rolling-window estimation of CEO tweeting skill starts from January 2009 and ends at December 2015, while the sample period for the subsequent monthly stock returns is from January 2012 to December 2018. *T*-statistics are calculated using the Newey-West (1987) method with six-period lag and shown in parentheses. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6 (continued)

Panel A: $Skill_{low} * Tweets_{more}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROA	ROA	Sales	Sales	Revenues	Revenues	Profits	Profits
$Skill_{low} * Tweets_{more}$	-0.12***	-0.10**	-0.32***	-0.29***	-0.11**	-0.15***	-0.08*	-0.10**
	(-3.01)	(-2.27)	(-3.66)	(-3.56)	(-2.09)	(-2.95)	(-1.95)	(-2.42)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Firm Characteristics Controls	N	Y	N	Y	N	Y	N	Y
CEO Characteristics Controls	N	Y	N	Y	N	Y	N	Y
Number of quarters	28	28	28	28	28	28	28	28
R^2	0.10	0.13	0.08	0.11	0.06	0.08	0.05	0.07

Panel B: $Skill_{high} * Tweets_{more}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROA	ROA	Sales	Sales	Revenues	Revenues	Profits	Profits
$Skill_{high} * Tweets_{more}$	0.10***	0.09**	0.36***	0.35***	0.14***	0.19***	0.11**	0.16***
	(2.82)	(2.31)	(3.99)	(3.59)	(2.87)	(3.56)	(2.38)	(3.26)
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Firm Characteristics Controls	N	Y	N	Y	N	Y	N	Y
CEO Characteristics Controls	N	Y	N	Y	N	Y	N	Y
Number of quarters	28	28	28	28	28	28	28	28
R^2	0.09	0.13	0.07	0.11	0.05	0.07	0.04	0.06

Table 7: Mechanisms: investors' limited attention and limits to arbitrage

This table presents the monthly abnormal returns on the portfolios triple-sorted on the CEO tweeting skill, the number of CEO tweets, and the mechanism proxy (for investors' limited attention or limits to arbitrage). The CEO tweeting skill is estimated from the time-series regression with a rolling window of 36 months. In each month *t*, we run the monthly time-series regression $log\left(\frac{MktCap_{i,t}}{MktCap_{i,t-1}}\right) = \alpha_i + \beta_i\, log\left(1 + Tweets_{i,t-1}\right) + \epsilon_{i,t}$ for the previous 36 months to estimate the CEO tweeting skill β_i, based on the monthly number of tweets posted by the CEO of firm *i* and the change of market capitalization. A firm is included in the rolling-window sample only if the corresponding CEO has tweeted in at least 18 months among the 36 months of the rolling window and the CEO does not change within the same 36 months as well as in the subsequent month when portfolio returns are calculated. In each month *t,* stocks are sorted on the proxy of mechanism into two equal groups (top 50% and bottom 50%), then independently sorted into two CEO tweeting skill groups (top 50% and bottom 50%), and finally independently sorted on the number of CEO tweets of the previous month into two groups (top 50% and bottom 50%). We calculate the long/short Fama and French (2018) six-factor alphas in the two extreme equal-weighted portfolios and the consequent difference between the two alphas. Panel A presents the results on investors' limited attention, proxied by advertising expenses (*Advertising*), analyst coverage (*Analyst Coverage*), and residual institutional ownership (*Res Inst Own*). *Advertising* is the focal firm's advertising expenses in the prior year. *Analyst Coverage* is the number of analysts covering the focal firm at the end of previous month. *Res Inst Own* is the institutional ownership of the parent firm orthogonalized with regard to firm size at the end of the December of the prior year. Panel B reports the results on limits to arbitrage, proxied by quarterly stock volatility ($StVol$), idiosyncratic volatility (*IdVol*), and illiquidity (*illiquidity*). $StVol$ is the stock volatility in the previous quarter. *IdVol* is the standard error of the residuals from a regression of daily stocks returns in the previous month on the Fama and French (1993) three-factor model. *Illiquidity* is the Amihud (2002) illiquidity measure. Stocks with price less than $5 at the end of previous year are excluded. The sample period for the rolling-window estimation of CEO tweeting skill starts from January 2009 and ends at December 2015, while the sample period for the subsequent monthly stock returns is from January 2012 to December 2018. *T*-statistics are calculated using the Newey-West (1987) method with six-period lag and shown in parentheses. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Investors' limited attention

