Company Name Fluency and Stock Returns[†]

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Abstract

Recent research shows that stocks with fluent names trade at higher prices. It is not clear, however, whether fluency simply appeals to naive investors, or conveys information on the quality of the firm. In this paper, we tease out these two stories. We show that companies with fluent names exhibit higher profitability, but this information is not fully captured by investors and analysts. Stocks with fluent names then yield higher abnormal returns than stocks with nonfluent names, especially when beginning-of-period sentiment is high. Overall, we provide a new kind of confirmation of the tendency of investors to undervalue intangibles.

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1. Introduction

A novel strand of research shows that stocks with fluent names trade at higher prices (Green and Jame, 2013). There are two competing hypotheses that can explain this result. On the one hand, unsophisticated investors may exhibit a naive preference, or affect, for fluent stimuli (Oppenheimer, 2006; Alter and Oppenheimer, 2006, 2008, 2009), and bid up the prices of fluently named stocks (henceforth: "fluent stocks"). An alternative line of reasoning is that company names convey information on the quality of the firm (Fombrun and Shanley, 1990; Tadelis, 1999). Firms with more fluent names might then be superior firms, for example because of higher brand recognition (Bao, Shao, and Rivers, 2008).

In this paper, we tease out these two stories. From an asset pricing perspective, we show that

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while they both imply higher valuations for fluent stocks, they yield different predictions on stock returns. In the affect hypothesis, the overbidding of fluent stocks from naive investors leads to overpricing, and then lower returns. Under the alternative scenario, fluency correlates with the profitability of the firm. If this information is fully reflected in prices, there are no abnormal returns. If naive investors do not recognize the meaning of fluency, however, fluent stocks become underpriced and yield higher returns.

Using fluency data on U.S. company names from Green and Jame (2013), we provide strong support for the information hypothesis. We find that when naive trader demand is high, the price differential between fluent and nonfluent stocks decreases. As a result, fluent stocks yield higher abnormal returns than nonfluent ones over the following month. Consistent with our theoretical arguments, we also show that companies with fluent names exhibit higher profitability, larger sales, and positive earnings surprises.

To the best of our knowledge, this paper is the first to shed light on the economic meaning of fluency. Previous research finds correlation between fluency and IPO returns (Alter and Oppenheimer, 2006), valuations (Green and Jame, 2013), and liquidity (Green and Jame, 2013; Anderson and Larkin, 2018), but remains silent on the mechanism that drives the results. We show that fluency does not merely attract the attention of naive investors, but rather conveys information on the quality of the firm. Our findings, then, provide a new kind of confirmation of the tendency of investors to undervalue intangibles (see, e.g., Edmans, 2011).

To derive theoretical guidance, we consider an economy from Hirshleifer and Teoh (2003) with publicly traded firms. Each of these firms is endowed with a risky project that pays a final dividend, and characterized by a name that can be either fluent or nonfluent. Investors in the economy are risk-averse and can be either sophisticated or unsophisticated, which maps into the well-known dichotomy between arbitrageurs and noise (or naive) traders, respectively. The distinctive feature of arbitrageurs is that they evaluate stocks correctly, while naive investors neglect relevant information in their evaluations.

Company name fluency can affect the stock price in two alternative ways. In the first setting, there is no correlation between fluency and the quality of the project, but naive investors are unduly attracted to fluent stocks and averse to nonfluent ones. In the presence of downward-sloping demand curves (Shleifer, 1986; Kaul, Mehrotra, and Morck, 2000), naive trader demand pushes the equilibrium prices of the two types of stock apart from each other, whereas in fact they should be equal. Fluent stocks then become overpriced and earn lower returns than nonfluent stocks.

In the second setting, we explore the hypothesis that firms with fluent names have better projects, for example because their products are more appealing to customers. Naive traders, however, neglect this information, which brings the equilibrium prices of the two types of stock closer to each other than they should be. As a result, fluent stocks are underpriced and yield higher returns than nonfluent stocks. In either setting, the return difference increases (in absolute value) with the size of naive trader demand.

In the empirical analysis, we take these predictions to the data. We consider the data set of U.S. company name fluency scores from Green and Jame (2013), which covers the sample period from 1981 to 2008, and complement it with CRSP-Compustat data. The overall fluency score of a company name is the sum of length, Englishness, and dictionary scores. The length score equals two if the company name is made up of one word, one if it includes two words, and zero otherwise. The Englishness variable takes on value zero if the company name is in the bottom quintile of Englishness, as assessed using the linguistic algorithm by Travers and Olivier (1978), and one otherwise. Finally, the dictionary variable takes on value one if all words in the name pass the Microsoft spell-check and zero otherwise. Overall, then, the index takes on integer values between zero and four.

In the first part of the analysis, we construct portfolios for specific fluency scores. Simple descriptive statistics reveal an interesting pattern. We find that nonfluent stocks (score zero) yield an average return of 0.87% per month. This average increases almost monotonically to 1.06% for score one, 1.18% for score two, 1.17% for score three, and 1.31% for the most fluent stocks (score four). The difference in stock returns between the top and the bottom fluency category is then 0.44%. The average return for the top two categories combined (score 3 or 4) is 1.18% per month, and 1.03% per month for the bottom two categories combined (score 0 or 1).

We then analyze abnormal returns, using a variety of factor models. With the five-factor model from Fama and French (2015), we find that the difference in alphas between single-score portfolios, i.e., stocks with fluency scores of four or zero, is 1.05% per month (t-stat 3.23). Then we construct dual-score portfolios, defining fluent stocks as those with a fluency score of three or four and nonfluent stocks as those with a fluency score of zero or one, and find that the difference in abnormal returns is 0.39% per month (t-stat 3.52).

The estimates are similar for Carhart's (1997) four-factor model, where we control for momentum, and after including the liquidity factor from Pástor and Stambaugh (2003), which allays the concern that the return differential might represent a liquidity premium (Green and Jame, 2013; Anderson and Larkin, 2018). We also obtain similar results when using factor models from Novy-Marx (2013) and Stambaugh and Yuan (2017), which tackles the concern that the effect of fluency may reflect, to some extent, other well-known anomalies. These first results, then, are consistent with the information story.

The model predicts that if fluency is informative, the difference in returns between fluent and nonfluent stocks should increase with the size of naive investor demand. To test for this, we proceed in two ways. First, we acknowledge that such demand is high among stocks with relatively subjective valuations, such as extreme growth and distressed firms (Baker and Wurgler, 2006, 2007). Therefore, these stocks should be most affected by the trading activity of unsophisticated investors. Following this line of reasoning, we repeat the analysis in subsamples of stocks ranked along market-to-book and price-to-earnings ratios. We indeed find that the effect of fluency on excess returns is large among stocks with extreme price-to-book ratios (top and bottom 30%), and absent among other stocks (middle 40%).

Second, we acknowledge that high investor sentiment leads to greater participation of naive investors in the market, which in turn is followed by a larger mispricing correction (Baker and Wurgler, 2006, 2007; Yu and Yuan, 2011; Stambaugh, Yu, and Yuan, 2012). Building on this mechanism, we repeat the analysis conditioning on the beginning-of-period level of the monthly investor sentiment index from Baker and Wurgler (2007). We find that the difference in alphas between fluent and nonfluent stocks increases with beginning-of-period sentiment, and that the effect is entirely driven by fluent stocks. We also find that sentiment explains away the alphas from the extreme price-to-book regressions, which suggests that time variation in naive trader demand is an important dimension to consider in the tests that follow. Overall, these results lend further support to the information hypothesis.

A potential concern is that factor models may not entirely capture systematic risk. In particular, fluency may be correlated with other firm characteristics that affect stock returns in their own right. To address this issue, we estimate panel regressions controlling for a large vector of firm characteristics from Brennan, Chordia, and Subrahmanyam (1998), such as the book-to-market ratio, the dividend yield, past returns, firm size, the market price, and trade volume, conditioning the analysis on beginning-of-period sentiment.

Consistent with the information story, we find that when beginning-of-period sentiment increases by one standard deviation, a one point increase in the fluency score is associated with higher excess returns of 0.05% per month (t-stat 2.44), and a fluency increase from either of the bottom two fluency scores (zero or one) to either of the top fluency scores (three or four) is associated with a 0.12% increase in monthly excess returns (t-stat 2.46). We find similar results when we analyze within-firm changes in fluency through firm fixed effects. Then, the results from the time series regressions do not seem to be driven by fluency being correlated with other firm characteristics, or time-invariant omitted variables.

Green and Jame (2013) find that the impact of fluency on valuations decreases with firm size. This can be due to at least two reasons. First, investors are more familiar with large firms (e.g., through higher media and analyst coverage), and repeated exposure makes information processing easier (Labroo, Dhar, and Schwarz, 2008). Second, small stocks are more prone to mispricing (Baker and Wurgler, 2006). We find evidence that is consistent with these lines of reasoning, as the effect of fluency on returns is concentrated among stocks with below-median number of employees or market capitalization.

After considering returns, we test the model's predictions on valuations. Green and Jame (2013) find a positive and robust relation between company name fluency and Tobin's q. In our analysis, we extend their results by testing the prediction of the information hypothesis that the prices of fluent and nonfluent stocks should be closer to each other when naive investor demand is large. We find evidence consistent with our conjecture. Fluent stocks exhibit a higher Tobin's q than nonfluent stocks, but this difference shrinks when investor sentiment increases. These findings on valuations, then, like those on returns, also support the information story.

Harvey (2017) makes the compelling point that research in asset pricing can produce spurious results if the underlying economic mechanism is not clear. To address this concern, we develop tests for the two underpinnings of the information story. First, we test the basic assumption that fluent companies are better firms than nonfluent ones. To this end, we examine the relation between fluency and operating performance. In line with our conjecture, we show that a one-point increase in the fluency score is associated with a higher return on assets of 0.90 percentage points over the next year (t-stat 5.98), and 0.79 percentage points over a longer horizon of two to four years ahead (t-stat 4.46).

If the higher profitability of fluent firms is due to a superior reputation among consumers (i.e., brand recognition), then high fluency scores should also be associated with larger sales. We find evidence consistent with this conjecture. We show that a one-point increase in the fluency score is associated with a significant increase of 14% in real net sales over the next year (t-stat 3.88), and 9% over the subsequent two to four years (t-stat 2.04). Interestingly, previous literature finds estimates of comparable magnitude when analyzing the relation between sales and survey-based brand quality perception (see, e.g., Morton, 1994).

Second, we test the assumption that the mispricing of fluency comes from biased expectations among a subset of investors. Following Engelberg, McLean, and Pontiff (2018), we conjecture that this bias, if present among naive traders, should also characterize the forecasts of less sophisticated analysts. The intuition is as follows. If some analysts neglect the information about good fundamentals captured by fluency, their expectations should be systematically too pessimistic for fluent firms. When aggregating forecasts across all analysts, then, fluent firms should produce positive earnings surprises. Consistent with this prediction, we find that standardized unexpected earnings are higher for companies with high fluency scores.

The results contribute to the recent finance literature on fluency. Green and Jame (2013) find that companies with fluent names exhibit higher valuations, but leave the analysis of the economic meaning of fluency to future research. In this paper, we shed light on this issue. We provide evidence that fluent companies are better firms, but this information is not fully captured by investors and analysts. The results also speak to Alter and Oppenheimer (2006), who also document a positive relation between fluency and stock returns, but only consider IPOs, and do not use standard methods and controls from the asset pricing literature.

Cooper, Orlin, and Rau (2001) also propose a story about investors and misplaced attention. They find that naive investors react to irrelevant features of company names, such as a mere association with the Internet, leading to a large value increase for the firm. In this paper, we explore the flip-side of this story. We show that investors fail to react to relevant information in company names, such as fluency. Put together, these findings seem to cover two aspects of the same phenomenon: investor naiveté can take the form of paying attention to something they should not, or failing to attend to something they should. In this sense, then, our results are complementary to those from Cooper et al. (2001).

The findings also lend support to an emerging literature that shows that investors tend to underprice intangibles, such as employee satisfaction (Edmans, 2011), R&D (Lev and Sougiannis, 1996; Chan, Lakonishok, and Sougiannis, 2001), innovative efficiency (Hirshleifer, Hsu, and Li, 2018), advertising (Chan, Lakonishok, and Sougiannis, 2001), patent citations (Deng, Lev, and Narin, 1999), and software development costs (Aboody and Lev, 1998). Stocks that score high on these characteristics earn higher long-run returns. We find that a similar mechanism also applies to company name fluency.

The paper proceeds as follows. Section 2 introduces the theoretical framework. Section 3 describes the data and methodology. Section 4 presents the empirical results. Section 5 concludes.

2. The model

We consider an economy from Hirshleifer and Teoh (2003) with publicly traded firms. Each of these firms is endowed with a risky project that pays an expected final dividend D, and characterized by a name that can be either fluent or nonfluent. Investors in the economy can be either arbitrageurs or naive traders, and exhibit mean-variance preferences.

The distinctive feature of arbitrageurs is that they are sophisticated, and thus evaluate stocks correctly. Naive traders, instead, are prone to expectation errors. In particular, we define the probability that an investor fails to identify and process some aspect of the economic environment correctly as $f(c)$, with $f'(c) < 0$, where c represents the resources expended on attending to relevant information. Function f, then, also represents the proportion of naive traders in the economy. The key mechanism is that a positive level of f can survive in long-term equilibrium, provided that reducing f is costly. In light of this, we take f as exogenously given.

The economy has three dates. At date 0 investors form expectations. At date 1, public information arrives about firm value or its components. At date 2 the terminal payoff is realized and the firm is liquidated. There is no private information among investors, so there is nothing to learn from the market price in this economy. Naive investors, however, are not aware that they are not processing information fully, so they mistakenly believe that they too have nothing to learn. Therefore, we assume that naive investors do not update their beliefs based upon the market price.

We assume an initial wealth endowment of W_0 for all investors, and a per capita endowment of the single risky security of x_0. At date 1, investors can buy or sell the security in exchange for cash, defined as claims to terminal consumption, at price S_1. The position in the security thus attained is denoted as x. We denote the terminal payoff of the security as S_2. Then an individual's consumption is $C = W_0 - (x - x_0)S_1 + xS_2$.

