TWO ESSAYS ON BUSINESS DESCRIPTION CONTENT TREND AND THE CROSS-SECTION OF STOCK RETURNS

by

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ABSTRACT

This dissertation examines the business description firms include in their 10-Ks. Using the Latent Dirichlet Allocation topic extraction methodology, I identify the highest trending topic for each industry and each firm's loading on this topic. In the first chapter, after controlling for risk, I find that firms with higher loading on the highest trending topic are more likely to experience lower future returns. These findings are consistent with the notion that investors are willing to pay more for firms that use trendy language, even though the higher prices are not justified by their fundamental values. In the second chapter, I disentangle the relations between 10-K trend loading, earnings management, and analysts' forecast errors during the 10-K release. I find that 10-K trend loading and earnings management are conditionally uncorrelated, and that analysts can make forecast errors contrary to the level of 10-K trend loading, correcting the short-run market under-reactions.

To my belief.

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CHAPTER 1

CASTLE IN THE AIR: SEC 10-K BUSINESS DESCRIPTION TREND LOADING AND INVESTOR OVERREACTION

This paper examines the business description firms include in their 10-Ks. Using the Latent Dirichlet Allocation topic extraction methodology, I identify the highest trending topic for each year. After controlling for risk, I find that firms with higher loading on this highest trending topic are more likely to experience lower future returns. These findings are consistent with the notion that investors are willing to pay more for firms that use trendy language, even though the higher prices are not justified by fundamental values.

1.1 Introduction

The purpose of the company's 10-K business description (Item 1) is to communicate to investors the nature of its business and hence its risk. The choice of words in this description explicates its business in terms accessible to the investment zeitgeist. In this paper, I seek to separate the former from the latter.

To quantify the business risk, I use CAPM, and the Fama-French 3- and 4-factor models. To quantify the trendiness in the choice of words in the 10-K, I use textual analysis. I first create a vocabulary of all the words in the corpus of all business descriptions in my data set. I define a theme to be a distribution on the vocabulary: each word in the vocabulary is assigned a positive weight; the sum of all weights add up to one. For each year and each industry in my data set, I apply a Latent Dirichlet Allocation (LDA) algorithm to identify the common themes. Not only does the LDA algorithm identify the themes, it also specifies how each single business description loads on each of the common themes. By examining the loadings, I identify the most popular theme, hopefully capturing the investment zeitgeist in each year and for each industry. I then sort firms into portfolios according to how heavily they load on the most popular theme.

Controlling for risk factors, I find a 6% per annum negative abnormal return from the spread between the highest-loading and the lowest-loading portfolios. This anomaly substantiates the findings that the usage of trendy language drives stock prices up, only for them to revert later in the form of negative abnormal returns. This paper is not a study of the motivations behind word-choice; rather, it is a study of the market's reaction to these trendy words.

In this paper, the analysis is limited to the 10-K business description (Item 1), which is the least formal part of the 10-K. While the 10-K is not the only channel through which a company communicates information to its investors (examples of other channels are annual reports and shareholders meetings), the analysis within this paper focuses on the 10-K business description.

This paper contributes to the literature on predictable market reactions to the choice of trendy words. Cooper, Dimitrov, and Rau [11] demonstrate that the market reacts positively to the announcement that a corporation includes Internet-related dotcom in its name. Cooper, Gulen, and Rau [12] find that mutual funds which change their names to reflect a current trendy style experience, on average, an abnormal flow of 28%, with no improvement in their performance. In addition, Cooper et al. [15] investigate the market downturn following the Internet "crash" in mid-2000 once dotcom was no longer trendy. Their study shows that investors react positively to the deletion of dotcom from company names. The evidence of all these findings suggests that the choice of trendy words predicts returns.

Such findings of the short-run irrational price movement with respect to trendy words also add to the literature on market overreaction anomalies. Finance literature documents that investors often overreact to certain signals, push stock price away from its fundamental value in the short run, but eventually revert the price back to the fundamental value. DeBondt and Thaler [6] find that when portfolios are sorted on long-term past returns, low past returns have high future returns, and vice versa. They attribute this reversal of returns to investors' overreactions to past stock performance. Lakonishok et al. [26] argue that high ratio of earnings to price (E/P), cash flow to price (C/P), and book-to-market equity (B/M) proxy for poor past earnings growth. Because the market overreacts to past earnings growth, stocks with low(high) E/P, C/P and B/M tend to have high(low) future returns. Loughran and Ritter [29] document significant underperformance of stocks after IPOs or SEOs, as compared to the performance of nonissuing benchmark firms. They imply that firms list their stocks to take advantage of the market's overreaction to their recent strong performance.

The chapter proceeds as follows: Section 1.2 develops hypotheses; Section 1.3 discusses sample data and the algorithm used in the study; Section 1.4 outlines the empirical results; and Section 1.5 offers concluding remarks.

1.2 Hypothesis Development

We propose two competing hypotheses to explain stock price movements with respect to word choices. If the choice of words in the business description reflects new information about the stocks fundamental value, then the stock price will move to a new level, and thereafter stock returns should be normal again.

On the other hand, if the investors' reaction to the choice of words goes beyond what changes in fundamental values warrant (i.e., investors overreact to the choice of words), then the initial price reaction should be followed by a long-term reversal in returns, reflecting the notion that once the hype is over, prices revert to their fundamental values.

To formalize the hypotheses, I measure overall trends and firm-level exposure to the trend, which is refered to as "trend loading", in a given year. I identify the top and bottom trend loading firms. I then compute the next year's difference in returns, risk-adjusted, between these top and bottom trend loading firms.

Therefore, the main hypotheses of this study are[1] :

Hypothesis 1. *If the market does not overreact to the choice of words in the business description, then the trend loading premium will be zero.*

Hypothesis 2. *If the market overreacts to the choice of words, then the trend loading premium will be negative.*

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[1]Moreover, if the market keeps underreacting to 10-K trend loading in the next calendar year, then the premium will be positive. If this projection hypothesis proves true, however, then this 9th month to 21st month return momentum will be inconsistent with the well-documented 3rd month to 12th month return momentum in the literature (Jegadeesh and Titman [24]).