	(1)	(2)	(3)
$Skill_{low}$: $Tweets_{few} - Tweets_{more}$	*Advertising*	*Analyst Coverage*	*Res Inst Own*
High	0.69	0.76	0.72
Low	2.01	1.94	1.98
High-Low	-1.32***	-1.18***	-1.26***
	(-3.43)	(-3.07)	(-3.29)
$Tweets_{more}$: $Skill_{high} - Skill_{low}$	*Advertising*	*Analyst Coverage*	*Res Inst Own*
High	0.91	0.83	0.88
Low	2.53	2.61	2.56
High-Low	-1.62***	-1.78***	-1.68***
	(-4.16)	(-4.61)	(-4.35)

Table 7 (continued)

Panel B: Limits to arbitrage

	(1)	(2)	(3)
$Skill_{low}$: $Tweets_{few} - Tweets_{more}$	*StVol*	*IdVol*	*Illiquidity*
High	1.85	1.92	1.88
Low	0.85	0.78	0.82
High-Low	1.00***	1.14***	1.06***
	(2.59)	(2.94)	(2.73)
$Tweets_{more}$: $Skill_{high} - Skill_{low}$	*StVol*	*IdVol*	*Illiquidity*
High	2.36	2.44	2.39
Low	1.08	1.00	1.05
High-Low	1.28***	1.44***	1.34***
	(3.28)	(3.71)	(3.46)

Table 8: Comparison between mechanisms

This table reports the horse-race tests among the two mechanism. To compare mechanisms, we use Fama-MacBeth regressions and interaction terms between the dummy value of the CEO tweeting skill and the number of CEO tweets ($Skill * Tweets_{i,t-1}$) and the dummy variable (D_x, D_y). D_1 (limited attention) equals one if the limited attention characteristic (*Advertising, Analyst coverage,* or *Res Inst Own*) is above the median and zero otherwise. D_2 (limits to arbitrage) equals one if the limits to arbitrage characteristic (*StVol, IdVol,* or *Illiquidity*) is above the median and zero otherwise. $RET_{i,t} = \alpha + \beta_1 Skill_{i,t-1} * Tweets_{i,t-1} + \beta_2 D_x + \beta_3 Skill_{i,t-1} * Tweets_{i,t-1} * D_x + \beta_4 D_y + \beta_5 Skill_{i,t-1} * Tweets_{i,t-1} * D_y + \lambda X_{i,t-1} + \varepsilon_{i,t}$. The independent variable ($Skill * Tweets_{i,t-1}$) equals $Skill_{low} * Tweets_{more}$ (Panel A) or $Skill_{high} * Tweets_{more}$ (Panel B). $Skill_{high}$ ($Skill_{low}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% group based on CEO tweeting skill during the past 12 quarters and zero otherwise. $Tweets_{more}$ ($Tweets_{few}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% of the number group based on the number of CEO tweets in month $t-1$. The CEO tweeting skill is estimated from the time-series regression with a rolling window of 36 months. In each month *t*, we run the monthly time-series regression $log\left(\frac{MktCap_{i,t}}{MktCap_{i,t-1}}\right) = \alpha_i + \beta_i \, log\left(1 + Tweets_{i,t-1}\right) + \epsilon_{i,t}$ for the previous 36 months to estimate the CEO tweeting skill β_i, based on the monthly number of tweets posted by the CEO of firm *i* and the change of market capitalization. A firm is included in the rolling-window sample only if the corresponding CEO has tweeted in at least 18 months among the 36 months of the rolling window and the CEO does not change within the same 36 months as well as in the subsequent month when portfolio returns are calculated. All regressions contain firm and CEO control variables (as in table 3), and industry fixed effects. The standard errors are calculated using the Newey-West (1987) method with six lags. The absolute t-statistics are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: $Skill_{low} * Tweets_{more}$