An investor of type ϕ solves:

$$\max_{x^\phi} \; x^\phi \left(E_1^\phi (S_2 - S_1) \right) - \frac{\gamma}{2} var_1^\phi (x^\phi S_2), \tag{1}$$

where the index ϕ indicates arbitrageurs ($\phi = A$) or naive investors ($\phi = N$), and γ is the coefficient of absolute risk aversion. The security market clearing condition is $fx^N + (1-f)x^A = x_0$, where x_0 is the security's net supply. Without loss of generality we set $x_0 = 0$, and obtain the equilibrium price $S_1 = \kappa E_1^N(S_2) + (1-\kappa)E_1^A(S_2)$, where $\kappa \in [0, 1]$ is a function of the proportion of naive investors in the market. In particular, $\kappa = 0$ if there are no naive traders. In equilibrium, then, the price represents a weighted average of valuations of investors with different beliefs.

Then, we consider two scenarios. First, naive investors exhibit a naive preference for fluent stocks. Second, the level of fluency of the company name conveys information on the quality of the project. We refer to these scenarios as the affect and the information hypothesis, respectively.

2.1. Affect hypothesis

Under the affect hypothesis, there is no correlation between fluency and the quality of the firm. However, naive investors are unduly attracted to fluent stocks and averse to nonfluent ones. In particular, they mistakenly perceive fluent stocks to be better companies. Their evaluations of the final payment are therefore $D + b_H$ and $D - b_L$ for stocks with high and low fluency, respectively, where $b_H, b_L > 0$ and $b_H \neq b_L$ (the bias can be asymmetric). Sophisticated investors, instead, correctly estimate the expected final payment as equal to D.

The market clearing conditions for stocks with high and low fluency yield the following equilibrium prices:

$$S_1^H = D + \kappa b_H, \tag{2}$$

$$S_1^L = D - \kappa b_L. \tag{3}$$

Therefore, fluent stocks are overpriced, while nonfluent stocks are underpriced. This implies

Proposition 1. *Under the affect hypothesis, the price of fluent stocks is higher than that of nonfluent stocks. The price differential is proportional to the size of naive trader demand and the fluency bias:*

$$S_1^H - S_1^L = \kappa(b_H + b_L). \tag{4}$$

Next, we define expected returns as the difference between the expected final cash flow and the stock price at time 1 (see, e.g., Chen, Hong, and Stein, 2002). In equilibrium, fluent stocks earn negative abnormal returns while nonfluent stocks earn positive abnormal returns:

$$E(\tilde{r}_2^H) = -\kappa b_H, \tag{5}$$

$$E(\tilde{r}_2^L) = \kappa b_L. \tag{6}$$

This implies

Proposition 2. *Under the affect hypothesis, returns on fluent stocks are lower than those on nonfluent stocks. The return differential is proportional to the size of naive trader demand and the fluency bias:*

$$E(\tilde{r}_2^H) - E(\tilde{r}_2^L) = -\kappa(b_H + b_L). \tag{7}$$

Note that in the absence of naive investors (i.e., $\kappa = 0$), fluent and nonfluent stocks trade at the same price and earn zero abnormal returns.

2.2. Information hypothesis

In this alternative setting, we explore the possibility that the level of fluency of the company name may actually convey information on the quality of the project. Without loss of generality, we identify firms with projects of either high or low quality, and the proportion of high-quality firms in the economy is equal to π. Such firms make an expected final payment equal to λD, with $\lambda > 1$, while other firms make an expected final payment of D.

Arbitrageurs know that fluent firms have high-quality projects, and correctly evaluate their expected payoff. Naive traders, instead, neglect this information, and therefore price all stocks equally. In particular, they evaluate the payoff to be $D(1 + \pi(\lambda - 1))$ for all firms. The market clearing conditions yield the following equilibrium prices:

$$S_1^H = \lambda D - \kappa D(\lambda - 1)(1 - \pi), \tag{8}$$

$$S_1^L = D + \kappa D(\lambda - 1)\pi. \tag{9}$$

In this setting, then, fluent stocks are underpriced, while nonfluent stocks are overpriced, as long as there are naive investors in the market ($\kappa > 0$). The mispricing comes from the fact that naive traders do not tease out high-quality firms from the others, which brings the two equilibrium prices closer to each other than they should be. Then we derive

Proposition 3. *Under the information hypothesis, fluent stocks trade at a higher price than nonfluent stocks. The price differential is proportional to the difference in quality between projects, and inversely related to the size of naive trader demand:*

$$S_1^H - S_1^L = (1-\kappa)D(\lambda - 1) > 0. \tag{10}$$

Abnormal returns are respectively:

$$E(\tilde{r}_2^H) = \kappa D(\lambda - 1)(1-\pi), \tag{11}$$

$$E(\tilde{r}_2^L) = -\kappa D(\lambda - 1)\pi, \tag{12}$$

which implies

Proposition 4. *Under the information hypothesis, fluent stocks yield higher returns than nonfluent stocks. The return differential is proportional to the difference in firm quality and to the size of naive trader demand:*

$$E(\tilde{r}_2^H) - E(\tilde{r}_2^L) = \kappa D(\lambda - 1) > 0. \tag{13}$$

Again, the return difference is zero in the absence of naive investors ($\kappa = 0$).

2.3. Testable implications

Following the propositions above, we derive a number of testable implications. Propositions 2 and 4 imply:

Hypothesis 1. *If the level of fluency of company names correlates with firm quality, there should be a positive relation between fluency and abnormal returns. If company name fluency merely attracts the attention of naive investors, the relation should be negative.*

Hypothesis 2. *The relation between fluency and abnormal returns is stronger following periods of high naive investor participation.*

Hypothesis 1 reflects the opposite predictions of the affect and the information story on the relation between fluency and stock returns. Hypothesis 2 states that this relation becomes especially strong following high demand from naive investors, even though with opposite signs in the two settings.

From Propositions 1 and 3, we derive:

Hypothesis 3. *There is a positive relation between fluency and firm valuations. If fluency correlates with firm quality, the price differential between fluent and nonfluent stocks increases when naive investor participation is low. If company name fluency merely attracts the attention of naive investors, the price differential increases when naive investor participation is high.*

It is important to notice the difference in timing between Hypotheses 2 and 3. The effect of fluency on prices is contemporaneous. The effect of fluency on returns, instead, represents mispricing correction, and therefore takes place over the following period.

In the empirical analysis that follows, we take these predictions to the data.

3. Data and methods

We use the data set of U.S. company name fluency scores from Green and Jame (2013), which covers the sample period from 1981 to 2008 for all stocks in CRSP. The overall fluency score of a firm is the sum of length, Englishness, and dictionary scores. Length is defined as the number of words in a company name, ignoring articles, conjunctions, the state of incorporation, hyphens, and expressions that are an official but often omitted part of the legal name (such as Corp., Inc., Ltd., LLC, and FSB). The length score takes on a value of two if it is made up of one word, one for two words, and zero for more than two words. The Englishness variable takes on value zero if the company name is in the bottom quintile of Englishness, as assessed using the linguistic algorithm by Travers and Olivier (1978), and one otherwise. Finally, the dictionary variable takes on value one if all words in the name pass the Microsoft spell-check and zero otherwise. Overall, then, the index varies between zero and four. Scores are recorded on December 31 of the fiscal year ending before the most recent June 30, and the total number of firm-year observations is 127,720.

Table 1 presents the summary statistics for the fluency measure and its components. The mean length score is 1.01, with standard deviation 0.71. The mean dictionary score is 0.33, with standard deviation 0.47. The mean Englishness score is 0.81, with standard deviation 0.40. The fluency index, then, has mean 2.14, with standard deviation 0.88. In unreported analyses, we find that this value is quite stable over time, starting at 2.16 in 1981 and ending at 2.10 in 2008.

Next, we explore the distribution of fluency scores across stocks. The categories with the fewest observations are those with extreme fluency scores, i.e., zero (4,202) and four (3,729). The category with the most observations is score two (50,719), followed by scores three (44,161) and one (24,909). The industry breakdown reveals no major differences across the main U.S. industries. The list includes Agriculture, Forestry, and Fishing (2.11), Mining and Construction (2.20), Manufacturing (2.28), Transportation, Communications, Electric, Gas, and Sanitary service (2.00), Wholesale and Retail Trade (2.18), Finance, Insurance, and Real Estate (1.83), Services (2.23), and Public Administration (2.24).

In Table 2, we present the summary statistics for the firm-level variables. Accounting variables are from Compustat, and refer to the fiscal year ending before the most recent June 30. Market prices, like fluency scores, are measured on December 31 of the same fiscal year. In Panel A, we consider the full sample. Average total assets across firms and years are \$7.7 billion, net sales \$3.3 billion, employees 15.7 thousand, EBITDA \$0.61 billion, and EBIT \$0.46 billion. Among the multiples of interest, the average price-to-EBITDA ratio is 0.86, price-to-EBIT 1.80, the market-to-book ratio 2.46, and Tobin's q 1.54. As for operating performance, the average return on assets, defined as EBITDA divided by the book value of assets, is 13%. In Panel B, we break down these mean values into different beginning-of-year fluency scores. We find that fluent firms tend to exhibit higher Tobin's q, return on assets, and sales. In the empirical analysis that follows, we shed further light on these patterns.

In Table 3, we present the summary statistics for returns and investor sentiment. In Panel A, we consider value-weighted returns on portfolios of stocks with specific fluency scores. We find that average returns follow an interesting pattern. The least fluent stocks (score zero) yield 0.87% per month. This average increases to 1.06% for score one, 1.18% for score two, 1.17% for score three, and 1.31% for the most fluent stocks (score four). The difference in stock returns between the top and the bottom fluency category is then 0.44%. Similarly, the average return for the top two categories combined (score 3 or 4) is 1.18% per month, versus 1.03% per month for the bottom two categories combined (score 0 or 1).

In Panel B, we consider factor returns and investor sentiment. The list includes the factor-mimicking portfolios from Carhart (1997), Fama and French (2015), and Pástor and Veronesi (2003), and the monthly investor sentiment index from Baker and Wurgler (2007). The average return is equal to 0.40% for the market factor, -0.20% for the size factor, 0.49% for the book-to-market factor, 0.76% for the momentum factor, 0.37% for the investment factor, 0.41% for the profitability factor, and 0.47% for the liquidity factor. The average value for the investor sentiment index is -0.03, and almost half of the monthly observations in our sample (49%) fall in high-sentiment periods.

To estimate abnormal returns, we first consider a battery of factor models:

$$R_{it} = \alpha_i + \beta^{'} Z_t + \epsilon_{it}, \tag{14}$$

where the dependent variable is the value-weighted excess return over the one-month Treasury bill rate of the least fluent stocks (score zero, and scores zero or one collapsed) and the most fluent stocks (score four, and scores three or four collapsed), and the return of the long-short portfolio on fluency scores (single and dual scores). Vector Z_t includes factor-mimicking portfolios from Carhart (1997) or Fama and French (2015), while in robustness checks we also consider factors from Pástor and Stambaugh (2003), Novy-Marx (2013), and Stambaugh and Yuan (2017). Under the information (affect) story, Hypothesis 1 implies $\alpha_i > 0$ ($\alpha_i < 0$) for the long-short portfolios.

Hypothesis 2 implies that the magnitude of abnormal returns on the long-short portfolios should increase with naive investor demand. To test for this, we proceed in two ways. First, we acknowledge that such demand is high among stocks with relatively subjective valuations, such as extreme growth and distressed firms (Baker and Wurgler, 2006, 2007). Following this line of reasoning, we re-estimate Eq. (14) in subsamples of stocks ranked along book-to-market and earnings-to-price ratios. Second, we build on the insight that high investor sentiment leads to greater participation of naive investors in the market (Baker and Wurgler, 2006, 2007; Yu and Yuan, 2011; Stambaugh, Yu, and Yuan, 2012), and add a dummy variable to Eq. (14) that takes on value one when Baker and Wurgler's (2007) investor sentiment index is positive at the beginning of the month, and zero otherwise.

One concern is that factor models may not entirely capture systematic risk, and specifically, that fluency may be correlated with other firm characteristics that affect stock returns in their own right. To address this issue, we test Hypothesis 1 through the following Fama-MacBeth regressions:

$$R_{it} = \beta_1 F_{it-1} + \gamma^{'} Z_{it} + \epsilon_{it}, \tag{15}$$

where R_{it} is the excess return on stock i in month t, F_{it-1} is the beginning-of-year company name's fluency score, and Z_{it} is a vector of controls that includes market beta, calculated through CAPM regressions over a 36-month moving window, and firm characteristics from Brennan, Chordia, and Subrahmanyam (1998). Such characteristics are firm size, defined as the log of market capitalization at the end of month $t-2$; the log of the book-to-market ratio, calculated each July and held constant through the following June; the ratio of dividends in the previous fiscal year to market value at calendar year-end, calculated each July and held constant through the following June; cumulative returns over months $t-3$ through $t-2$, months $t-6$ through $t-4$, and months $t-12$ through $t-7$; the log of the dollar volume of trading in the stock in month $t-2$; the log of the stock price at the end of month $t-2$. Hypothesis 1 implies $\beta_1 > 0$ ($\beta_1 < 0$) under the information (affect) story.

To define fluency scores, we primarily consider the raw (unrestricted) version of the fluency index. One concern, however, is that the extreme fluency categories (zero and four) exhibit a relatively small number of firm-year observations. In additional tests, then, we create a restricted version of the fluency index, reducing the number of scores from five to three, grouping together the least fluent scores (0 and 1) and the most fluent scores (3 and 4), respectively. The restricted fluency index then takes on integer values between one and three. We also construct a dummy variable that takes on value one if the fluency index takes on the most fluent scores (3 and 4), and zero otherwise, and in the spirit of Mueller, Ouimet, and Simintzi (2017) we exclude company names with a middle score (2) from the analysis.