1.3 Data and Algorithm

1.3.1 SEC 10-K Filings

This paper studies the market's reaction to the firm usage of trendy language. Whereas Cooper, Dimitrov, and Rau [11], whose work inspires this paper, examine firm names, this study investigates the firm self-description from SEC 10-K (Item 1).[2] Item 1 is at the beginning of 10-K and provides a general description of the firm. According to the SEC, "Item 1 – 'Business' requires a description of the company's business, including its main products and services, what subsidiaries it owns, and what markets it operates in...This is a good place to start to understand how the company operates." Therefore, Item 1 is the least constrained part of the 10-K to allow managers to present a polished general impression to the investors.

Admittedly, there are large overlaps between 10-K and the SEC required "Annual Report to Shareholders" at the annual meetings.[3] Nevertheless, according to the SEC website (https://www.sec.gov/answers/reada10-K.htm), SEC admits that the 10-K is more detailed and "less colorful or glossy" compared to the annual reports. This statement ratifies the importance of the findings in this paper for two reasons. First, investors should pay more attention to the 10-K compared to the annual report since the 10-K is required by the SEC to be more accurate and less flashy. Second, 10-K trend loading in this paper is an underestimation of the overall efforts that managers make in hopes of attracting investors' attention.

I collect the universe of available 10-K files which have corresponding Central Index Key (CIK) in Compustat. I use python package "SECEdgar" and download a total number of 65986 10-K files from the years 1994 through 2016. I remove HTML tags from the raw files and extract Item 1. This results in 56,566 cleaned Item 1 files, 8,139 10-KA files, and 243 10-K405 files, which add up to 64,948 files out of a total of 65,986 files (98.5%).[4]

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[2] The U.S. Securities and Exchange Commission (SEC) requires most U.S. public companies to produce a 10-K on yearly bases, which offers a detailed picture about the business of the company, the risks, and the operating and financial results.

[3] Some firms directly apply the beginning part of 10-K in their annual reports.

[4] The remaining 1,038 files are files with useless information (485 files) or parsing error (553 files).

1.3.2 Market Reaction Data

To evaluate the market reactions to the trendiness of 10-Ks, I examine stock return movements after 10-K releases. I collect monthly stock price data from CRSP, and other firm-related data from Compustat Annual. In order to adjust the stock returns for common risk, I collect Fama-French 3-factors [17, 18] and Carhart momentum factor [9] from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

Out of the total 56,566 10-Ks in the sample, 95% have specific release dates. According to SEC regulation, firms have up to 90 days to file their 10-Ks after the end of the fiscal year. Hence, for the 10-Ks which don't specify their release dates, I define the release date as 90 days plus the end of the fiscal year which I collect from Compustat. I aggregate the 10-Ks by each calendar year based on this release date.

For each 10-K, I collect the firm's next calendar year's monthly returns from CRSP. Because the calendar year with complete annual data ends at 2015, the 10-K files applied in this paper are from the years 1994 to 2014. This study ends up with a whole sample of 48,107 firm-years. The number of 10-Ks in each year increases from 456 in 1994 to 3,638 in 2014. I plot the 10-Ks histogram by their release months in Figure 1.1. It shows that most firms release their 10-Ks between March and April. This indicates that a large number of firms (59%) choose the calendar year to be the fiscal year, since firms have up to 90 days to file their 10-Ks after the fiscal year ends.

1.3.3 The Latent Dirichlet Allocation (LDA) Algorithm

Recent textual analysis and financial reporting literature show that the 10-K file provides information to investors beyond its numerical content. For example, Loughran and McDonald [28] link a negative word list of 10-Ks to returns and unexpected earnings. Li [27] claims a positive relation between 10-K readability and persistent positive earnings. Campbell et al. [7] examine the number of risk-related words identified in the risk factor section of 10-K, and find it predicts future stock-return volatility and market-based beta.

Different from the above studies, which use the Dictionary Method to count the appearance of words, I apply the machine learning algorithm Latent Dirichlet Allocation (LDA) to construct a probabilistic measure of the 10-K Item 1 trendiness. First developed by Blei et al. [4], LDA is a probabilistic topic model using hierarchical Bayesian analysis to calculate the underlying semantic structure of textual documents. In finance, the application of LDA is still at its early stage, but is attracting increasing interest and attention. Feuerriegel et al. [20] use LDA to analyze the German stock market, and show some topics have large effect on abnormal returns. Jegadeesh and Wu [25] apply LDA to Federal Open Market Committee (FOMC) minutes, and find significant incremental informational value from the topic tone and uncertainty level. Distinct from the above studies, which focus on LDA topics, this study focuses on LDA topic loadings. I use these loadings to construct stock portfolios and examine market reactions and returns. The finding indicates that the topic loading information from LDA is also consequential, which illustrates the value of LDA as a textual tool in finance.

In this subsection, I give a brief introduction to the Latent Dirichlet Allocation (LDA) algorithm. LDA is widely applied in textual analysis to perform topic extraction. The basic intuition of this model is: it considers the underlying data, in this case the 10-K, to be generated from an underlying process with hidden variables. The LDA assumes that there exists K prespecified topics, $\beta_1 ... \beta_K$, over the collection of 10-K documents, where each topic β_k is defined as a distribution over a fixed list of words. Words in each document are created by a two-stage process:

1. There is a randomly generated distribution over topics for each 10-K document. I denote the topic distribution for document d by θ_d and the proportion of topic k in document d by $\theta_{d,k}$.

2. For each word in the document, a topic is randomly chosen from the distribution θ_d. Specifically, I denote the assigned topic to the n_{th} word in the document by $z_{d,n}$ and the collection of the topic assignments to the document d by z_d. $z_{d,n}$ follows a multinominal distribution, topic β_k follows a Dirichlet distribution, and the actual choice of word, $w_{d,n}$, follows a multinational distribution.