		(1)	(2)	(3)
		Advertising	Analyst coverage	Res. Inst. Ownership
StVol	$Skill_{low} * Tweets_{more} \times D_1$	0.56***	0.35**	0.43***
	$Skill_{low} * Tweets_{more} \times D_2$	-0.13*	-0.06	-0.14*
IdVol	$Skill_{low} * Tweets_{more} \times D_1$	0.62***	0.38**	0.47***
	$Skill_{low} * Tweets_{more} \times D_2$	-0.10*	-0.05	-0.11*
Illiquidity	$Skill_{low} * Tweets_{more} \times D_1$	0.59***	0.37**	0.45***
	$Skill_{low} * Tweets_{more} \times D_2$	-0.11*	-0.06	-0.13*

Table 8 (continued)

Panel B: $Skill_{high} * Tweets_{more}$

		(1)	(2)	(3)
		Advertising	Analyst coverage	Res. Inst. Ownership
StVol	$Skill_{high} * Tweets_{more} \times D_1$	-0.37***	-0.61***	-0.46***
	$Skill_{high} * Tweets_{more} \times D_2$	0.09	0.28**	0.17*
IdVol	$Skill_{high} * Tweets_{more} \times D_1$	-0.43***	-0.70***	-0.53***
	$Skill_{high} * Tweets_{more} \times D_2$	0.08	0.24**	0.14*
Illiquidity	$Skill_{high} * Tweets_{more} \times D_1$	-0.41***	-0.67***	-0.51***
	$Skill_{high} * Tweets_{more} \times D_2$	0.09	0.27**	0.16*

Table 9: Effect of CEO tweeting on the daily stock return around earnings announcements

This table presents the effect of both the CEO tweeting skill and the number of tweets on the daily stock return within the three-day window around earnings announcements ([-1,1]). *Daily Ret* is the firm daily stock return. *EDAY* is a dummy variable that equals 1 if day *t* is within the three-day window [-1,1] around a firm's earnings announcement and zero otherwise. Following Engelberg et al. (2018), we collect earnings announcement dates from the Compustat quarterly database, calculate the trading volume of the firm stock scaled by market trading volume for the day before, the day of, and the day after the reported earnings announcement date, and define the day with the highest volume as the earnings announcement day. $Skill_{high}$ ($Skill_{low}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% group based on CEO tweeting skill during the past 36 months and zero otherwise. $Tweets_{more}$ ($Tweets_{few}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% of the number group based on the number of CEO tweets for month $t-1$. The CEO tweeting skill is estimated from the time-series regression with a rolling window of 36 months. In each month *t*, we run the monthly time-series regression $log\left(\frac{MktCap_{i,t}}{MktCap_{i,t-1}}\right) = \alpha_i + \beta_i\, log\left(1 + Tweets_{i,t-1}\right) + \epsilon_{i,t}$ for the previous 36 months to estimate the CEO tweeting skill β_i, based on the monthly number of tweets posted by the CEO of firm *i* and the change of market capitalization. A firm is included in the rolling-window sample only if the corresponding CEO has tweeted in at least 18 months among the 36 months of the rolling window and the CEO does not change within the same 36 months as well as in the subsequent month when portfolio returns are calculated. Industry dummy is included in all regressions. Control variables are the lagged values of stock return, stock return squared, and trading volume, up to ten days before *t*. For brevity, the coefficients on control variables are not reported. Standard errors are clustered by time. All variables are defined in Appendix. The sample period for the rolling-window estimation of CEO tweeting skill starts from January 2009 and ends at December 2015, while the sample period for the subsequent monthly stock returns is from January 2012 to December 2018. *T*-statistics are shown in parentheses. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: $Skill_{low} * Tweets_{more}$

	Three-day window	*Three-day window*
Dep Variable	*Daily Ret*	*Daily Ret*
$Skill_{low} * Tweets_{more} * EDAY$	-0.05***	-0.03***
	(-5.43)	(-4.58)
$Skill_{low} * Tweets_{more}$	-0.01**	-0.01**
	(-2.44)	(-2.17)
EDAY	0.02***	0.02***
	(3.40)	(2.68)
Dummy ($Skill_{low}$, $Tweets_{more}$)	Y	Y
Lagged Controls	N	Y
Day Fixed Effects	Y	Y
R^2	0.20	0.20