Next, we introduce fixed effects regressions. It is important to distinguish them from the Fama-MacBeth specifications because fixed effects allow us to include variables that have a pure time series dimension, such as investor sentiment. To test Hypothesis 2, we estimate:

$$R_{it} = \beta_{0i} + \beta_{0t} + \beta_1 F_{it-1} + \beta_2 S_t + \beta_3 S_t \times F_{it-1} + \gamma^{'} Z_{it} + \epsilon_{it}, \tag{16}$$

where R_{it} is the excess return on stock i in month t; F_{it-1} is either the beginning-of-year company name's fluency score (unrestricted or restricted), or a dummy variable that takes on value one if the fluency score is among the top two categories (three or four); S_{t-1} is beginning-of-period Baker and Wurgler's (2007) investor sentiment index, orthogonalized to business cycle indicators, and expressed in changes due to its high persistence; and Z_{it} is the vector of controls introduced above. Again, when we use the fluency dummy we leave out the stocks whose fluency score lies in the middle of the fluency distribution (i.e., score two), so that we can effectively measure the difference in returns between the top two and the bottom two fluency categories. We introduce year fixed effects to control for potential time trends (β_{0t}), and in additional tests we make the analysis within-firm by introducing firm fixed effects (β_{0i}). Hypothesis 1 implies $\beta_1 > 0$ ($\beta_1 < 0$) under the information (affect) story, while Hypothesis 2 implies $\beta_3 > 0$ ($\beta_3 < 0$).

To identify beginning-of-period sentiment, we follow an approach similar to Brennan, Chordia, and Subrahmanyam (1998), who warn that the return during the immediate prior month may exhibit a spurious association with the return during the current month, for example due to thin trading or bid–ask spread effects. Then, they define past returns as a cumulative sum of different return lags. Since returns partly reflect the current level of investor sentiment (Baker and Wurgler, 2007), we may encounter a similar issue with lagged sentiment on the right-hand side of the test equation. For this reason, we define beginning-of-period sentiment as a cumulative sum of sentiment changes over months $t-4$ through $t-1$.[1]

Finally, we test Hypothesis 3 using the valuation regressions from Mueller, Ouimet, and Simintzi (2017):

$$V_{it} = \beta_{0t} + \beta_1 F_{it} + \beta_2 S_t + \beta_3 S_t \times F_{it} + \gamma Z_{it} + \epsilon_{it}, \tag{17}$$

where V_{it} is Tobin's q of company i, F_{it} is either the end-of-year company name's fluency score (unrestricted or restricted), or a dummy variable that takes on value one if the fluency score is among the top two categories (three or four), S_t is Baker and Wurgler's (2006) annual investor sentiment index, orthogonalized and expressed in levels, β_{0t} is year fixed effects, and Z_{it} is the number of employees working for the company, used as a proxy for firm size. All variables refer to the same year t. Standard errors are clustered by firm. Hypothesis 3 implies $\beta_1 > 0$ and $\beta_3 < 0$ ($\beta_3 > 0$) under the information (affect) story.

4. Empirical results

We present our empirical findings as follows. First, we analyze the relation between fluency and abnormal returns in canonical asset pricing models. Second, we examine how these results change when we take into account variations in naive trader demand. Third, we explore within-firm fluency changes. Fourth, we test the model's predictions on the relation between fluency and firm valuations. Last, we perform additional tests to validate two key assumptions of the model.

[1] The results that follow are similar for the alternative specifications $t-3$ through $t-1$ and $t-3$ through $t-2$, and when controlling for cumulative sentiment over months $t-6$ through $t-4$ and $t-12$ through $t-7$.

4.1. Abnormal returns

Table 4 reports the estimates of Eq. (14). In Panel A, we consider Carhart's (1997) four-factor model. In columns (1) to (3), we construct portfolios on single fluency scores. We find that monthly abnormal returns are equal to 0.48% for the portfolio of stocks with a fluency score of zero (t-stat 5.25), 0.92% for the portfolio of stocks with a fluency score of four (t-stat 5.25), and the difference of 0.44% is significant (t-stat 2.08). In columns (4) to (6), we find similar results for portfolios of aggregate fluency scores. Monthly abnormal returns are equal to 0.62% for a portfolio of stocks with fluency scores of zero or one (t-stat 8.24), 0.83% for a portfolio with fluency scores of three or four (t-stat 13.77), and the 0.21% difference is significant (t-stat 2.37).

In Panel B, we repeat the analysis using the five-factor model from Fama and French (2015), which includes the market, size, and book-to-market factors, and adds an investment and a profitability factor. The difference in abnormal returns between fluent and nonfluent stocks rises to 1.05% for the single-score portfolios (t-stat 3.27), and 0.39% for the dual-score portfolios (t-stat 3.52). This model provides a better fit for all specifications, and the alpha t-stats also clear the critical value of three proposed by Harvey, Liu, and Zhu (2015).

Frazzini and Pedersen (2014) find that a high market beta is associated with low alpha, because leverage- and margin-constrained investors bid up high-beta assets. One concern, then, is that our results may partly reflect this effect. Reassuringly, however, we find that the difference in market betas between fluent and nonfluent stocks is not significant in any of the tests except one, in which fluent stocks actually exhibit a higher market beta than nonfluent stocks (0.10, t-stat 2.84). Our results, then, do not seem to be driven by the low-beta anomaly.

In Table 5, we check whether the results are robust to the simultaneous inclusion of all of the above factors. In addition, we also include Pástor and Stambaugh's (2003) liquidity factor, to rule out the concern that the difference in returns might represent a liquidity premium (Anderson and Larkin, 2018; Green and Jame, 2013). The results are virtually unchanged. The difference in abnormal returns between fluent and nonfluent stocks is 0.90% for the single-score portfolios (t-stat 3.29), and 0.38% for the dual-score portfolios (t-stat 3.66).

To make sure that the mispricing of fluency is not driven by other well-known effects, we also consider the factor model from Novy-Marx (2013), which includes a market, book-to-market, momentum, and profitability factor, and the behavioral factor model from Stambaugh and Yuan (2017), which includes a market, size, management, and performance factor. The latter model is particularly important, because it captures other behavioral biases. The results are in Table 6. In either model, we find that the pattern of abnormal returns is again unchanged. Altogether these results suggest that fluency constitutes indeed a novel effect, and the robust outperformance of high-fluency stocks supports the information hypothesis.

One concern is that portfolios with low fluency scores also exhibit positive abnormal returns.

This result might reflect the fact that the sample period we consider is rather special, in the sense that canonical asset pricing models do not fully explain returns (see, e.g., Davis, Fama, and French (2000) for an insightful discussion). As long as the pricing error applies to all assets, however, then it should cancel out in the long-short portfolios. We also address this concern more directly in the analysis that follows, when we replace factor models with panel regressions.

4.2. Naive investor participation

To test Hypothesis 2, we need to identify the size of naive investor demand, i.e., the term κ from the model. We proceed in two ways. First, we follow Baker and Wurgler (2006), and check whether the mispricing of fluent stocks relative to nonfluent ones is more pronounced among stocks that are harder to evaluate and/or arbitrage. The intuition is that the size of naive investor demand is larger among such stocks, which should amplify the impact of naive investors' evaluations on the stock price.

To test for this, we construct separate long-short portfolios – long in stocks with a fluency score of four and short in stocks with a fluency score of zero – for separate subsamples of the universe of stocks ranked along the book-to-market ratio, defined as book value of equity divided by market capitalization, and the earnings-to-price ratio, defined as EBIT or EBITDA per share divided by the stock price. In particular, we define stocks as speculative if these ratios lie in the top or bottom 30% of the distribution, and non-speculative otherwise. Then, we re-estimate our main equations for each of the six subsamples.

The results are in Table 7. In the extreme book-to-market subsample, we find that the long-short portfolio yields positive and significant monthly abnormal returns of 0.36% in the four-factor model (t-stat 2.02), and 0.60% in the five-factor model (t-stat 2.53). As predicted, none of the coefficients are significant in the subsample of stocks with intermediate book-to-market values. The results are analogous for the two earnings-to-price ratios. In the extreme EBIT-to-price subsample, the long-short portfolio yields a positive and significant alpha of 0.39% in the four-factor model (t-stat 2.10), and 0.54% in the five-factor model (t-stat 3.23). Again, the coefficients are not significant in the intermediate subsample. In the extreme EBITDA-to-price subsample, the alphas exhibit a similar pattern.

In our second batch of tests, we acknowledge that high investor sentiment leads to greater participation of naive investors in the market, which in turn is followed by a larger mispricing correction (Baker and Wurgler, 2006, 2007; Yu and Yuan, 2011; Stambaugh, Yu, and Yuan, 2012). Building on this mechanism, we repeat the analysis conditioning on the beginning-of-period level of the monthly investor sentiment index from Baker and Wurgler (2007), orthogonalized to several

U.S. business cycle indicators.[2] In particular, we introduce a dummy variable that takes on value one when sentiment is high (i.e., above its zero mean) at the end of the previous month, and zero otherwise. Under the affect hypothesis, high naive investor participation should be followed by lower stock returns on fluent stocks, while the opposite holds under the information hypothesis.

The results are in Table 8. In Panel A, we re-estimate our regressions for the full sample. In columns (1) to (3), we consider single-score portfolios. We find that the portfolio of stocks with a fluency score of zero yields positive, even though not significant, abnormal returns when beginning-of-period sentiment is low (0.21%, t-stat 1.13), and zero additional abnormal returns when sentiment is high (-0.01%, t-stat -0.03). On the other hand, the portfolio of stocks with a fluency score of four yields a positive and significant alpha of 0.73% when beginning-of-period sentiment is low (t-stat 3.58), while excess returns increase by an additional 0.87% when sentiment is high (t-stat 3.56). Similarly, the long-short portfolio yields positive and significant abnormal returns of 0.52% when beginning-of-period sentiment is low (t-stat 2.09), which increases by 0.88% when sentiment is high (t-stat 2.81).

In columns (4) to (6), we find a similar pattern for dual-score portfolios. The portfolio of stocks with fluency scores of zero or one yields excess returns of 0.43% (t-stat 5.07), and this result does not vary with sentiment (t-stat 0.09). The portfolio of stocks with fluency scores of three or four, on the other hand, yields a positive and significant alpha of 0.66% when beginning-of-period sentiment is low (t-stat 6.55), while excess returns increase by an additional 0.27% in times of high sentiment (t-stat 2.15). Similarly, abnormal returns on the long-short portfolio are positive and significant when beginning-of-period sentiment is low (0.24%, t-stat 2.00), and increase by 0.26% when sentiment is high (t-stat 1.84).

To shed further light on these findings, we repeat the analysis in the six valuation subsamples introduced above. The results are in Panel B. We find that the beginning-of-period sentiment dummy is positive and highly significant in the subsamples of stocks with extreme book-to-market (0.89%, t-stat 2.45), extreme EBIT-to-price (0.62%, t-stat 2.40), and extreme EBITDA-to-price ratios (0.64%, t-stat 2.46), and completely explains away the alphas from the previous regressions. Therefore, the difference in returns between fluent and nonfluent speculative stocks only takes place when beginning-of-period naive trader participation is high.

An important concern is that factor models may not entirely capture systematic risk. In particular, fluency may be correlated with other firm characteristics that are also known to affect stock returns. To address this issue, we test Hypothesis 1 through the Fama-MacBeth regressions from Eq. (15), and Hypothesis 2 through the fixed effects regressions from Eq. (16).

[2]This measure is based on a number of proxies suggested in previous literature, including the closed-end fund discount, NYSE share turnover, the number and average first-day returns of IPOs, the equity share in new issues, and the dividend premium.

The results are in Table 9. In column (1), we find that the coefficient of the unrestricted fluency index in Fama-MacBeth regressions is not significant and close to zero (-0.01%, t-stat -0.76). Green and Jame (2013) obtain the same point estimate in untabulated Fama-MacBeth regressions without controls (see Green and Jame (2013), page 823, Section 5.3), and conclude that the effect of fluency on stock returns is too small to be detected.

In column (2), however, the fixed effects panel regressions shed new light on this issue. We find that there is a strong conditional effect of fluency on stock returns when taking into account time variation in naive trader demand. The coefficient of the interaction term between fluency and beginning-of-period investor sentiment is positive and significant. In particular, following a one standard deviation increase in sentiment, a one point increase in the unrestricted fluency index is associated with higher excess returns of 0.05% per month (t-stat 2.44). This result is consistent with the information story.

Among the other variables, the coefficient of the unrestricted fluency index as a stand-alone variable is virtually unchanged from that of the Fama-MacBeth regressions (-0.01%, t-stat -0.87). The coefficient of sentiment is negative and highly significant, which is consistent with the mispricing correction mechanism from Baker and Wurgler (2006). In particular, a one standard deviation increase in beginning-of-period sentiment is followed by a decrease in excess stock returns 0.35% (t-stat -7.78).

The estimates are similar in columns (3) and (4), where we consider the restricted fluency index. In columns (5) and (6), we find that the coefficient of the interaction term between the fluency dummy and beginning-of-period sentiment is also positive and significant (t-stat 2.46), which indicates that following a one standard deviation increase in sentiment, an increase in fluency from either of the bottom two fluency scores (zero or one) to either of the top fluency scores (three or four) is associated with a 0.12% increase in stock returns (t-stat 2.32).

4.3. Within-firm variation in fluency

Green and Jame (2013) find that within-firm improvements in fluency are associated with higher firm valuations. To analyze whether such changes also affect stock returns, we proceed to re-estimate Eq. (16) with firm fixed effects. This is an important test to alleviate the concern that the between-firm estimates could be driven by time-invariant omitted variables.

The results are in Table 10. In columns (1) to (3), we find again an interesting pattern across different sentiment states. The coefficient of the interaction term between fluency and investor sentiment is positive and significant all throughout. When beginning-of-period sentiment increases by one standard deviation, a within-firm one point increase in the unrestricted fluency index is associated with higher excess returns of 0.05% per month (t-stat 2.22). We find an analogous result for the restricted fluency index (0.05%, t-stat 2.24), while a within-firm fluency shift from either of the bottom two fluency scores (zero or one) to either of the top fluency scores (three or four) is associated with a 0.12% increase in stock returns (t-stat 2.34).

Among the other variables, the coefficient of fluency as a stand-alone variable is not significant, while the coefficient of sentiment is negative and highly significant, which is again consistent with Baker and Wurgler's (2006) mispricing correction mechanism. The use of firm fixed effects indicates that the results are not driven by specific sectors, because firms typically belong to the same industry throughout the entire sample period. Unreported tests show that the results are indeed virtually unchanged with different specifications of industry fixed effects. All the results are also robust to the inclusion of an interaction term between size and book-to-market, which allays the concern that the mispricing might be driven by small growth firms (Davis, Fama, and French, 2000).