Hence, the overall data generating process can be defined by the joint distribution of latent variables $\{\beta_k\}_{k=1}^K$,$\{\theta_d\}_{d=1}^D$,$\{z_d\}_{d=1}^D$ and the observed $\{w_d\}_{d=1}^D$:

$$P(\{\beta_k\}_{k=1}^K, \{\theta_d\}_{d=1}^D, \{z_d\}_{d=1}^D, \{w_d\}_{d=1}^D) = \prod_{k=1}^K P(\beta_k) \prod_{f=1}^F P(\theta_d) \prod_{f=1}^F [P(z_{d,n}|\theta_d) P(w_{d,n}|\beta_{1:K}, z_{d,n})]$$

Since the document $\{w_d\}_{d=1}^{D}$ is observable, the posterior document topic structure can be computed by the Bayesian equation:

$$P(\{\beta_k\}_{k=1}^{K}, \{\theta_d\}_{d=1}^{D}, \{z_d\}_{d=1}^{D} | \{w_d\}_{d=1}^{D}) = \frac{P(\{\beta_k\}_{k=1}^{K}, \{\theta_d\}_{d=1}^{D}, \{z_d\}_{d=1}^{D}, \{w_d\}_{d=1}^{D})}{P(\{w_d\}_{d=1}^{D})}$$

With the above posterior probabilities, one can further compute the major outputs of the LDA algorithm: the posterior word distribution for each topic and the posterior topic distribution for each document.

1.3.4 10-K Trend Loading

I apply the LDA algorithm to the collection of 10-K Item 1's with Python package "lda" (https://pypi.python.org/pypi/lda). As described in the previous subsection, LDA assumes "a bag of words", hence one should be careful about the choice of the vocabulary for the LDA algorithm. On one hand, it is important to choose vocabulary with economically meaningful words. I employ the Loughran and McDonald 2014 Master Dictionary from Bill McDonald's website: http://goo.gl/I5GtZ5.[5] This word list contains 85,132 words.[6]

On the other hand, stop words (such as articles and conjugates) and sparse words (words that have shown to be used less than a certain percentage threshold of the total sample) may potentially weaken the LDA results. I apply a threshold on the sparse words: 1 %, and the vocabulary ends up with 8729 words. This means that I only remove words that show up in 1% of the total sample and hence keep a large amount of words of which some may still show up very rarely. This sparse vocabulary potentially gives a downward bias to the trend loading measure. Following linguistic morphology and information retrieval literature, to reduce inflected (and sometimes derived) words, I stem the vocabulary further to the words' root form and get 4261 stemmed words in the final vocabulary [7].

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[5]Loughran and McDonald [28] imply that their word lists better reflect economic meaning in financial text.

[6]It also includes reports counts, proportion of total, average proportion per document, standard deviation of proportion per document, document count, nine sentiment category identifiers, Harvard Word List identifier, number of syllables, and source for each word.

[7]An example of stemmed words is that, after stemming, "accounting", "accountant", and "account" all count as "account".

To estimate the LDA topics of each 10-K in year t, I run LDA at a 3-year rolling window $[t-2, t-1, t]$ with the stemmed vocabulary. Because different industries have by and large different business styles, their self-introductions in 10-K can have different topics. To further control industry idiosyncratic topics, I run LDA for each separate industry.[8] Take the year 2015 as an example. I run separate LDAs for each of the 12 industries from 2013 to 2015: $D_{1,2013-2015}, D_{2,2013-2015}, ..., D_{i,2013-2015}, ..., D_{12,2013-2015}$ where $D_{i,2013-2015}$ stands for the collection of 10-Ks for industry i from the year 2013 to 2015.

Given an arbitrary topic number, LDA generates a probability distribution over the LDA topics for each document. For instance, if the topic number of LDA is set to be 20, then for an arbitrary document, the LDA topic loading will be $(\theta_1, \theta_2, ..., \theta_{20})$ with $\sum_{i=1}^{20} \theta_i = 1$. The topic itself calculated by LDA is also a vector of probability measure over the whole vocabulary. In this paper, each topic is a vector $(\beta_1, \beta_2, ..., \beta_{4261})$ with $\sum_{i=1}^{4261} \beta_i = 1$, where β_i is the arbitrary topic's probability on words i.

I define the "hottest" or the highest trending topic of the year t and industry i to be the topic which has the highest aggregate loading across all firms in industry i in the same year t. For firm n ($n \in \{1, 2, \ldots, N\}$) and topic m ($m \in \{1, \ldots, M\}$), I calculate the vector of the sums of each topic's loadings across firms in year t and industry i by:

$$\left(\sum_{n=1}^{N} \theta_{1,n,i,t}, \sum_{n=1}^{N} \theta_{2,n,i,t}, \ldots, \sum_{n=1}^{N} \theta_{m,n,i,t}, \ldots, \sum_{n=1}^{N} \theta_{M,n,i,t} \right)$$

where $\sum_{n=1}^{N} \theta_{m,n,i}$ is the sum of the topic m's loadings for all N firms in industry i in year t. The "hottest" topic, which I term the "trend", of 10-Ks in year t and industry i is defined by:

$$Trend_{t,i} = \arg\max_{m} \{ \sum_{n=1}^{N} \theta_{1,n,i}, \sum_{n=1}^{N} \theta_{2,n,i}, \ldots, \sum_{n=1}^{N} \theta_{m,n,i}, \ldots, \sum_{n=1}^{N} \theta_{M,n,i} \}$$

I define trend loading of a 10-K to be this 10-K's loading on its corresponding $Trend_{t,i}$. I then pool all 10-Ks trend loadings together within the same year t across 12 industries.

In finance literature, the choice of the number of topics of a LDA model is arbitrary. To avoid the "cherry picking" bias and to investigate the best number of topics for the sample 10-Ks, however, I launch a horse-race of LDA models with topic numbers between 5 and 50. One should expect topic number less than 20 to work better, since the more topics

[8] The 12 industries information is downloaded from Ken French's website: http://goo.gl/iyNmS.