Table 9 (continued)

Panel B: $Skill_{high} * Tweets_{more}$

	Three-day window	*Three-day window*
Dep Variable	*Daily Ret*	*Daily Ret*
$Skill_{high} * Tweets_{more} * EDAY$	0.04***	0.04***
	(4.58)	(4.30)
$Skill_{high} * Tweets_{more}$	0.01**	0.02**
	(2.12)	(2.06)
$EDAY$	0.01**	0.01**
	(2.45)	(2.56)
Dummy ($Skill_{high}$, $Tweets_{more}$)	Y	Y
Lagged Controls	N	Y
Day Fixed Effects	Y	Y
R^2	0.18	0.18

Table 10: Future standardized unexpected earnings

This table reports the results from cross-sectional Fama-MacBeth regressions of future standardized unexpected earnings (SUE) on the dummy variables for the CEO tweeting skill and the number of tweets, with control variables and industry fixed effects. SUE is defined as the unexpected earnings (year-over-year change in quarterly earnings before extraordinary items) scaled by the standard deviation of unexpected earnings over the eight preceding quarters. Results on the future SUE for the next four fiscal quarters are reported. The CEO tweeting skill is estimated from the time-series regression with a rolling window of 12 quarters; i.e. in each quarter t, we run the quarterly time-series regression $log\left(\frac{MktCap_{i,t}}{MktCap_{i,t-1}}\right) = \alpha_i + \beta_i \, log\left(1 + Tweets_{i,t-1}\right) + \epsilon_{i,t}$ for the previous 12 quarters to estimate the CEO tweeting skill β_i, based on the quarterly number of tweets by the CEO of firm *i* and the quarterly market capitalization of the firm or a quarterly firm operating performance measure. $Skill_{high}$ ($Skill_{low}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% group based on CEO tweeting skill in the past 12 quarters and zero otherwise. $Tweets_{more}$ ($Tweets_{few}$) is a dummy variable that equals one if a stock is in the top (bottom) 30% of the number group based on the number of CEO tweets for quarter $t-1$. A firm is included in the rolling-window sample only if the corresponding CEO has tweeted in at least 6 quarters among the 12 quarters of the rolling window and the CEO does not change within the same 12 quarters. For consistency, the sample is restricted to firms with fiscal quarters ending in March, June, September, and December. Lagged SUEs up to four quarters prior are included as control variables. The sample period for the rolling-window estimation of CEO tweeting skill starts from January 2009 and ends at December 2015, while the sample period for the subsequent monthly stock returns is from January 2012 to December 2018. *T*-statistics are calculated using the Newey-West (1987) method with four-period lag and shown in parentheses. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: $Skill_{low} * Tweets_{more}$

	(1)	(2)	(3)	(4)
Dep Variable	$SUE_{i,t}$	$SUE_{i,t+1}$	$SUE_{i,t+2}$	$SUE_{i,t+3}$
$(Skill_{low} * Tweets_{more})_{i,t-1}$	-0.28***	-0.22**	-0.17	-0.14
	(-3.03)	(-2.25)	(-1.61)	(-1.20)
Lagged SUEs (4 quarters)	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y
Dummy ($Skill_{low}$, $Tweets_{more}$)	Y	Y	Y	Y
# of quarters	28	28	28	28
R^2	0.36	0.34	0.30	0.26

Panel B: $Skill_{high} * Tweets_{more}$

	(1)	(2)	(3)	(4)
Dep Variable	$SUE_{i,t}$	$SUE_{i,t+1}$	$SUE_{i,t+2}$	$SUE_{i,t+3}$
$\left(Skill_{high} * Tweets_{more}\right)_{i,t-1}$	0.23***	0.20**	0.16*	0.13
	(2.88)	(2.31)	(1.75)	(1.39)
Lagged SUEs (4 quarters)	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y
Dummy ($Skill_{high}$, $Tweets_{more}$)	Y	Y	Y	Y
# of quarters	28	28	28	28
R^2	0.33	0.32	0.29	0.26