Another potential concern is that investors might exhibit aversion towards foreign firms. If so, then the fluency effect might be partly driven by firms with foreign origin, and in particular, company names with a low Englishness score. To look into this issue, we re-estimate our baseline regressions by excluding all firms with an Englishness score of zero. As a result, the minimum value for the fluency score becomes one, rather than zero, for these tests. The results, reported in columns (4) to (6), are similar across all three fluency specifications. The coefficient of the interaction term between fluency and beginning-of-period sentiment is positive and significant, and the economic magnitudes are similar to those from the full sample for the unrestricted fluency index (0.05%, t-stat 2.03), the restricted fluency index (0.07%, t-stat 2.26), and the fluency dummy (0.18%, t-stat 2.48). Then, the fluency effect does not seem to be driven by non-English company names.[3]

Next, we look into three specific categories of stocks. Green and Jame (2013) find that the impact of fluency on valuations decreases with firm size. They argue that investors are more familiar with large firms, and repeated exposure makes information processing easier (see, e.g., Labroo, Dhar, and Schwarz, 2008). Also, small stocks are more prone to mispricing (Baker and Wurgler, 2006). To assess the effect of firm size in our analysis, we replace the monthly size variable from the baseline regressions with a dummy variable that takes on one for firms whose number of employees lies above the median at the end of the previous fiscal year, or whose market capitalization lies above the median on December 31 of the previous fiscal year, and introduce a battery of interaction terms with the fluency and sentiment variables.

The results are in Table 11. In column (1), the coefficient of the interaction term between the unrestricted fluency index and beginning-of-period sentiment is positive and highly significant,

[3]Green and Jame (2013) also consider this alternative story in their analysis of firm valuations. They re-estimate their regressions excluding firms whose headquarters are located outside the US, and find similar results.

and even larger in magnitude with respect to the baseline model. Following a one standard deviation increase in beginning-of-month sentiment, a within-firm one point increase in the unrestricted fluency index is associated with higher excess returns of 0.11% per month (t-stat 3.14). The effect, however, entirely vanishes for firms whose market capitalization is above-median (-0.12%, t-stat -2.74).

Among the other variables of interest, the coefficient of sentiment is again negative and highly significant (t-stat -6.47). The coefficient of the size dummy is close to zero in both magnitude and significance, while the coefficient of the interaction term between size and sentiment is positive and highly significant (t-stat 3.49), which is in line with the mispricing correction mechanism from Baker and Wurgler (2006). The results are similar for the other fluency specifications in columns (2) and (3), and when defining size as market capitalization in columns (4) to (6). Overall, then, the effect of fluency on stock returns is mostly confined to firms with below-median size.

Another line of reasoning is that the fluency effect might be specific to tech firms, due to their high level of intangible assets. Moreover, firms related to the internet attracted undue attention from investors during the dot.com bubble, which resulted in an increase in valuations (Cooper, Dimitrov, and Rau, 2001). To shed light on this issue, we introduce a dummy variable that takes on value one for firms that belong in the high-tech industries from Kile and Phillips (2009). The list includes (three-digit SIC codes between brackets): computer hardware manufacturing (357), software development (737), medical technology (283, 382, 384, 873), communications (366, 481, 484, 489), and electrical (361-365, 367).

The results are in Table 12, columns (1) to (3). In column (1), the coefficient of the interaction term between the tech dummy and the unrestricted fluency index indicates that the effect of a within-firm one point increase in fluency on excess returns is 0.25% higher among tech firms. Despite the large magnitude, however, statistical significance is weak (t-stat 1.75). The coefficients of the other interaction terms with the tech dummy are not significant. Among the other variables, the coefficient of the interaction term between fluency and beginning-of-period sentiment is positive and significant, while the coefficient of sentiment as a standalone variable is negative and significant, both with similar magnitudes to those from the baseline specifications. We find a comparable pattern for the other fluency specifications, in columns (2) and (3).

Finally, we explore whether the fluency effect might be specific to firms with high volatility. Due to their high uncertainty about future performance, the information contained in fluency might be more important for such firms, which implies greater underpricing. To test for this, we follow Ang, Hodrick, Xing, and Zhang (2006, 2009), and introduce idiosyncratic volatility (iVol) in the analysis. In particular, we construct a dummy variable that takes on value one for firms whose annual standard deviation of residuals from Carhart's (1997) four-factor model lies above the median on December 31 of the previous fiscal year. The estimates are in Table 12, columns (4) to (6). We find that the inclusion of iVol does not alter the results from the baseline specifications, and the coefficient of the iVol dummy is never significant, either as a standalone variable or as an interaction term.

Overall, then, the results show that the effect of fluency on stock returns reflects not only cross-sectional differences in fluency across firms, but also variations in fluency within firms. In either case, the empirical evidence lends support to the information hypothesis.

4.4. Company valuations

After considering returns, we test the model's predictions on valuations. Green and Jame (2013) find a positive and robust relation between company name fluency and Tobin's q. They argue that this result could reflect either a naive preference for fluency from unsophisticated investors, or better quality of fluent firms, but leave the task of disentangling the two to future research. In the next batch of tests, we address this point by testing Hypothesis 3. Under the information hypothesis, the model predicts that the prices of fluent and nonfluent stocks should be closer to each other when naive investor demand is large.

To this end, we study the contemporaneous relation between Tobin's q, fluency, and sentiment through Eq. (17). The results are in Table 13. In Panel A, we find that a one-unit increase in the unrestricted fluency index is associated with an increase in Tobin's q of 0.07 (t-stat 4.59), or 0.06 when controlling for firm size (t-stat 3.76). In line with the information hypothesis, the coefficient of the interaction term between fluency and sentiment is negative and significant (t-stat -2.52), which implies that the difference in valuations between fluent and nonfluent firms shrinks by 0.02 when sentiment increases by one standard deviation. In Panel B, we find a similar pattern using the restricted fluency index.

The magnitudes become even larger in Panel C, where we use the fluency dummy. The difference in Tobin's q between firms with a fluency score of either three or four and firms with a fluency score of either zero or one is 0.18 (t-stat 4.80), or 0.16 when controlling for firm size (t-stat 4.02). When investor sentiment increases by one standard deviation, this difference in valuations shrinks by 0.05 (t-stat -2.65), or 0.04 when we add firm size as a control (t-stat -2.33).

The findings provide support to Hypothesis 3, and specifically to the information story. Overall, the empirical evidence is in line with the model prediction that high naive investor participation is associated with a decrease in the price differential between fluent and nonfluent stocks, and thus followed by a higher return differential between these two categories of stocks.

4.5. Additional tests

In his 2017 AFA Presidential Address, Campbell R. Harvey tells a valuable cautionary tale on how research in asset pricing can produce spurious results in the absence of a clear economic mechanism. In this paper, we address this concern with specific tests for the two underpinnings of the information story.

First, we test the basic assumption that fluent companies are better firms than nonfluent ones. In our next batch of regressions, then, we analyze the relation between fluency and operating performance. To this end, we re-estimate Eq. (17) using return on assets as dependent variable, defined as EBITDA divided by the book value of assets. The results are in Table 14. We find that a one point increase in the unrestricted fluency index is associated with an increase in return on assets of 1.12 percentage points over the next year (t-stat 7.60), or 0.90 when controlling for firm size (t-stat 5.98).

We find that fluency also predicts operating performance over a longer time horizon.[4] A one point increase in the unrestricted fluency index is associated with an increase of 1.07 percentage points in the firm's average operating performance over the subsequent three years, i.e., two to four years ahead (t-stat 6.18), or 0.79 when including firm size as a control (t-stat 4.46). We obtain analogous estimates in Panel B, where we use the restricted version of the fluency index. In Panel C, the coefficients become even larger when using the fluency dummy. In unreported tests, we find similar results when we alternatively define return on assets using EBIT in place of EBITDA.

If the higher profitability of fluent firms is due to a superior reputation among consumers, then high fluency scores should also be associated with larger sales. The argument is as follows. Products with fluent names exhibit higher brand recognition (Bao, Shao, and Rivers, 2008). In turn, brand recognition makes products more likable to customers (Baker, Hutchinson, Moore, and Nedungadi, 1986; Keller, 1993), helps companies build an image of higher quality (Biel, 1992; Buil, Martínez, and de Chernatony, 2013), and ultimately leads to higher sales (Cobb-Walgren, Ruble and Donthu, 1995; Morton, 1994).[5] Since company names convey information on the quality of the firm (Fombrun and Shanley, 1990; Tadelis, 1999), a similar mechanism might also apply to fluent company names.

To test for this, we re-estimate Eq. (17) using real net sales as a dependent variable. The results are in Table 15. Consistent with our conjecture, we find that a one unit increase in the unrestricted fluency index is associated with a significant increase in sales over the next year by 18% (t-stat 4.46), or 14% when controlling for size (t-stat 3.88). The results are similar for the restricted fluency index (17%, t-stat 3.85), and even larger for the fluency dummy (34%, t-stat

[4]This is an important test, as accounting data are released with some delay.

[5]Names are widely regarded as the most important element in creating a brand (see, e.g., Herbig and Milewicz, 1993; Turley and Moore, 1995; Janiszewski and Van Osselaer, 2000). For example, Nelson (1974) suggests that brand names reflect most of the information content of advertising. Similarly, Erdem and Swait (1998) show that consumers may use brand names as a signal for the credibility of product claims. From a behavioral perspective, Brown and Stayman (1992) argue that a favorably perceived brand name can lead to an overall positive judgment of the product through a "halo" effect.

3.81).[6]

As with ROA, high fluency is also associated with larger sales over a longer time span. A one point increase in the unrestricted fluency index is followed by an 11% increase in the firm's average sales over the subsequent three years, (t-stat 2.20), or 9% when including firm size as a control (t-stat 2.04). The estimates are analogous in Panel B, when we use the restricted version of the fluency index. In Panel C, we find that the difference in average future sales over the next three years between companies with fluency scores of three or four and companies with fluency scores of zero or one is 22% (t-stat 2.06).

Second, we test the assumption that the mispricing of fluency comes from expectation errors among a subset of investors. Following Engelberg, McLean, and Pontiff (2018), we conjecture that this bias, if present among naive traders, should also characterize the forecasts of less sophisticated analysts. The mechanism we hypothesize is as follows. If some analysts neglect the information about good fundamentals captured by fluency, their expectations should be systematically too pessimistic for fluent firms. When aggregating forecasts across all analysts, then, fluent firms should produce positive earnings surprises.

To test for this, we follow Latané and Jones (1977, 1979), and analyze the relation between standardized unexpected earnings and fluency scores. In addition to firm and year fixed effects, we also consider quarter fixed effects to make sure that expectation errors (if any) are not specific to a seasonal time of the year. The results are in Table 16, Panel A. We find that the most fluent firms (score 4) exhibit positive and highly significant quarterly earnings surprises, while the coefficient is not significant for firms with lower fluency scores. The empirical evidence then lends support to our conjecture that the mispricing of fluency comes from expectation errors.

If analysts are systematically less optimistic about fluent firms, we expect this bias to be particularly large when the average analyst evaluation is less optimistic for all firms. To test for this, we build again on the mapping between naive traders and less sophisticated analysts, and identify times of high pessimism as those in which Baker and Wurgler's (2007) index of investor sentiment takes on negative values at the end of the previous quarter. Then, we re-estimate our baseline specifications in subsamples of negative and positive sentiment, respectively. The results are in Table 16, Panels B and C. Consistent with the line of reasoning we propose, the expectation error becomes even larger in times of negative sentiment, and disappears in times of positive sentiment.

[6]Morton (1994) reports that a one point increase in survey-based brand quality perception on an 11-point scale coincides with a 30% increase in sales. Interestingly, our estimates are of similar economic magnitude.

5. Conclusion

Building on the insight that fluent stocks trade at a premium, we explore two ways in which fluency can affect asset prices. On the one hand, unsophisticated investors may exhibit a naive preference for stocks with fluent names. Alternatively, firms that carry better names also exhibit superior fundamentals.

Our empirical analysis lends support to the latter story. We show that fluent companies achieve higher profitability and larger sales, and systematically surprise investors and analysts. As a consequence, fluent stocks yield higher abnormal returns than nonfluent ones, especially when sentiment-driven demand is high.

Green and Jame (2013) find a positive and robust association between fluent company names and valuations, but leave the analysis of the underlying economic mechanism to future research. Our results provide an answer to this question. The identification of a specific channel through which fluency affects stock prices also addresses the concern that the analysis may be driven by spurious correlations.

This paper also speaks to a burgeoning literature that shows how investors tend to underprice intangibles (see, e.g, Edmans, 2011). We find that this mechanism, which leads to higher long-run returns, also applies to company name fluency.

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Table 1. Summary statistics: Fluency measures

Summary statistics for the overall fluency scores and its components (Panel A), distribution across scores (Panel B), and fluency scores across industries (Panel C) for the U.S. company name fluency scores from Green and Jame (2013). The overall fluency score is split into its three components: Length, Dictionary, and Englishness. Scores are recorded on December 31 of the fiscal year ending before the most recent June 30. The sample period is from 1981 through 2007, for an overall number of 127,720 firm-year observations.