LDA assumes, the more scattered and delicate the topic themes will be [9]. Hence it is more difficult to detect the economic significance for LDA with large topic number.

I report the summary statistics of trend loadings for different topics in Table 1.1. The average trend loading decreases as the number of topics increases, and the standard deviation also decreases. Taking the 5-topic model as an example, the unconditional average loading should be 0.2 while the observed average is 0.359, showing a skewness to the right. This implies that the hottest topic has relatively more weight than other topics, consistent with the argument that these topics are popular and trendy. Notice that the more topics the models have, the higher weight the hottest topic ("trend") takes. For the 5-topic model, the ratio between average trend loading and unconditional topic loading is 1.8 (0.36/0.2) while for the 50-topic model it is 3.6. Hence the more topics a LDA model has, the more able it is to capture the most important topics.

Since Table 1.1 only shows both the cross-section and cross-time statistics, in Figure 1.2, I plot the annual average trend loadings from 1996 to 2014 across LDA models with different topics. The average trend loading is around 10% to 20% in a stable pattern when topic number is greater than 5. As the topic number increases, the mean of trend loading is decreasing and becomes less scattered across years.

An interesting pattern is that, during the years of market downturns, such as the year 2001 and 2008, the average trend loading is relatively lower compared to market booms. It is likely that during the market downturns, firms have relatively less trendy language to use, because when the whole economy is underperforming the innovative growth opportunities are less widely available.

To further illustrate the meaning of the trend, I choose 3 out of top-10 ranked words from the trend of each year from the manufacturing sector and report them in Table 1.4. Admittedly since LDA is a probabilistic model, it does not necessarily "think" the same way as human beings. In addition, there is a large amount of noise in 10-K documents. One can still observe meaningful patterns, however. For example, in the year 1998, the LDA selects "cargo" and "eurodollar", which are related to foreign trade; from the year

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[9] An anecdotal discussion from Wray Buntine actually points out that with a sample of 600 documents, approximate 20 topics is recommended (https://goo.gl/k9cHJd). Since in this part of paper, the number of documents for each year and each industry is between 300 to 800, topic number around 20 is consistent with this insight.

2001 to 2004, “Shanghai”, “domestic”, and “machinery” are chosen and suggest that the topic is related to China; from the year 2007 to 2011, the topics mainly consist of economics-downturn-related words: “solvency” in 2007, “embargo”, and “rebuild” in 2008, “unhedged” in 2009, and 2010, “indebt” in 2011; after 2012, the trendy words show a recovery theme, such as “local” in 2012, “import” and “creation” in 2013, and “green” in 2014.

1.3.5 Performance-Scaled 10-K Trend Loading

While the 10-K trend measure, by design, captures the “hotness” of the current topic of a group of 10-Ks, it treats the trend with different “tone” indifferently. Some topics may be very popular, but their tones can be vastly different. For example, the word “dotcom” was trendy both before and after the doccom bubble, but to the market, it had different perceptions and tones. Investors had an impression of “good trend” for the “dotcom” in the year 1999 before the dotcom bubble burst and an impression of “bad trend” for it in the year 2000 after the dotcom bubble burst.

It is thus natural to infer that such differences in “tone” have opposite market reactions. Cooper, Dimitrov, and Rau [11] study the market reaction of firms adding “dotcom” in their names in the year 1999 before the dotcom bubble burst and document a striking positive stock price reaction to the announcement of such corporate name changes—this “dotcom” effect produces a 74 percent abnormal return for the 10 days surrounding the announcement day. The investors react positively to the tentative, though appealing, prospects of firms whose businesses are related to cyber technology when the market of this sector is moving upwards. Moreover, Cooper et al. [12] further examine the market downturn following the Internet “crash” in the year 2000 and find that investors reacted positively to name changes for firms that deleted dotcom from their names. This is likely because cyber technology lost favor with investors.

In sum, the investors appreciate managerial use of language with “good trends” and dislike that with “bad trends”, even if both “good” and “bad” trends are “hot” at the time. Notice that the trend measure has not taken this difference into consideration; therefore, to further include the investors’ “good” and “bad” perceptions of the firm language choice, I construct a robust measure of 10-K trend.

Inspired by Cooper et al. [11, 12], I scale the LDA trend loading of each firm by the average past-3-month performance of its sorted decile. I define the past performance-scaled trend for firm i at year t as:

$$ScaledTrend_{i,t} = Trend_{i,t} * \overline{Ret_{-3,0}}$$

where the $\overline{Ret_{-3,0}}$ is the average past-3-month buy-and-hold returns of stocks from the same decile of stocks sorted by the trend loading at year t.

I report the summary statistics of the performance-scaled trend loadings across years in Table 1.2. Compared to Table 1.1, the performance-scaled trend loading is more symmetrically distributed. Because it is scaled by the past-3-month stock returns, the distribution has a median of 0. Moreover, it is still right skewed, showing that the trend loading in the market booms is higher than in the market downturns, consistent with the findings in Figure 1.2 that the average trend loading (as defined in subsection 1.3.4) underperforms during the market downturns. In Figure 1.3, I plot the average performance-scaled trend loadings across years. For most of the models, the absolute values are higher for positive-trend-loading years, and further confirm the pattern of higher trend loadings during market booms.

1.3.6 Pooled Industry 10-K Trend Loading

In this subsection, I provide a robust trendiness measure which examines the 10-K trend from the entire sample in each year, ignoring the industry idiosyncrasy. For each year, instead of running LDA, calculating the 10-K trend for each industry, and pooling the trend loading across 12 different industries as the main test, I then run LDA by the year for the entire sample with all the firms from different industries pooled together and calculate each firm's trend loading afterwards.