Appendix
Variable definitions and data sources

Variable	Description	Source	Frequency
$Skill_{low} * Tweets_{few}$	Dummy variable that equals one if a stock is in the bottom 30% of the CEO tweeting skill in the preceding 36 months and in the bottom 30% of the number of CEO tweets in month $t-1$.	Twitter, CRSP, Eikon, Compustat	Monthly
$Skill_{low} * Tweets_{more}$	Dummy variable that equals one if a stock is in the bottom 30% of the CEO tweeting skill in the preceding 36 months and in the top 30% of the number of CEO tweets in month $t-1$.	Twitter, CRSP, Eikon, Compustat	Monthly
$Skill_{high} * Tweets_{more}$	Dummy variable that equals one if a stock is in the top 30% of the CEO tweeting skill in the preceding 36 months and in the top 30% of the number of CEO tweets in month $t-1$.	Twitter, CRSP, Eikon, Compustat	Monthly
$Skill_{high} * Tweets_{few}$	Dummy variable that equals one if a stock is in the top 30% of the CEO tweeting skill for recent 36 months and in the bottom 30% of the number of CEO tweets in month $t-1$.	Twitter, CRSP, Eikon, Compustat	Monthly
$RET_{i,t}^{MKT}$	Focal firm's market-adjusted return over one-month T-bill.	Twitter, CRSP, Eikon	Monthly
$RET_{i,t}^{FF6}$	Focal firm's Fama and French (2018) six-factor adjusted return.	Twitter, CRSP, Eikon	Monthly
$RET_{i,t}^{DHS}$	Focal firm's Daniel et al. (2020) DHS-factor adjusted return.	Twitter, CRSP, Eikon	Monthly
Ln(Size)	Log market capitalization.	CRSP, Eikon, Compustat	Monthly
Ln(B/M)	Log book value at the end of December over the market capitalization in month $t-1$.	CRSP, Eikon, Compustat	Monthly
Mom	Focal firm's cumulative return over $t-12$ to $t-2$ months.	CRSP, Eikon	Monthly
Ind_Mom	Fama-French 48 industry return of a focal firm.	CRSP, K. French Data	Monthly
AG	Asset growth – a yearly growth rate of the total asset.	CRSP, Eikon, Compustat	Monthly
GP	Gross profitability – the revenue minus the cost of goods sold divided by the total asset.	CRSP, Eikon, Compustat	Monthly
Turnover	# of shares traded during a day divided by the # of shares outstanding at the end of the	CRSP, Eikon	Monthly

	day, averaged over the past 12 months.		
MktCap	Market capitalization of the focal firm.	CRSP, Eikon Compustat	Monthly
Advertising	The cost of advertising media and promotional expenses.	CRSP, Eikon Compustat	Yearly
Analyst coverage	Number of analysts of the focal firm.	CRSP, Eikon Compustat, IBES	Monthly
Res Inst Ownership	Residual from the cross-sectional regression of the percentage of shares held by institutional investors on log market capitalization.	CRSP, Eikon, Thomson-Reuters Holdings (13F)	Monthly
StVol	The quarterly stock price volatility.	CRSP, Eikon, Compustat	Quarterly
IdVol	Inverse of the standard deviation of residuals from the Fama and French (1993) regression of daily stock returns in the previous month.	CRSP, Eikon, Compustat, K. French Data	Monthly
Illiquidity	Illiquidity is measured following Amihud (2002).	CRSP, Eikon, Compustat	Monthly
Fortune 500 CEO	Dummy variable that equals one if the CEO serves in a Fortune 500 firm.	Fortune	Yearly
CEO age	CEO's age in year t.	ExecuComp	Yearly
CEO gender	Dummy variable that equals one if the CEO's gender is female, zero otherwise.	ExecuComp	Yearly
CEO compensation	Total compensation obtained by the CEO.	ExecuComp	Yearly
CEO ownership	Percentage of shares outstanding held by the CEO.	ExecuComp	Yearly
CEO tenure	Number of years the CEO has served as the firm's CEO.	ExecuComp	Yearly
CEO (Chairman/President)	Dummy variable that equals one if the CEO also holds the title of the chairman of the board and/or the president of the firm, zero otherwise.	ExecuComp	Yearly