Panel A

Variable	Mean	Standard Deviation	Min	Max
Fluency	2.14	0.88	0	4
Length	1.01	0.71	0	2
Dictionary	0.33	0.47	0	1
Englishness	0.81	0.40	0	1

Panel B

Variable	Scores	Frequency	Percent	Cumulative
Fluency	0	4,202	3.29	3.29
	1	24,909	19.50	22.79
	2	50,719	39.71	62.50
	3	44,161	34.58	97.08
	4	3,729	2.92	100.00
Length	0	31,272	24.48	24.48
	1	63,801	49.95	74.44
	2	32,647	25.56	100.00
Dictionary	0	85,985	67.32	67.32
	1	41,741	32.68	100.00
Englishness	0	24,804	19.42	19.42
	1	102,922	80.58	100.00

Panel C

Industry	Mean	Standard Deviation	Min	Max
Agriculture	2.11	0.98	0	4
Construction	2.20	0.86	0	4
Manufacturing	2.28	0.84	0	4
Communications	2.00	0.90	0	4
Trade	2.18	0.87	0	4
Finance	1.83	0.89	0	4
Services	2.23	0.85	0	4
Public Administration	2.24	0.78	1	3

Table 2. Summary statistics: Firm-level variables

Summary statistics for the firm-level variables in our sample. The list includes total assets; net sales, defined as the amount of billings to customers for regular sales completed during the period reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers; the number of employees; EBITDA; EBIT; common dividends; the closing stock price; the price-to-dividend ratio; the price-to-EBITDA ratio; the price-to-EBIT ratio; the market-to-book ratio, defined as market capitalization divided by the book value of equity; Tobin's q, defined as enterprise value (debt plus market value of equity) divided by book value (debt plus book value of equity); return on assets (ROA), defined as EBITDA divided by book value of assets; and total R&D expenses divided by total sales. Panel A presents the mean, standard deviation, and 25^{th}, 50^{th}, and 75^{th} percentiles for the full sample, while Panel B reports the mean value of each variable for firms with different beginning-of-year company name fluency scores. Accounting variables refer to the fiscal year ending before the most recent June 30, stock prices are measured on December 31 of the same fiscal year, and fluncy scores are measured on December 31 of the previous fiscal year. Firm data are from Compustat, while fluency data are from Green and Jame (2013). The sample period is from 1981 to 2007, for an overall number of 127,720 firm-year observations.

Panel A. Full sample

Variable	Mean	St. Dev.	p25	Median	p75
Total Assets ($ millions)	7,673	50,411	214	757	2,880
Net Sales ($ millions)	3,302	11,907	150	562	2,125
Employees (thousands)	15.68	50.96	0.85	3.27	11.40
EBITDA ($ millions)	610	2,585	20	75	310
EBIT ($ millions)	462	2,160	14	54	224
Dividends ($ millions)	0.74	0.88	0.24	0.52	1.00
Closing Price ($)	29.28	30.54	15.25	24.25	36.50
Price-to-Dividend	84.74	209.64	27.42	44.82	82.21
Price-to-EBITDA	0.86	6.87	0.10	0.31	0.88
Price-to-EBIT	1.80	27.80	0.14	0.44	1.21
Market-to-Book	2.46	8.62	1.22	1.72	2.58
Tobin's q	1.54	0.94	1.05	1.23	1.68
ROA	0.13	0.09	0.07	0.13	0.18
R&D-to-Sales	0.03	0.04	0.00	0.02	0.04

Panel B. Mean breakdown by fluency score

Variable	Score 0	Score 1	Score 2	Score 3	Score 4
Total Assets ($ millions)	6,520	8,736	7,774	8,417	5,107
Net Sales ($ millions)	2,971	2,943	3,193	3,976	4,090
Employees (thousands)	12.58	14.10	15.89	17.45	17.25
EBITDA ($ millions)	477	604	620	697	658
EBIT ($ millions)	355	493	473	504	453
Dividends ($ millions)	0.85	0.75	0.72	0.73	0.74
Closing Price ($)	30.54	28.65	29.87	29.39	37.43
Price-to-Dividend	74.18	80.15	80.37	92.20	79.68
Price-to-EBITDA	0.88	0.95	0.90	0.73	0.69
Price-to-EBIT	1.57	1.62	1.77	1.70	1.31
Market-to-Book	2.32	2.27	2.44	2.66	2.99
Tobin's q	1.44	1.47	1.54	1.64	1.55
ROA	0.11	0.11	0.13	0.14	0.15
R&D-to-Sales	0.02	0.03	0.03	0.03	0.02

Table 3. Summary statistics: Returns and investor sentiment

Summary statistics for returns and investor sentiment in our sample. Panel A presents the mean, standard deviation, and 25^{th}, 50^{th}, and 75^{th} percentiles for the full sample of monthly returns on value-weighted portfolios of U.S. stocks with specific company name fluency scores formed on December 31 of the previous fiscal year. Panel B includes the factor-mimicking portfolios from Carhart (1997), Fama and French (2015), and Pástor and Stambaugh (2003), namely the market (MKT), size (SMB), book-to-market (HML), momentum (UMD), investment (CMA), profitability (RMW), and liquidity (IML) factors, along with Baker and Wurgler's (2007) investor sentiment, orthogonalized to business cycle indicators, expressed as an index and as a dummy variable (d) that takes on value one if the index is positive and zero otherwise. Stock data are from CRSP, fluency data are from Green and Jame (2013), factor data are from Kenneth French's website, except for the liquidity factor which is from Ľuboš Pástor's website, and the investor sentiment index is from Jeffrey Wurgler's website. The sample period is from January 1982 to December 2008, for an overall number of 324 months.

Panel A. Returns on fluency portfolios

	Mean	St. Dev.	p25	Median	p75
R0	0.0087	0.0460	-0.0190	0.0118	0.0363
R1	0.0106	0.0413	-0.0140	0.0111	0.0356
R2	0.0118	0.0436	-0.0158	0.0152	0.0377
R3	0.0117	0.0468	-0.0146	0.0139	0.0410
R4	0.0131	0.0555	-0.0199	0.0152	0.0416
R4−R0	0.0103	0.0413	-0.0161	0.0114	0.0353
R01	0.0118	0.0470	-0.0159	0.0138	0.0407
R34	0.0044	0.0418	-0.0155	0.0034	0.0195
R34−R01	0.0015	0.0191	-0.0098	0.0014	0.0119

Panel B. Factor returns and investor sentiment

	Mean	St. Dev.	p25	Median	p75
MKT	0.0040	0.0456	-0.2645	0.0105	0.1175
SMB	-0.0020	0.0334	-0.2526	-0.0018	0.0811
HML	0.0049	0.0302	-0.0987	0.0035	0.1302
UMD	0.0076	0.0432	-0.2878	0.0093	0.1687
CMA	0.0037	0.0212	-0.0705	0.0022	0.0908
RMW	0.0041	0.0253	-0.1932	0.0048	0.1150
IML	0.0047	0.0367	-0.1353	0.0066	0.1060
Sentiment	-0.0345	0.9778	-0.5308	-0.0192	0.4611
Sentiment (d)	0.4846	0.5005	0	0	1

Table 4. Returns on portfolios formed on fluency scores

OLS regressions of value-weighted excess returns on low and high fluency stocks, and returns on a long-short portfolio of high-minus-low fluency stocks. The regressions include the four-factor model from Carhart (1997) in Panel A, and the five-factor from Fama and French (2015) in Panel B. The fluency scores are from Green and Jame (2013), refer to company names, and take on integer values between 0 (least fluent) to 4 (most fluent). The portfolios are formed on December 31 of the previous fiscal year. Observations are monthly. Stock data are from CRSP, fluency data are from Green and Jame (2013), and factor data are from Kenneth French's website. The sample period is from January 1982 to December 2008. Heteroskedasticity and autocorrelation-robust t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Four-factor model from Carhart (1997)

	(1) R0−Rf	(2) R4−Rf	(3) R4−R0	(4) R01−Rf	(5) R34−Rf	(6) R34−R01
MKT	0.9096***	1.0197***	0.1102	0.8901***	0.9931***	0.1030***
	(19.17)	(17.67)	(1.15)	(28.17)	(51.45)	(2.84)
SMB	-0.0533	-0.0334	0.0199	-0.1284***	-0.0765**	0.0518
	(-0.57)	(-0.34)	(0.11)	(-3.38)	(-2.43)	(0.95)
HML	0.1788**	-0.1966***	-0.3754**	0.1081	-0.0724**	-0.1805***
	(2.04)	(-2.71)	(-2.46)	(1.55)	(-2.20)	(-2.85)
UMD	-0.1046*	0.0962	0.2008	-0.0347	-0.0372*	-0.0024
	(-1.73)	(1.02)	(1.63)	(-0.93)	(-1.71)	(-0.04)
Constant	0.0048***	0.0092***	0.0044**	0.0062***	0.0083***	0.0021**
	(5.25)	(5.25)	(2.08)	(8.24)	(13.77)	(2.37)
Observations	324	324	324	324	324	324
Adj. R-squared	0.76	0.77	0.14	0.90	0.96	0.23

Panel B. Five-factor model from Fama and French (2015)

	(1) R0−Rf	(2) R4−Rf	(3) R4−R0	(4) R01−Rf	(5) R34−Rf	(6) R34−R01
MKT	1.0029***	0.9144***	-0.0885	0.9591***	0.9890***	0.0298
	(21.70)	(26.26)	(-1.25)	(36.19)	(53.51)	(1.39)
SMB	-0.0529	-0.0634	-0.0104	-0.1271***	-0.0692***	0.0579*
	(-0.84)	(-0.99)	(-0.09)	(-5.51)	(-2.83)	(1.65)
HML	0.0195	-0.1359**	-0.1554*	0.0200	-0.0648	-0.0848*
	(0.27)	(-2.03)	(-1.72)	(0.54)	(-1.45)	(-1.84)
CMA	0.3781***	-0.1530	-0.5311**	0.2068***	-0.0128	-0.2196***
	(3.02)	(-1.14)	(-2.26)	(3.43)	(-0.22)	(-2.63)
RMW	0.2469**	-0.4747***	-0.7215***	0.2594***	-0.0421	-0.3015***
	(2.24)	(-4.83)	(-3.29)	(4.13)	(-1.27)	(-6.40)
Constant	0.0021*	0.0125***	0.0105***	0.0043***	0.0082***	0.0039***
	(1.70)	(5.01)	(3.27)	(7.75)	(7.06)	(3.52)
Observations	324	324	324	324	324	324
Adj. R-squared	0.78	0.81	0.30	0.93	0.96	0.40

Table 5. Returns on portfolios formed on fluency scores: All factors

OLS regressions of value-weighted excess returns on low and high fluency stocks, and returns on a long-short portfolio of high-minus-low fluency stocks. The regressions include the risk factors from Carhart's (1997) four-factor model, the investment and profitability factors from Fama and French (2015), and the liquidity factor from Pástor and Stambaugh (2003). The fluency scores are from Green and Jame (2013), refer to company names, and take on integer values between 0 (least fluent) to 4 (most fluent). The portfolios are formed on December 31 of the previous fiscal year. Observations are monthly. Stock data are from CRSP, fluency data are from Green and Jame (2013), and factor data are from Kenneth French's website, except for the liquidity factor which is from Ľuboš Pástor's website. The sample period is from January 1982 to December 2008. Heteroskedasticity and autocorrelation-robust t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

	(1) R0−Rf	(2) R4−Rf	(3) R4−R0	(4) R01−Rf	(5) R34−Rf	(6) R34−R01
MKT	0.9881***	0.9230***	-0.0651	0.9564***	0.9849***	0.0285
	(26.99)	(27.44)	(-1.26)	(38.85)	(56.28)	(1.31)
SMB	-0.0782	-0.0421	0.0361	-0.1349***	-0.0775***	0.0573*
	(-1.24)	(-0.75)	(0.38)	(-5.76)	(-2.97)	(1.74)
HML	0.0004	-0.1341*	-0.1345	0.0209	-0.0680	-0.0889*
	(0.01)	(-1.79)	(-1.50)	(0.52)	(-1.62)	(-1.78)
UMD	-0.1079**	0.0980**	0.2060***	-0.0364*	-0.0370*	-0.0007
	(-2.32)	(2.15)	(3.43)	(-1.77)	(-1.82)	(-0.02)
CMA	0.3887***	-0.1544	-0.5431**	0.2065***	-0.0109	-0.2175**
	(2.78)	(-1.10)	(-2.23)	(3.53)	(-0.22)	(-2.57)
RMW	0.2523**	-0.4733***	-0.7256***	0.2583***	-0.0416	-0.2999***
	(2.56)	(-6.59)	(-5.04)	(5.03)	(-1.31)	(-6.22)
IML	0.0689	0.0343	-0.0347	-0.0228	0.0025	0.0253
	(1.63)	(0.83)	(-1.05)	(-0.98)	(0.13)	(0.70)
Constant	0.0026**	0.0116***	0.0090***	0.0047***	0.0085***	0.0038***
	(2.56)	(5.36)	(3.29)	(7.94)	(8.35)	(3.66)
Observations	324	324	324	324	324	324
Adj. R-squared	0.79	0.81	0.34	0.93	0.96	0.40

Table 6. Returns on portfolios formed on fluency scores: Other factor models

OLS regressions of value-weighted excess returns on low and high fluency stocks, and returns on a long-short portfolio of high-minus-low fluency stocks. In Panel A, the regressions include the market, book-to-market, momentum, and profitability factors from Novy-Marx (2013). In Panel B, the regressions include the market, size, management, and performance factors from Stambaugh and Yuan (2017). The fluency scores are from Green and Jame (2013), refer to company names, and take on integer values between 0 (least fluent) to 4 (most fluent). The portfolios are formed on December 31 of the previous fiscal year. Observations are monthly. Stock data are from CRSP, while factor data are from Robert F. Stambaugh and Robert Novy-Marx's websites. The sample period is from January 1982 to December 2008. Heteroskedasticity and autocorrelation-robust t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Four-factor model from Novy-Marx (2013)

	(1) R0−Rf	(2) R4−Rf	(3) R4−R0	(4) R01−Rf	(5) R34−Rf	(6) R34−R01
MKT	0.9157***	0.9865***	0.0708	0.9039***	0.9977***	0.0938***
	(30.14)	(23.93)	(1.22)	(37.84)	(49.25)	(3.97)
HML	0.3378**	-0.4146***	-0.7525***	0.2091*	-0.1196**	-0.3288***
	(2.15)	(-4.14)	(-3.36)	(1.82)	(-2.11)	(-3.84)
UMD	-0.2002**	0.2107	0.4109**	-0.0634	-0.0431	0.0204
	(-1.99)	(1.39)	(1.98)	(-1.22)	(-0.94)	(0.22)
PMU	0.4135**	-0.6173***	-1.0308***	0.4747***	0.0563	-0.4184***
	(1.97)	(-2.91)	(-3.32)	(3.64)	(0.92)	(-2.87)
Constant	0.0032*	0.0122***	0.0091***	0.0041***	0.0084***	0.0043***
	(1.86)	(5.69)	(3.31)	(4.14)	(7.15)	(3.06)
Observations	324	324	324	324	324	324
Adj. R-squared	0.76	0.79	0.20	0.90	0.96	0.23

Panel B. Four-factor model from Stambaugh and Yuan (2017)