In Table 1.3, I report the summary statistics of the pooled trend loading. Similar to Table 1.1 and Table 1.2, the mean and standard deviations of trend loading decrease as the number of topics increases. The scale of average loading here is much larger; the 50-topic model has an average of 0.617, compared to 0.072 for the industry-specific model in Table 1.1. This difference implies that the pooled industry LDA model has a more concentrated topic distribution on the hottest topic than the separate industry LDA model. This may be because the bigger a sample of documents is, the more concentrated the topics become, or because the pooled sample has a more obvious hottest topic (trend).

1.4 Empirical Results

1.4.1 10-K Trend Loading Premiums

To test whether investors overreact to the 10-K trend loading, I examine the relation between each year's firm trend loading and the return in the following calendar year. Following Fama and French [17, 18], in each calendar year, I sort portfolios based on the deciles of ranked firm trend loading, and collect monthly CRSP returns for the next calendar year.

In Table 1.5, I present each equal-weighted portfolio's compound average returns and risk-adjusted spread returns (alpha) for LDA models from 5 topics to 50 topics. In the top half of Table 1.5, I report the average returns for each sorted decile from low trend loading to high trend loading. There is a clear pattern that, as the 10-K trend loading increases, the stock return decreases, although the pattern is not perfectly monotone. For the 5-topic LDA model, the average return decreases from 0.204 to 0.187 with some outliers such as 0.219 in the sixth decile. The spread between the top and bottom deciles is negative 170 basis points. This spread indicates that stocks with high trend loadings relatively underperform against stocks with low trend loadings. For the 20-topic LDA model, the spread decreases in absolute value to -0.012. As the number of topics increases to 50, the negative spread increases in absolute value again, with a peak at 30 topics (negative 870 base points). The volatility of portfolio returns across trend loading deciles also increases as the topic number increases.

I then report risk-adjusted returns for the spread (i.e., alphas) at the bottom half of Table 1.5. To control for *value and glamours effect* (Daniel and Titman [16]; Lakonishok, Shleifer, and Vishny [26]), I report Fama-French 3-factor alphas. To address the concern of *momentum effect* (Jagadeesh and Titman [24]; Carhart [9]; Cooper, Guitierrez, and Hameed [14]), I also include the 4-factor model. I find systematic evidence of the existence of negative alpha. When the topic number equals 5, the CAPM and 3-factor model give insignificant negative alphas. But the 4-factor model reports a significant negative alpha with T-stats equal to -4.642, implying the market overreacts to the 10-K trend loading when momentum is controlled. When the number of topics increase to 10, all alphas from the three risk models become significant with P-value less than 5%. When topic number equals 15, the CAPM gives an alpha equal to -5.6% with T-stats equal to -2.85 and the 3-factor model reports a -5.4% alpha with T-stats equal to 2.55. When momentum factor is added, the alpha shrinks to -4.2% a year, with t-ratio equal to -1.84. For this 15-topic LDA model, the decreasing pattern of alphas for increased number of factors is consistent with the literature (Fama and French, 1992, 1993, 1996). It indicates the equal-weighted portfolio returns sorted on 10-K trend are sensitive to all 4-factor. As the number of topics increases to 20, neither of the 3-factor nor 4-factor models reports a significant alpha, but the sign is still negative, consistent with all the other models.

When topic number increases from 25 to 40, the pattern of alphas becomes less stable and less significant for both CAPM and the 3-factor model, consistent with our former conjecture that it becomes more difficult to capture the "trend" of textual content when the number of LDA topics is large. This finding contributes to the LDA literature from the application of finance data by providing new guidance about the threshold in choice of topic numbers. Although the CAPM and Fama-French 3-factor models report insignificant alphas across the 25-50 topic LDA models, the 4-factor models still give a consistent pattern of negative alphas. They decrease in absolute values from -14.2% per year to -12.8% per year while the absolute T-stats increase from 3.314 to 3.483, satisfying the requirement from recent discussion on avoiding data snooping (Havery, Liu, and Zhu [21]). As for the 50-topic model, it reports significant negative alphas for CAPM and the 3-factor model, but not for the 4-factor model.

Together, Table 1.5 shows negative and significant 10-K trend loading premiums. It indicates that investors systematically overreact to the 10-K trend loading and suffer from negative returns in the next calendar year if they chase trendy words chosen by managers. This is consistent with former literature on the "bubble" phenomenon (Shiller [33]) and Hong and Stein's [23] prediction of long-term return reversals. To my knowledge, this is the first paper that reports that managers try to "polish" their firms' images by incorporating trendy language into the 10-Ks and shows direct evidence that investors overreact to the trendiness of the managerial word choices.

Admittedly, an equal-weighted portfolio puts more weight on small-sized firms and thus suffers from both of the potential liquidity frictions (Amihud [1]; Amihud and Mendelson [2]; Pastor and Stambaugh [30]), and noise in prices (Blume and Stambaugh [5]; Asparouhova, Bessminbinder, and Kalcheva [3]). So, to address potential concerns and to choose a model with a proper number of topics, I first control for noise in price by examining the lag-return sorted portfolio. I find that the 5-, 15-, and 40-topic models report significant, negative alphas. To be consistent with literature (Wu [35]; Jegadeesh and Wu [25]), I choose the 15-topic LDA model for further tests.

Blume and Stambaugh [5] show that zero-mean noise in prices leads to strictly positive biases in mean returns of individual security. The magnitude of the biases in each security's mean return is approximately equal to the variance of the noise in the security's prices. Asparouhova, Bessminbinder, and Kalcheva [3] provide a collection of corrections of such biases. They point out that lag-return sorted portfolios minimize potential biases in the mean-returns. Following their approach, for the 15-topic LDA model, I sort portfolios based on the last period's raw return, and report the results in column 2 of Table 1.6. For CAPM, the alpha is -6.3% per year with T-stats equal to -2.18; for the 3-factor model, the alpha is -5.9% with less significant T-stats -1.89; for the 4-factor model, both the alpha and the T-stats are highest in absolute value among the 3 risk models—an alpha of -7.7% and a T-stats of -2.23. The fact that both equal-weighted and lag-return-weighted portfolios' alphas are significantly negative across different risk models implies that the 10-K trend loading premium is robust to the noise in prices.