	(1) R0−Rf	(2) R4−Rf	(3) R4−R0	(4) R01−Rf	(5) R34−Rf	(6) R34−R01
MKT	1.0066***	1.0224***	0.0158	0.9722***	1.0341***	0.0619**
	(24.43)	(20.81)	(0.30)	(51.16)	(77.92)	(2.22)
SMB	-0.1551***	0.1901**	0.3452***	-0.1387***	-0.0038	0.1349***
	(-2.75)	(2.21)	(3.29)	(-3.50)	(-0.17)	(2.65)
MGMT	0.2630**	-0.1648*	-0.4278**	0.2040***	-0.0119	-0.2159***
	(2.17)	(-1.72)	(-2.05)	(3.45)	(-0.65)	(-3.18)
PERF	0.0228	0.0701	0.0473	0.0516	0.0250	-0.0267
	(0.35)	(0.85)	(0.45)	(1.50)	(1.21)	(-0.52)
Constant	0.0019	0.0079***	0.0060**	0.0039***	0.0065***	0.0026**
	(1.63)	(4.70)	(2.28)	(6.50)	(5.73)	(2.39)
Observations	324	324	324	324	324	324
Adj. R-squared	0.78	0.78	0.19	0.92	0.97	0.29

Table 7. Returns on portfolios formed on fluency scores: Cross-sectional breakdown

OLS regressions of value-weighted excess returns on a long-short portfolio of high-minus-low fluency stocks. The regressions include the the four-factor model from Carhart (1997) in Panel A, and the five-factor from Fama and French (2015) in Panel B. The fluency scores are from Green and Jame (2013), refer to company names, and take on integer values between 0 (least fluent) to 4 (most fluent). The portfolios are formed on December 31 of the previous fiscal year, and further split into middle 40% and extreme (i.e., top and bottom) 30% stocks in terms of book-to-market ratio, EBITDA over price, and EBIT over price. Observations are monthly. Stock data are from CRSP, accounting data are from Compustat, fluency data are from Green and Jame (2013), and factor data are from Kenneth French's website. The sample period is from January 1982 to December 2008. Heteroskedasticity and autocorrelation-robust t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Four-factor model from Carhart (1997)

Dep. Var.: R4−R0	**Book-to-market**		**EBITDA/P**		**EBIT/P**	
	(1) Middle	(2) Extreme	(3) Middle	(4) Extreme	(5) Middle	(6) Extreme
MKT	-0.1712*	0.1913**	0.4285***	-0.0363	0.4113***	-0.0268
	(-1.78)	(2.30)	(4.23)	(-0.85)	(3.50)	(-0.62)
HML	-0.2352*	-0.0100	-0.0834	-0.1225	-0.0937	-0.1212
	(-1.76)	(-0.09)	(-0.72)	(-1.07)	(-0.63)	(-1.14)
SMB	-0.0347	0.1152	-0.0411	0.1366	-0.0727	0.1374
	(-0.34)	(0.63)	(-0.35)	(0.98)	(-0.48)	(0.99)
UMD	0.1627	-0.0978	-0.0328	-0.0137	0.0471	-0.0155
	(1.26)	(-1.30)	(-0.38)	(-0.17)	(0.47)	(-0.19)
Constant	0.0022	0.0036**	0.0017	0.0039**	0.0010	0.0040**
	(1.08)	(2.02)	(0.71)	(2.10)	(0.38)	(2.23)
Observations	324	324	324	324	324	324
Adj. R-squared	0.05	0.07	0.14	0.03	0.11	0.03

Panel B. Five-factor model from Fama and French (2015)

Dep. Var.: R4−R0	**Book-to-market**		**EBITDA/P**		**EBIT/P**	
	(1) Middle	(2) Extreme	(3) Middle	(4) Extreme	(5) Middle	(6) Extreme
MKT	-0.1614	0.0783	0.3177***	-0.1013*	0.2498***	-0.0891*
	(-1.51)	(1.35)	(5.53)	(-1.96)	(4.67)	(-1.65)
HML	-0.1987	0.1594	0.0914	-0.0071	0.1061	-0.0062
	(-1.15)	(1.50)	(0.78)	(-0.06)	(0.89)	(-0.05)
SMB	-0.0495	0.1468	-0.0185	0.1525	-0.0716	0.1543
	(-0.46)	(1.09)	(-0.21)	(1.35)	(-0.70)	(1.34)
CMA	-0.1027	-0.3768	-0.3973	-0.2628	-0.4652*	-0.2618
	(-0.42)	(-1.50)	(-1.50)	(-1.59)	(-1.93)	(-1.57)
RMW	0.2378**	-0.5047***	-0.4334**	-0.2309***	-0.6437***	-0.2163***
	(2.04)	(-4.36)	(-2.30)	(-3.24)	(-2.62)	(-3.06)
Constant	0.0026	0.0060**	0.0043	0.0054***	0.0053	0.0055***
	(0.99)	(2.53)	(1.49)	(3.23)	(1.64)	(3.28)
Observations	324	324	324	324	324	324
Adj. R-squared	0.04	0.16	0.18	0.07	0.19	0.06

Table 8. Returns on portfolios formed on fluency scores: High vs. low sentiment
OLS regressions of value-weighted excess returns on low and high fluency stocks, and returns on a long-short portfolio of high-minus-low fluency stocks, the risk-factors from Fama and French (2015), and a dummy variable that takes on value one if Baker and Wurgler's (2007) investor sentiment index, orthogonalized to business cycle indicators, is positive at the beginning of the period, and zero otherwise. In Panel A, we consider the full sample, while in Panel B we split the sample into middle 40% and extreme (i.e., top and bottom) 30% stocks in terms of in terms of book-to-market ratio, EBITDA over market capitalization, and EBIT over market capitalization. The portfolios are formed on December 31 of the previous fiscal year. Observations are monthly. Stock data are from CRSP, accounting data are from Compustat, fluency data are from Green and Jame (2013), factor data are from Kenneth French's website, and the investor sentiment index is from Jeffrey Wurgler's website. The sample period is from January 1982 to December 2008. Heteroskedasticity and autocorrelation-robust t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Full sample

	(1) R0−Rf	(2) R4−Rf	(3) R4−R0	(4) R01−Rf	(5) R34−Rf	(6) R34−R01
MKT	1.0030***	0.9105***	-0.0925	0.9591***	0.9877***	0.0286
	(20.16)	(26.19)	(-1.46)	(34.34)	(54.06)	(1.32)
SMB	-0.0530	-0.0567	-0.0037	-0.1271***	-0.0671***	0.0599*
	(-0.80)	(-0.94)	(-0.03)	(-5.22)	(-2.81)	(1.68)
HML	0.0196	-0.1431**	-0.1626	0.0199	-0.0671	-0.0870**
	(0.31)	(-2.26)	(-1.51)	(0.50)	(-1.59)	(-1.98)
CMA	0.3782***	-0.1651	-0.5433***	0.2067***	-0.0166	-0.2233***
	(2.61)	(-1.22)	(-3.01)	(3.62)	(-0.29)	(-2.80)
RMW	0.2470*	-0.4904***	-0.7374***	0.2592***	-0.0470	-0.3063***
	(1.82)	(-5.26)	(-4.05)	(4.69)	(-1.42)	(-6.87)
Sentiment (-1)	-0.0001	0.0087***	0.0088***	0.0001	0.0027**	0.0026*
	(-0.03)	(3.56)	(2.81)	(0.09)	(2.15)	(1.84)
Constant	0.0021	0.0073***	0.0052**	0.0043***	0.0066***	0.0024**
	(1.13)	(3.58)	(2.09)	(5.07)	(6.55)	(2.00)
Observations	324	324	324	324	324	324
Adj. R-squared	0.78	0.81	0.31	0.93	0.96	0.40

Panel B. Stock categories

Dep. Var.: R4−R0	**Book-to-market**		**EBITDA/P**		**EBIT/P**	
	(1) Middle	(2) Extreme	(3) Middle	(4) Extreme	(5) Middle	(6) Extreme
MKT	-0.1614	0.0742	0.3174***	-0.1041**	0.2494***	-0.0920*
	(-1.54)	(1.25)	(5.55)	(-2.02)	(4.52)	(-1.73)
HML	-0.1987	0.1520	0.0909	-0.0122	0.1054	-0.0114
	(-1.17)	(1.55)	(0.76)	(-0.11)	(0.84)	(-0.10)
SMB	-0.0496	0.1536	-0.0180	0.1572	-0.0710	0.1592
	(-0.43)	(1.17)	(-0.21)	(1.37)	(-0.71)	(1.38)
CMA	-0.1026	-0.3893	-0.3982	-0.2714	-0.4664*	-0.2707
	(-0.49)	(-1.57)	(-1.49)	(-1.64)	(-1.78)	(-1.60)
RMW	0.2378*	-0.5208***	-0.4345**	-0.2421***	-0.6452**	-0.2279***
	(1.94)	(-4.64)	(-2.20)	(-3.58)	(-2.47)	(-3.51)
Sentiment (-1)	-0.0000	0.0089**	0.0006	0.0062**	0.0008	0.0064**
	(-0.01)	(2.45)	(0.09)	(2.40)	(0.11)	(2.46)
Constant	0.0027	0.0006	0.0039	0.0017	0.0049	0.0017
	(0.77)	(0.29)	(0.69)	(0.87)	(0.82)	(0.85)
Observations	324	324	324	324	324	324
Adj. R-squared	0.03	0.17	0.18	0.07	0.19	0.07

Table 9. Returns, fluency scores, and investor sentiment: Panel regressions

Panel regressions of U.S. monthly excess stock returns on company name fluency scores, investor sentiment, an interaction term between fluency and investor sentiment, market beta, calculated through CAPM regressions of any given stock over a 36-month moving window, and a set of controls from Brennan, Chordia, and Subrahmanyam (1998). The fluency scores are from Green and Jame (2013), measured on December 31 of the previous fiscal year, and take on integer values between 0 (least fluent) and 4 (most fluent). In columns (1) and (2), we consider the raw (unrestricted) version of the fluency index. In columns (3) and (4), we create a restricted version of the fluency index, reducing the number of scores from five to three, grouping together the least fluent scores (0 and 1) and the most fluent scores (3 and 4), respectively. In columns (5) and (6), we construct a dummy variable that takes on value one if the fluency index takes on the most fluent scores (3 and 4), and zero otherwise, and exclude company names with a middle score (2). We define sentiment as Baker and Wurgler's (2007) investor sentiment index, expressed in changes and orthogonalized to business cycle indicators, and calculated as a cumulative sum over months $t-4$ through $t-1$, due to endogeneity concerns. In columns (1), (3), and (5), we estimate Fama-MacBeth regressions. In columns (2), (4), and (6), we estimate panel regressions with year fixed effects, and standard errors clustered by firm. Stock data are from CRSP, accounting data are from Compustat, and the investor sentiment index is from Jeffrey Wurgler's website. The sample period is from January 1982 to December 2008, and t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Dep. Var.: Ri−Rf	Unrestricted		Restricted		Dummy	
	(1)	(2)	(3)	(4)	(5)	(6)
Fluency	-0.0001	-0.0001	-0.0003	-0.0003	-0.0005	-0.0005
	(-0.76)	(-0.87)	(-1.17)	(-1.45)	(-1.10)	(-1.26)
Sentiment (-1,-4)		-0.0020***		-0.0021***		-0.0019***
		(-7.78)		(-7.10)		(-9.03)
Fluency x Sentiment (-1,-4)		0.0003**		0.0003**		0.0007**
		(2.44)		(2.42)		(2.46)
Beta (-1)	0.0018	0.0011***	0.0018	0.0011***	0.0022	0.0015***
	(0.60)	(2.78)	(0.60)	(2.80)	(0.74)	(3.11)
Book-to-Market (-1)	0.0013**	0.0014***	0.0013**	0.0014***	0.0010	0.0011***
	(2.18)	(4.43)	(2.17)	(4.41)	(1.60)	(2.62)
Dividend Yield (-1)	0.0009**	0.0008***	0.0009**	0.0008***	0.0010*	0.0009***
	(2.07)	(3.66)	(2.06)	(3.66)	(1.95)	(2.81)
CumRet (-2,-3)	0.0069*	-0.0260***	0.0068*	-0.0260***	0.0082*	-0.0256***
	(1.70)	(-15.77)	(1.69)	(-15.77)	(1.88)	(-12.30)
CumRet (-4,-6)	0.0121***	-0.0067***	0.0121***	-0.0067***	0.0130***	-0.0076***
	(3.96)	(-4.99)	(3.96)	(-4.98)	(4.00)	(-4.18)
CumRet (-7,-12)	0.0135***	0.0045***	0.0135***	0.0045***	0.0120***	0.0034***
	(6.50)	(4.69)	(6.49)	(4.69)	(5.35)	(2.80)
Size (-2)	-0.0003	-0.0005*	-0.0003	-0.0005*	-0.0003	-0.0004
	(-0.61)	(-1.78)	(-0.61)	(-1.78)	(-0.44)	(-1.10)
Price (-2)	-0.0012*	-0.0019***	-0.0012*	-0.0019***	-0.0012	-0.0017***
	(-1.66)	(-4.10)	(-1.67)	(-4.11)	(-1.48)	(-2.86)
Volume (-2)	-0.0002	0.0003	-0.0002	0.0003	-0.0003	0.0001
	(-0.54)	(1.17)	(-0.54)	(1.19)	(-0.70)	(0.37)
Constant	0.0145***	0.0180***	0.0148***	0.0183***	0.0181***	0.0208***
	(2.92)	(11.01)	(2.98)	(11.10)	(3.49)	(10.21)
Fama-MacBeth	Y	N	Y	N	Y	N
Year FE	N	Y	N	Y	N	Y
Observations	340,520	337,077	340,520	337,077	204,928	202,850
Adj. R-squared	0.1165	0.0027	0.1165	0.0027	0.1260	0.0026

Table 10. Panel regressions of returns and fluency scores: Firm fixed effects

Panel regressions of U.S. monthly excess stock returns on company name fluency scores, investor sentiment, an interaction term between fluency and investor sentiment, market beta, calculated through CAPM regressions of any given stock over a 36-month moving window, and a set of controls from Brennan, Chordia, and Subrahmanyam (1998). The fluency scores are from Green and Jame (2013), measured on December 31 of the previous fiscal year, and take on integer values between 0 (least fluent) and 4 (most fluent). In columns (1) and (4), we consider the raw (unrestricted) version of the fluency index. In columns (2) and (5), we create a restricted version of the fluency index, reducing the number of scores from five to three, grouping together the least fluent scores (0 and 1) and the most fluent scores (3 and 4), respectively. In columns (3) and (6), we construct a dummy variable that takes on value one if the fluency index takes on the most fluent scores (3 and 4), and zero otherwise, and exclude company names with a middle score (2). We define sentiment as Baker and Wurgler's (2007) investor sentiment index, expressed in changes and orthogonalized to business cycle indicators, and calculated as a cumulative sum over months $t-4$ through $t-1$, due to endogeneity concerns. In columns (1) to (3), we include the full sample; in columns (4) to (6), we only include stocks with a high Englishness score from Green and Jame (2013). All specifications include firm and year fixed effects. Observations are monthly. Stock data are from CRSP, accounting data are from Compustat, and the sample period is from January 1982 to December 2008. Heteroskedasticity-robust t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Dep. Var.: Ri−Rf	Full sample			High Englishness stocks		
	(1) Unrestricted	(2) Restricted	(3) Dummy	(4) Unrestricted	(5) Restricted	(6) Dummy
Fluency	0.0005	0.0000	-0.0003	-0.0004	-0.0007	-0.0038
	(0.93)	(0.06)	(-0.18)	(-0.47)	(-0.81)	(-1.44)
Sentiment (-1,-4)	-0.0019***	-0.0020***	-0.0018***	-0.0021***	-0.0022***	-0.0021***
	(-6.60)	(-6.08)	(-7.67)	(-5.12)	(-5.13)	(-6.02)
Fluency x Sentiment (-1,-4)	0.0003**	0.0003**	0.0007**	0.0003**	0.0004**	0.0010**
	(2.22)	(2.24)	(2.34)	(2.03)	(2.26)	(2.48)
Beta (-1)	-0.0006	-0.0006	0.0000	-0.0008	-0.0008	-0.0002
	(-1.13)	(-1.11)	(0.07)	(-1.41)	(-1.40)	(-0.33)
Book-to-Market (-1)	0.0003	0.0003	0.0001	-0.0004	-0.0004	-0.0010
	(0.52)	(0.52)	(0.18)	(-0.61)	(-0.61)	(-1.13)
Dividend Yield (-1)	0.0004	0.0004	0.0004	0.0001	0.0001	0.0001
	(1.25)	(1.24)	(1.14)	(0.48)	(0.47)	(0.17)
CumRet (-2,-3)	-0.0276***	-0.0276***	-0.0277***	-0.0272***	-0.0272***	-0.0288***
	(-15.93)	(-15.93)	(-12.41)	(-14.13)	(-14.13)	(-11.50)
CumRet (-4,-6)	-0.0093***	-0.0093***	-0.0104***	-0.0098***	-0.0098***	-0.0103***
	(-6.44)	(-6.44)	(-5.54)	(-6.08)	(-6.08)	(-4.85)
CumRet (-7,-12)	0.0030***	0.0030***	0.0021	0.0027**	0.0027**	0.0011
	(2.77)	(2.77)	(1.55)	(2.27)	(2.27)	(0.73)
Size (-2)	-0.0155***	-0.0155***	-0.0153***	-0.0160***	-0.0160***	-0.0160***
	(-26.55)	(-26.55)	(-19.92)	(-24.24)	(-24.24)	(-18.28)
Price (-2)	-0.0048***	-0.0048***	-0.0054***	-0.0052***	-0.0052***	-0.0057***
	(-6.24)	(-6.23)	(-5.38)	(-6.10)	(-6.10)	(-5.01)
Volume (-2)	-0.0005	-0.0005	-0.0009**	-0.0005	-0.0005	-0.0008
	(-1.49)	(-1.48)	(-2.14)	(-1.35)	(-1.35)	(-1.64)
Constant	0.2401***	0.2411***	0.2442***	0.2501***	0.2510***	0.2569***
	(38.52)	(38.23)	(29.57)	(34.78)	(34.44)	(26.62)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	337,077	337,077	202,850	269,883	269,883	157,449
Adj. R-squared	0.0113	0.0113	0.0115	0.0117	0.0117	0.0120

Table 11. Panel regressions of returns and fluency scores: Company size breakdown

Panel regressions of U.S. monthly excess stock returns on company name fluency scores, investor sentiment, an interaction term between fluency and investor sentiment, a variable that takes on value one if the company belongs exhibits above-median size, defined as market capitalization (columns 1 to 3) or real net sales (columns 4 to 6), market beta, calculated through CAPM regressions of any given stock over a 36-month moving window, and a set of controls from Brennan, Chordia, and Subrahmanyam (1998). The fluency scores are from Green and Jame (2013), measured on December 31 of the previous fiscal year, and take on integer values between 0 (least fluent) to 4 (most fluent). In columns (1) and (4), we consider the raw (unrestricted) version of the fluency index. In columns (2) and (5), we create a restricted version of the fluency index, reducing the number of scores from five to three, grouping together the least fluent scores (0 and 1) and the most fluent scores (3 and 4), respectively. In columns (3) and (6), we construct a dummy variable that takes on value one if the fluency index takes on the most fluent scores (3 and 4), and zero otherwise, and exclude company names with a middle score (2). We define sentiment as Baker and Wurgler's (2007) investor sentiment index, expressed in changes and orthogonalized to business cycle indicators, and calculated as a cumulative sum over months $t-4$ through $t-1$, due to endogeneity concerns. Stock data are from CRSP, accounting data are from Compustat, and the sample period is from January 1982 to December 2008. Heteroskedasticity-robust t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Dep. Var.: Ri−Rf	Size (Employees)			Size (Market Cap)		
	(1) Unrestricted	(2) Restricted	(3) Dummy	(4) Unrestricted	(5) Restricted	(6) Dummy
Fluency	0.0011	0.0011	0.0016	0.0007	0.0006	-0.0005
	(1.38)	(1.08)	(0.66)	(0.64)	(0.46)	(-0.16)
Sentiment (-1,-4)	-0.0029***	-0.0032***	-0.0026***	-0.0030***	-0.0034***	-0.0026***
	(-6.47)	(-6.30)	(-7.57)	(-4.49)	(-4.34)	(-5.03)
Fluency x Sentiment (-1,-4)	0.0006***	0.0008***	0.0016***	0.0008***	0.0010***	0.0020***
	(3.14)	(3.41)	(3.45)	(2.73)	(2.82)	(2.81)
Large	0.0001	0.0010	0.0007	-0.0103***	-0.0100***	-0.0125***
	(0.05)	(0.49)	(0.42)	(-4.32)	(-3.75)	(-6.47)
Sentiment (-1,-4) x Large	0.0020***	0.0025***	0.0017***	0.0014*	0.0017**	0.0011*
	(3.49)	(3.66)	(3.80)	(1.92)	(2.02)	(1.88)
Fluency x Large	-0.0005	-0.0009	-0.0016	-0.0000	-0.0002	0.0007
	(-0.59)	(-0.97)	(-0.81)	(-0.05)	(-0.17)	(0.27)
Fluency x Large Sentiment (-1,-4)	-0.0007***	-0.0009***	-0.0019***	-0.0007**	-0.0008**	-0.0016**
	(-2.74)	(-3.00)	(-3.05)	(-2.03)	(-2.11)	(-2.09)
Beta (-1)	-0.0000	-0.0000	0.0005	-0.0001	-0.0000	0.0004
	(-0.04)	(-0.03)	(0.80)	(-0.10)	(-0.09)	(0.58)
Book-to-market (-1)	0.0038***	0.0038***	0.0038***	0.0037***	0.0037***	0.0036***
	(6.36)	(6.37)	(4.91)	(6.41)	(6.41)	(4.76)
Dividend Yield (-1)	0.0007**	0.0007**	0.0008**	0.0007**	0.0007**	0.0008**
	(2.28)	(2.28)	(2.08)	(2.39)	(2.39)	(2.16)
CumRet (-2,-3)	-0.0273***	-0.0273***	-0.0276***	-0.0295***	-0.0295***	-0.0301***
	(-15.42)	(-15.43)	(-12.09)	(-16.99)	(-16.99)	(-13.45)
CumRet (-4,-6)	-0.0093***	-0.0093***	-0.0106***	-0.0110***	-0.0110***	-0.0125***
	(-6.23)	(-6.23)	(-5.50)	(-7.56)	(-7.56)	(-6.65)
CumRet (-7,-12)	0.0040***	0.0040***	0.0031**	0.0025**	0.0025**	0.0013
	(3.66)	(3.66)	(2.18)	(2.31)	(2.31)	(0.91)
Price (-2)	-0.0160***	-0.0160***	-0.0165***	-0.0143***	-0.0143***	-0.0147***
	(-22.45)	(-22.44)	(-17.56)	(-20.74)	(-20.73)	(-15.98)
Volume (-2)	-0.0055***	-0.0055***	-0.0057***	-0.0049***	-0.0049***	-0.0050***
	(-19.11)	(-19.12)	(-14.89)	(-17.71)	(-17.70)	(-13.79)
Constant	0.1149***	0.1151***	0.1187***	0.1123***	0.1126***	0.1171***
	(28.26)	(27.20)	(23.24)	(26.11)	(24.82)	(22.91)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	323,677	323,677	195,055	337,077	337,077	202,850
Adj. R-squared	0.0352	0.0352	0.0362	0.0355	0.0355	0.0366

Table 12. Panel regressions of returns and fluency scores: Tech and high iVol firms breakdown
Panel regressions of U.S. monthly excess stock returns on company name fluency scores, investor sentiment, an interaction term between fluency and investor sentiment, a variable that takes on value one if the company belongs in a specific stock category, namely technology (columns 1 to 3), or high idiosyncratic volatility (columns 4 to 6), market beta, calculated through CAPM regressions of any given stock over a 36-month moving window, and a set of controls from Brennan, Chordia, and Subrahmanyam (1998). The fluency scores are from Green and Jame (2013), measured on December 31 of the previous fiscal year, and take on integer values between 0 (least fluent) to 4 (most fluent). In columns (1) and (4), we consider the raw (unrestricted) version of the fluency index. In columns (2) and (5), we create a restricted version of the fluency index, reducing the number of scores from five to three, grouping together the least fluent scores (0 and 1) and the most fluent scores (3 and 4), respectively. In columns (3) and (6), we construct a dummy variable that takes on value one if the fluency index takes on the most fluent scores (3 and 4), and zero otherwise, and exclude company names with a middle score (2). We define sentiment as Baker and Wurgler's (2007) investor sentiment index, expressed in changes and orthogonalized to business cycle indicators, and calculated as a cumulative sum over months $t-4$ through $t-1$, due to endogeneity concerns. We define technology stocks as companies that belong in high-tech industries from Kile and Phillips (2009), and companies with high idiosyncratic volatility as those that exhibit above-median annual standard deviation of residuals from Carhart's (1997) four-factor model on December 31 of the previous fiscal year. All specifications include firm and year fixed effects. Observations are monthly. Stock data are from CRSP, accounting data are from Compustat, and the sample period is from January 1982 to December 2008. Heteroskedasticity-robust t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Dep. Var.: Ri−Rf		Tech firms			High iVol firms	
	(1) Unrestricted	(2) Restricted	(3) Dummy	(4) Unrestricted	(5) Restricted	(6) Dummy
Fluency	0.0003	-0.0003	-0.0009	0.0005	0.0000	-0.0003
	(0.49)	(-0.37)	(-0.49)	(0.90)	(0.06)	(-0.15)
Sentiment (-1,-4)	-0.0020***	-0.0020***	-0.0019***	-0.0020***	-0.0022***	-0.0018***
	(-6.56)	(-5.94)	(-7.64)	(-7.03)	(-6.55)	(-7.85)
Fluency x Sentiment (-1,-4)	0.0003**	0.0003**	0.0007**	0.0003**	0.0004**	0.0008**
	(2.16)	(2.08)	(2.18)	(2.50)	(2.56)	(2.56)
Category	-0.0043	-0.0052	-0.0030	-0.0010	-0.0007	-0.0003
	(-1.22)	(-1.30)	(-0.93)	(-0.54)	(-0.32)	(-0.18)
Category x Sentiment (-1,-4)	0.0010	0.0007	0.0007	0.0011	0.0013	0.0004
	(1.03)	(0.62)	(0.93)	(1.00)	(1.01)	(0.40)
Fluency x Category	0.0025*	0.0029*	0.0047	0.0003	0.0001	-0.0007
	(1.75)	(1.74)	(1.29)	(0.31)	(0.11)	(-0.36)
Fluency x Category x Sentiment(-1,-4)	-0.0002	-0.0001	-0.0002	-0.0003	-0.0004	-0.0005
	(-0.46)	(-0.13)	(-0.17)	(-0.69)	(-0.74)	(-0.48)
Beta (-1)	-0.0006	-0.0006	0.0000	-0.0005	-0.0005	0.0001
	(-1.14)	(-1.13)	(0.06)	(-1.06)	(-1.05)	(0.14)
Book-to-Market (-1)	0.0003	0.0003	0.0001	0.0003	0.0003	0.0001
	(0.49)	(0.50)	(0.16)	(0.47)	(0.47)	(0.14)
Dividend Yield (-1)	0.0004	0.0004	0.0004	0.0004	0.0003	0.0004
	(1.25)	(1.24)	(1.14)	(1.24)	(1.24)	(1.14)
CumRet (-2,-3)	-0.0276***	-0.0276***	-0.0278***	-0.0276***	-0.0276***	-0.0276***
	(-15.97)	(-15.97)	(-12.44)	(-15.95)	(-15.95)	(-12.40)
CumRet (-4,-6)	-0.0094***	-0.0094***	-0.0104***	-0.0093***	-0.0093***	-0.0103***
	(-6.46)	(-6.46)	(-5.55)	(-6.41)	(-6.42)	(-5.51)
CumRet (-7,-12)	0.0030***	0.0030***	0.0021	0.0030***	0.0030***	0.0022
	(2.78)	(2.78)	(1.55)	(2.81)	(2.81)	(1.59)
Size (-2)	-0.0155***	-0.0155***	-0.0153***	-0.0155***	-0.0155***	-0.0153***
	(-26.54)	(-26.54)	(-19.91)	(-26.58)	(-26.59)	(-19.95)
Price (-2)	-0.0048***	-0.0048***	-0.0055***	-0.0048***	-0.0048***	-0.0054***
	(-6.27)	(-6.25)	(-5.40)	(-6.26)	(-6.25)	(-5.38)
Volume (-2)	-0.0005	-0.0005	-0.0009**	-0.0005	-0.0005	-0.0009**
	(-1.52)	(-1.51)	(-2.15)	(-1.44)	(-1.43)	(-2.06)
Constant	0.2404***	0.2416***	0.2445***	0.2404***	0.2414***	0.2446***
	(38.51)	(38.21)	(29.55)	(38.55)	(38.25)	(29.58)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	337,077	337,077	202,850	337,077	337,077	202,850
Adj. R-squared	0.0374	0.0374	0.0382	0.0374	0.0374	0.0382