The market microstructure literature provides voluminous evidence of stock return premiums from trading frictions (Amihud [1]; Amihud and Mendelson [2]). Some studies argue that some asset pricing anomalies with equal-weighted portfolios are likely to be driven by small-sized firms whose stocks are highly illiquid (Roll [32]; Pastor and Stambaugh [30]). To address the concern that the market's overreaction to 10-K trend loading is mainly driven by illquidity or trading friction from small-sized firms, I divide the sample into 3 subgroups. I sort the whole sample on the firm's market value into 4 quartiles. I denote the bottom quartile as the "small" subgroup, middle two quartiles as the "medium" subgroup, and the top quartile as the "large" subgroup. I then report the equal-weighted portfolios' decile average returns and alphas in Table MAINT2. For the "large subgroup", I do not find evidence of significant market overreaction to 10-K trend loading. For the "medium" subgroup, the results are consistent with previous findings; the CAPM reports

-6.2% alpha with a T-stats equal to -1.8; the 3-factor model reports -7% alpha with a T-stats equal to -1.8; the 4-factor model reports the highest alpha and T-stats: -9.8% and -2.47. The "small" group only reports significant alphas for CAPM and the 3-factor model, but not for the 4-factor model. The insignificance of the 4-factor model in the "small" subgroup implies that the significant results of the 4-factor model from the total sample are mainly driven by the medium-sized firms, rather than the small-sized firms. Besides, since 75% of the total sample ("medium" and "small" subgroups) has a consistent pattern of negative alphas across all 3 risk models, it is unlikely that the market overreaction to 10-K trend loading is a result of illiquidity from small-sized firms.

Overall, consistent with *Hypothesis 1a*, I show that the market overreacts to 10-K trend loading after controlling for market-, size-, growth-, and momentum-related risks. This result is robust across a set of LDA models with different numbers of topics. To further address potential concerns of equal-weighted portfolio, I choose the 15-topic LDA model which is robust to the lag-return-weighted portfolio scheme. I provide evidence that this 15-topic model is net of the biases from the noise in price and trading frictions.

The finding of negative alphas of the 15-topic model potentially sheds lights on a trading strategy using the machine learning algorithm LDA. This strategy uses a 3-year rolling window and takes consideration of industry effects. The significance of a lag-return-weighted portfolio suggests this strategy is not influenced by the bias from noise in prices and it is not driven by the small-sized firms. Therefore, this strategy is potentially tradable and profitable with an approximate 6% annual return.

1.4.2 Performance-Scaled 10-K Trend Loading Premiums

Rather than continuing to study the high versus low trend, in this subsection, I examine the market reaction to "good" versus "bad" trends. To capture such "tone effects" of trends, as introduced in subsection 1.3.5, I multiply the raw industry trend loading by the 3-month average returns of the same sorted decile and launch the portfolio sorting test.

I report the value-weighted portfolio test in Table 1.7, where I only report LDA models with 5 to 20 topics (the 25-topic to 50-topic models give consistent but insignificant results). Overall, the results show a negative pattern of alpha, with most significant results in the 15-

topic model—its 4-factor annual alpha is -9.8%. Such negative alphas of the scaled-trend-loading-sorted portfolio indicate that investors, in general, underreact to both "good" and "bad" 10-K trends. Therefore, consistent with the finding of Cooper et al. [11, 12], the market not only reacts positively to firms that chase "good" trends, but it also dislikes firms that follow "bad" trends. This result is net of the liquidity and noise in price since it applies the value-weighted schemes, further supporting the findings in the previous subsection.

1.4.3 Pooled Industry 10-K Trend Loading Premiums

In this subsection, I analyze the sorted portfolio from the pooled industries to examine whether the found alpha is purely driven by the separated-industry LDA outcomes. Instead of running LDA on each industry, calculating the trend loading for each firm, and pooling them at the per-annum cross-section, here I run LDA to this cross-section and get the direct trend loading of each firm. For each year, I sort the firms based on their trend loadings into value-weighted deciles and then calculate the abnormal returns after controlling for risk factors.

In Table 1.8, I report alphas from 5-topic to 20-topic models with CAPM, Fama-French 3- and 4-factor risk models. It still reports a consistent pattern of negative alphas with a decreasing pattern of significance from CAPM to 4-factor model. The scale of alpha is around 5% to 8%, also consistent with previous reported alphas. Overall, the finding shows that investors underreact to the trend of 10-K, with or without controlling for the industry idiosyncrasy.

1.4.4 Difference in Fundamental Values after 10-K Releases

The findings of negative alphas with respect to the 10-K hottest topics can either be understood as investor irrationality or fundamental change. In the latter case, it is possible that it is the change of fundamental values of the firm that leads to the long-term return reversals and the 10-K trend I construct is actually a measure of the insiders' information. Since the managers' choice of language reflects their inside information, they are correlated with the firm's later reviewed public information of the change in fundamental values. Therefore, instead of the market underreacting to the choice of language in 10-Ks, my findings actually reflect the change in the firms' fundamental values.

To test whether the previous results are driven by investors irrationality or corporate risk change, I examine the change in firm fundamental values that measured by return on asset (ROA) at the time of and two years after the release of 10-Ks. The variable of interest is expressed as:

$$\Delta ROA = ROA_{t+2} - ROA_t$$

If a 10-K trend reflects private information that is not available to the investors about the changes in firms' fundamental values, then such changes should be captured by ΔROA. The reason for this two-year window is to ensure that the time span of the sorted portfolio is covered. If there are changes in firm fundamental values that are not not shown directly on the financial statement but can be seen in the 10-K trend, then the return on asset should correspondingly change. On the other hand, if we don't observe a significant change in ROA, then the fact that it is less likely that the 10-K trend is capturing the change of unobserved fundamental values provides evidence of investor underreactions.