Table 13. Company valuations and fluency

Panel regressions of Tobin's q, defined as enterprise value (debt plus market value of equity) divided by book value (debt plus book value of equity), on company name fluency scores, Baker and Wurgler's (2006) annual investor sentiment index, orthogonalized to business cycle indicators, an interaction term between fluency and investor sentiment, and the number of employees as a proxy for firm size. The fluency scores are from Green and Jame (2013), measured on December 31 of the previous fiscal year, and take on integer values between 0 (least fluent) and 4 (most fluent). In Panel A, we consider the raw (unrestricted) version of the fluency index. In Panel B, we create a restricted version of the fluency index, reducing the number of scores from five to three, grouping together the least fluent scores (0 and 1) and the most fluent scores (3 and 4), respectively. In Panel C, we construct a dummy variable that takes on value one if the fluency index takes on the most fluent scores (3 and 4), and zero otherwise, and exclude company names with a middle score (2). All specifications include year fixed effects. We winsorize the 1% tails of the distribution of Tobin's q. Observations are annual. Accounting data are from Compustat, the investor sentiment index is from Jeffrey Wurgler's website, and the sample period is from 1981 to 2007. Heteroskedasticity-robust t-statistics, allowing for clustering by firm, are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Fluency (Unrestricted)

Dep. Variable: Wins. Tobin's q	(1)	(2)	(3)	(4)
Fluency	0.0710***	0.0602***	0.0769***	0.0646***
	(4.59)	(3.76)	(4.70)	(3.84)
Size		0.0009***		0.0009***
		(3.35)		(3.35)
Fluency x Sentiment			-0.0190**	-0.0160**
			(-2.52)	(-2.05)
Constant	1.3857***	1.4129***	1.3847***	1.4135***
	(40.62)	(39.68)	(40.42)	(39.78)
Year FE	Y	Y	Y	Y
Clustering by firm	Y	Y	Y	Y
Observations	34,786	32,655	34,347	32,655
Adj. R-squared	0.01	0.01	0.01	0.01

Panel B. Fluency (Restricted)

Dep. Variable: Wins. Tobin's q	(1)	(2)	(3)	(4)
Fluency (R)	0.0889***	0.0770***	0.0967***	0.0832***
	(4.76)	(3.99)	(4.88)	(4.08)
Size		0.0009***		0.0009***
		(3.31)		(3.30)
Fluency (R) x Sentiment			-0.0257***	-0.0228**
			(-2.79)	(-2.40)
Constant	1.3480***	1.3776***	1.3468***	1.3783***
	(33.44)	(32.84)	(33.29)	(32.94)
Year FE	Y	Y	Y	Y
Clustering by firm	Y	Y	Y	Y
Observations	34,786	32,655	34,347	32,655
Adj. R-squared	0.01	0.01	0.01	0.01

Panel C. Fluency (Dummy)

Dep. Variable: Wins. Tobin's q	(1)	(2)	(3)	(4)
Fluency (D)	0.1807***	0.1571***	0.1950***	0.1690***
	(4.80)	(4.02)	(4.91)	(4.12)
Size		0.0007*		0.0007*
		(1.89)		(1.88)
Fluency (D) x Sentiment			-0.0490***	-0.0444**
			(-2.65)	(-2.33)
Constant	1.4379***	1.4599***	1.4390***	1.4608***
	(52.98)	(51.31)	(52.83)	(51.52)
Year FE	Y	Y	Y	Y
Clustering by firm	Y	Y	Y	Y
Observations	20,980	19,722	20,709	19,722
Adj. R-squared	0.01	0.01	0.01	0.01

Table 14. Operating performance and fluency

Panel regressions of return on assets (ROA), defined as EBITDA divided by the book value of assets, on company name fluency, and the number of employees as a proxy for firm size. The fluency scores are from Green and Jame (2013), measured on December 31 of the previous fiscal year, and take on integer values between 0 (least fluent) and 4 (most fluent). In Panel A, we consider the raw (unrestricted) version of the fluency index. In Panel B, we create a restricted version of the fluency index, reducing the number of scores from five to three, grouping together the least fluent scores (0 and 1) and the most fluent scores (3 and 4), respectively. In Panel C, we construct a dummy variable that takes on value one if the fluency index takes on the most fluent scores (3 and 4), and zero otherwise, and exclude company names with a middle score (2). All specifications include year fixed effects. We winsorize the 1% tails of the distribution of ROA. Observations are annual. In columns (1) and (2), ROA is measured over the next fiscal year. In columns (3) and (4), we consider the average ROA over the subsequent three fiscal years, i.e., two to four years ahead. Accounting data are from Compustat, the investor sentiment index is from Jeffrey Wurgler's website, and the sample period is from 1981 to 2007. Heteroskedasticity-robust t-statistics, allowing for clustering by firm, are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Fluency (Unrestricted)

Dep. Variable: Wins. ROA	(1) Year 1	(2) Year 1	(3) Years 2-4	(4) Years 2-4
Fluency	0.0112***	0.0090***	0.0107***	0.0079***
	(7.60)	(5.98)	(6.18)	(4.46)
Size		0.0001***		0.0001**
		(3.08)		(2.06)
Constant	0.1085***	0.1163***	0.1123***	0.1231***
	(31.42)	(32.78)	(27.80)	(29.40)
Year FE	Y	Y	Y	Y
Clustering by firm	Y	Y	Y	Y
Observations	37,221	32,655	24,629	21,621
Adj. R-squared	0.02	0.01	0.02	0.01

Panel B. Fluency (Restricted)

Dep. Variable: Wins. ROA	(1) Year 1	(2) Year 1	(3) Years 2-4	(4) Years 2-4
Fluency (R)	0.0131***	0.0106***	0.0124***	0.0092***
	(7.55)	(5.95)	(6.07)	(4.37)
Size		0.0001***		0.0001**
		(3.08)		(2.04)
Constant	0.1046***	0.1131***	0.1087***	0.1204***
	(26.42)	(27.72)	(23.31)	(24.87)
Year FE	Y	Y	Y	Y
Clustering by firm	Y	Y	Y	Y
Observations	37,221	32,655	24,629	21,621
Adj. R-squared	0.02	0.01	0.02	0.01

Panel C. Fluency (Dummy)

Dep. Variable: Wins. ROA	(1) Year 1	(2) Year 1	(3) Years 2-4	(4) Years 2-4
Fluency (D)	0.0269***	0.0221***	0.0256***	0.0194***
	(7.62)	(6.09)	(6.15)	(4.52)
Size		0.0001**		0.0000
		(2.01)		(0.85)
Constant	0.1155***	0.1219***	0.1190***	0.1277***
	(41.23)	(41.70)	(36.02)	(36.63)
Year FE	Y	Y	Y	Y
Clustering by firm	Y	Y	Y	Y
Observations	22,442	19,722	14,790	13,020
Adj. R-squared	0.03	0.02	0.03	0.02

Table 15. Sales and fluency

Panel regressions of the logarithm of real net sales, defined as gross sales (the amount of actual billings to customers for regular sales completed during the period) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers, on company name fluency, and the number of employees as a proxy for firm size. The fluency scores are from Green and Jame (2013), measured on December 31 of the previous fiscal year, and take on integer values between 0 (least fluent) and 4 (most fluent). In Panel A, we consider the raw (unrestricted) version of the fluency index. In Panel B, we create a restricted version of the fluency index, reducing the number of scores from five to three, grouping together the least fluent scores (0 and 1) and the most fluent scores (3 and 4), respectively. In Panel C, we construct a dummy variable that takes on value one if the fluency index takes on the most fluent scores (3 and 4), and zero otherwise, and exclude company names with a middle score (2). All specifications include year fixed effects. We winsorize the 1% tails of the distribution of sales. Observations are annual. In columns (1) and (2), sales are measured over the next fiscal year. In columns (3) and (4), we consider the average sales over the subsequent three fiscal years, i.e., two to four years ahead. Accounting data are from Compustat, the investor sentiment index is from Jeffrey Wurgler's website, and the sample period is from 1981 to 2007. Heteroskedasticity-robust t-statistics, allowing for clustering by firm, are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Fluency (Unrestricted)

Dep. Variable: Wins. Real Net Sales	(1) Year 1	(2) Year 1	(3) Years 2-4	(4) Years 2-4
Fluency	0.1801***	0.1436***	0.1107**	0.0906**
	(4.46)	(3.88)	(2.20)	(2.04)
Size		0.0151***		0.0138***
		(4.19)		(4.68)
Constant	6.4251***	6.3759***	6.9168***	6.7705***
	(68.16)	(71.82)	(58.07)	(61.09)
Year FE	Y	Y	Y	Y
Clustering by firm	Y	Y	Y	Y
Observations	33,433	29,815	20,215	18,603
Adj. R-squared	0.01	0.20	0.00	0.21

Panel B. Fluency (Restricted)

Dep. Variable: Wins. Real Net Sales	(1) Year 1	(2) Year 1	(3) Years 2-4	(4) Years 2-4
Fluency (R)	0.2077***	0.1682***	0.1351**	0.1124**
	(4.43)	(3.85)	(2.30)	(2.15)
Size		0.0150***		0.0138***
		(4.19)		(4.68)
Constant	6.3669***	6.3241***	6.8654***	6.7246***
	(59.63)	(64.35)	(50.64)	(54.11)
Year FE	Y	Y	Y	Y
Clustering by firm	Y	Y	Y	Y
Observations	33,433	29,815	20,215	18,603
Adj. R-squared	0.01	0.20	0.00	0.21

Panel C. Fluency (Dummy)

Dep. Variable: Wins. Real Net Sales	(1) Year 1	(2) Year 1	(3) Years 2-4	(4) Years 2-4
Fluency (D)	0.4192***	0.3418***	0.2647**	0.2198**
	(4.41)	(3.81)	(2.21)	(2.06)
Size		0.0142***		0.0135***
		(3.16)		(3.76)
Constant	6.5571***	6.4907***	7.0151***	6.8549***
	(86.92)	(78.23)	(71.79)	(68.62)
Year FE	Y	Y	Y	Y
Clustering by firm	Y	Y	Y	Y
Observations	20,077	17,945	12,047	11,114
Adj. R-squared	0.01	0.20	0.01	0.22

Table 16. Standard unexpected earnings and fluency

Panel regressions of quarterly standard unexpected earnings (SUE), defined as the difference between actual earnings per share and the I/B/E/S surprise mean analyst forecast divided by the standard deviation of analyst forecasts, on a set of dummy variables that take on value one for each of the fluency scores from Green and Jame (2013), i.e., integer values between 0 (least fluent) to 4 (most fluent), measured on December 31 of the previous fiscal year. All specifications include firm, quarter, and year fixed effects. In Panel A, we consider the full sample. In Panels B and C, we split the sample into period in which Baker and Wurgler's (2007) investor sentiment index, orthogonalized to business cycle indicators and expressed in changes, is negative or positive, respectively, over the last month of the previous quarter. Stock data are from CRSP, analyst forecast data are from I/B/E/S, the investor sentiment index is from Jeffrey Wurgler's website, and the sample period is from the first quarter of 1992 to the fourth quarter of 2008. Heteroskedasticity-robust t-statistics are reported in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A. Full sample

Dep. Variable: SUE	(1)	(2)	(3)	(4)
Score 4	2.4155***	2.9403***	2.4753**	3.4134***
	(2.72)	(2.96)	(2.09)	(2.71)
Score 3		0.5046	0.0440	0.9812
		(1.37)	(0.06)	(1.14)
Score 2			-0.5796	0.3170
			(-0.75)	(0.42)
Score 1				1.0786
				(0.91)
Constant	0.5030***	0.3253*	0.7195	-0.2144
	(4.68)	(1.84)	(1.30)	(-0.26)
Firm/Quarter/Year FE	Y	Y	Y	Y
Observations	5,600	5,600	5,600	5,600
Adj. R-squared	0.16	0.16	0.16	0.16

Panel B. Negative sentiment

Dep. Variable: SUE	(1)	(2)	(3)	(4)
Score 4	3.2798***	3.4271**	2.7952*	3.3453**
	(2.87)	(2.54)	(1.76)	(2.00)
Score 3		0.1420	-0.4828	0.0674
		(0.25)	(-0.51)	(0.06)
Score 2			-0.7691	-0.2392
			(-0.79)	(-0.26)
Score 1				0.6298
				(0.43)
Constant	0.3785**	0.3270	0.8573	0.3080
	(2.08)	(1.10)	(1.17)	(0.30)
Firm/Quarter/Year FE	Y	Y	Y	Y
Observations	2,482	2,482	2,482	2,482
Adj. R-squared	0.28	0.28	0.28	0.28

Panel C. Positive sentiment

Dep. Variable: SUE	(1)	(2)	(3)	(4)
Score 4	0.6490	1.3908	1.0304	2.3121
	(0.71)	(1.29)	(0.75)	(1.47)
Score 3		0.7127	0.3582	1.6401
		(1.37)	(0.37)	(1.31)
Score 2			-0.4543	0.7631
			(-0.43)	(0.71)
Score 1				1.4879
				(0.88)
Constant	0.6221***	0.3769*	0.6826	-0.5932
	(5.47)	(1.73)	(0.91)	(-0.51)
Firm/Quarter/Year FE	Y	Y	Y	Y
Observations	3,118	3,118	3,118	3,118
Adj. R-squared	0.15	0.15	0.15	0.15