In Table 1.9, I examine the difference of ROA at, and two years after, 10-K releases ($ROA_{t+2} - ROA_t$). The first row reports an insignificant unconditional difference with a -0.6 T-stats; the second row reports an insignificant conditional difference. I compare the difference of the differences in ROAs between the top and bottom sorted trend loading deciles. This conditional difference measures the influence of trend loadings on the difference in ROAs. If the change in ROA is related to the firm trend loading, then this value should be significant. It is still insignificant, however, indicating that the 10-K trend loading is not related to the change in fundamental values.

Table 1.10 reports the cross-sectional tests of the difference of fundamental values. The dependent variable is the difference between ROAs at the time of and two years after the 10-K release. The independent variables include trend loading and a set of firm characteristics. Column 1 reports the raw regression result; column 2 controls for the year fixed effect; column 3 controls for firm fixed effect; and column 4 controls for both fixed effects. The overall results show that the intercept is insignificant after controlling for the firm fixed effect; therefore, the conditional difference of ROA is statistically zero. More importantly, the coefficients of the trend loading are insignificant, indicating that the corporate trend loading is not related to the change in ROA even without controlling for fixed effects. This finding provides evidence to support the investor underreaction to the trend of 10-K files, and this finding is less likely to be driven by the change in firm fundamental values.

1.4.5 Cross-Sectional Test of 10-K Trend Loading

To determine if the 10-K trend loading premium is a manifestation of other previously documented asset pricing factors, I provide cross-sectional regression tests in Panel A of Table 1.11. To further control the biases from panel data standard errors (Petersen [31]), I report regression results with clustered standard errors by firm and by year in Panel B and C of Table 1.11 for the 15-topic LDA model.

In Panel A of Table 1.11, I examine pooled cross-sectional OLS regressions with dependent variables of excess returns which cover different time intervals after the release of 10-Ks: *RET* is the calendar year return after the release year; *RET3*, *RET6*, *RET12*, *RET13_24*, *RET7_18*, and *RET13_36* separately stand for the aggregate CRSP monthly returns adjusted by risk free rate corresponding to 3 months, 6 months, 12 months, from 13th month to 24th monoth, from 7th month to 18th month, and from 13th month to 36th month after the released month of 10-Ks.

To control for the potential influences from stock size, growth, momentum, and reversal effects (DeBondt and Thaler [6]; Fama and French [17]; Jegadeesh and Titman [24]), I compete 10-K trend loading with a group of control variables in the OLS regression. I include BM equity (the ratio between book and market equity from last fiscal year), market capitalization, 6-month lagged returns, and 36-month lagged returns. I also consider other recently documented anomaly determinants such as the asset growth ratio (Cooper, Gulen, and Schill [13]), lagged asset growth ratio, accruals (Sloan [34]; Hirshleifer et al. [22]; Zhang [36]), return on asset (Chen and Zhang [10]), sales growth rate (Lakonishok, Shleifer, and Vishny [26]) and lagged sales growth rate. Furthermore, suggested by Fama and French [19], I also control for earnings-to-price ratio. Finally, I aggregate monthly Fama-French [17] 3-factor and Carhart [9] momentum factor for the corresponding testing period.

The OLS regressions reported in Panel A of Table 1.11 show an interesting pattern of the coefficients of the 10-K trend loading across different time intervals after the releases of 10-Ks. The excess returns first increase with the trend loading for the first 12 months, and then decrease for the following two years. This increasing-and-decreasing pattern of trend loading coefficient indicates a short-term underreaction and long-term overreaction of investors to the 10-K trend loading.

In Panel B of Table 1.11, I report the cross-sectional regressions with the same control variables as in Panel A with clustered standard errors by the firm, in the aim of controlling for biases from overestimated t-ratios due to the imbalanced panel data (Petersen [31]). Overall, I observe a consistent pattern of positive coefficients of the 10-K trend loading in short periods (from the 6th month to the 12th month) after the 10-K release and negative coefficients in longer periods (from the 13th month to the 36th month). Most of the coefficients for 10-K trend loading are significant, except for the period from the 13th month to 24th month. It is because this period is between the positive reaction months (first 12 months) and negative reaction months (from the 13th month to the 36th month). This positive-negative reaction transition period also explains the marginal performance on the calendar year return (which is calculated for the calendar year after the released date). Since most firms release their 10-K in March and April as shown in Fig 1.1, the calendar year majorly covers the 10th to the 21th month after 10-K release, overlapping largely with the period from the 13th month to the 24 month. The finding of less significant calendar year trend loading coefficients indicates that the portfolio sorting analyses from previous sections are to some extent an underestimation of the market overreactions to the 10-K trend loadings.

Panel C of Table 1.11 shows the results of regressions with clustered stand errors by year. Petersen [31] argues that, for the panel data, when there are only a few clusters in one dimension, clustering by the the other dimension yields results that are almost identical to clustering by both dimensions. In this panel, the year dimension is much smaller compared to the firm dimension, hence the panel regression is less biased by clustering standard error only by firm. To provide further evidence, I still present the results of clustering standard errors by the year. The signs of coefficients of 10-K trend loading are still consistent with Panel A and B of Table 1.11, but they are less significant. Most importantly, *RET* (the next calendar year return), *RET12*, and *RET13_36* are all significant, showing a complete pattern of short-term underreaction and long-term overreaction of the investors.

Overall, consistent with Campbell, Lo, and Mackinley [8] and Hong and Stein [23], I find evidence of the short-term continuations and long-term reversals of excess returns to 10-K trend loading. This finding is also in align with the short-term positive stock price reactions to the change of firm names to catch up with trend in Cooper, Dimitrov, and Rau [11] and Cooper, Gulen, and Rau [12] . Moreover, it provides supports to the findings from subsection 1.4.1 by showing the long-term return does respond negatively to the trend loadings in cross-sections after controlling for a large number of potential asset pricing anomaly determinants.

1.5 Conclusion

In this paper, I examine the business descriptions included by firms in their 10-Ks. Using Latent Dirichlet Allocation topic extraction methodology, I identify the most trending topic or trend for each year (1996-2014) in the data. I find systematic evidence of investor overreaction to the trendy word-choices found in SEC 10-K self-introductions. By sorting on the past calendar year's trend loading, I measure 10-K trend loading premiums and find robust negative alphas across a set of risk models. I also find that stock prices react positively to 10-K trend loading in the short-term (1-12 months) and then negatively in the long-term (13-36 months) after the release of the 10-K.

This paper contributes to the literature by providing direct evidence that investors are willing to pay more for firms that use trendy language, despite the fact that the higher prices are not justified by fundamental values. All of these findings suggest a potentially profitable trading strategy which sorts portfolios based on how trendy the firms are. This strategy is appealing, not only because it provides a 6% annual abnormal return, but also because the strategy is net of bias from noises in price and liquidity frictions.

1.6 References

[1] Y. Amihud, *Illiquidity and stock returns: cross-section and time-series effects*, Journal of Financial Market, 5 (2002), pp. 31–56.

[2] Y. Amihud and H. Mendelson, *Asset pricing and the bid-ask spread*, Journal of Financial Economics, 17 (1986), pp. 223–249.

[3] E. ASPAROUHOVA, H. BESSEMBINDER, and I. KALCHEVA, *Noisy prices and inference regarding returns*, Journal of Finance, 68 (2013), pp. 665–714.

[4] D. M. Blei, A. Y. Ng, and M. I. Jordan, *Latent dirichlet allocation*, Journal of Machine Learning Research, 3 (2003), pp. 993–1022.

[5] M. E. BLUME and R. F. STAMBAUGH, *Biases in computed returns: An application to the size effect*, Journal of Financial Economics, 12 (1983), pp. 387–404.

[6] W. F. M. D. Bondt and R. Thaler, *Does the stock market overreact?*, Journal of Finance, 40 (1985), pp. 793–805.

[7] J. L. Campbell, authorHsinchun Chen, D. S. Dhaliwal, H. min Lu, and L. B. Steele, *The information content of mandatory risk factor disclosures in corporate filings*, Review of Accuouting Studies, 19 (2014), pp. 396–455.

[8] J. Y. Campbell, A. W.-C. Lo, and A. C. MacKinlay, *The Econometrics of Financial Markets*, Princeton University Press, 1996.

[9] M. M. Carhart, *On persistence in mutual fund performance*, Journal of Finance, 52 (1997), pp. 57–82.

[10] L. CHEN and L. ZHANG, *A better three-factor model that explains more anomalies*, Journal of Finance, 65 (2010), pp. 563–594.

[11] M. J. Cooper, O. Dimitrov, and P. R. Rau, *A rose.com by any other name*, Journal of Finance, 56 (2001), pp. 2371–2388.

[12] M. J. Cooper, H. Gulen, and P. R. Rau, *Changing names with style: Mutual fund name changes and their effects on fund flows*, Journal of Finance, 60 (2005), pp. 2825–2858.

[13] M. J. COOPER, H. GULEN, and M. J. SCHILL, *Asset growth and the cross-section of stock returns*, Journal of Finance, 63 (2008), pp. 1609–1651.

[14] M. J. Cooper, R. C. G. Jr., and A. Hameed, *Market states and momentum*, Journal of Finance, 59 (2004), pp. 1345–1365.

[15] M. J. Cooper, A. Korana, I. Osobov, A. Patel, and P. R. Rau, *Managerial actions in response to a market downturn: Valuation effects of name changes in the dot.com decline*, Journal of Corporate Finance, 11 (2005), pp. 319–335.

[16] K. DANIEL and S. TITMAN, *Evidence on the characteristics of cross sectional variation in stock returns*, Journal of Finance, 52 (1997), pp. 1–33.

[17] E. F. Fama and K. R. French, *The cross-section of expected stock returns*, Journal of Finance, 47 (1992), pp. 427–465.

[18] ——, *Common risk factors in the returns on stocks and bonds*, Journal of Financial Economics, 33 (1993), pp. 3–56.

[19] ——, *Dissecting anomalies*, Journal of Finance, 63 (2008), pp. 1653–1678.

[20] S. Feuerriegel, A. Ratku, and D. Neumann, *Analysis of how underlying topics in financial news affect stock prices using latent dirichlet allocation*, HICSS '16 Proceedings of the 2016 49th Hawaii International Conference on System Sciences (HICSS), 49 (2016), pp. 1072–1081.

[21] C. R. Harvey, Y. Liu, and H. Zhu, *and the cross-section of expected returns*, Review of Financial Studies, 29 (2016), pp. 5–68.

[22] D. Hirshleifer, K. Hou, and S. H. T. Y. Zhang, *Do investors overvalue firms with bloated balance sheets?*, Journal of Accounting Economics, 38 (2004), pp. 297–331.

[23] H. Hong and J. C. Stein, *A unified theory of underreaction, momentum trading, and overreaction in asset markets*, Journal of Finance, 54 (1999), pp. 2143–2184.

[24] N. Jegadeesh and S. Titman, *Returns to buying winners and selling losers: Implications for stock market efficiency*, Journal of Finance, 48 (1993), pp. 65–91.

[25] N. Jegadeesh and D. Wu, *Deciphering fedspeak: The information content of fomc meetings*, working paper, (2016).

[26] A. S. Josef Lakonishok and R. W. Vishnyt, *Contrarian investment, extrapolation, and risk*, Journal of Finance, 49 (1994), pp. 1541–1578.

[27] F. Li, *Annual report readability, current earnings, and earnings persistence*, Journal of Accounting Economics, 45 (2008), pp. 221–274.

[28] T. Loughran and B. Mcdonald, *When is a liability not a liability? textual analysis, dictionaries, and 10-ks*, Journal of Finance, 66 (2011), pp. 35–65.

[29] T. Loughran and J. R. Ritter, *The new issues puzzle*, Journal of Finance, 50 (1995), pp. 23–51.

[30] L. Pastor and R. F. Stambaugh, *Liquidity risk and expected stock returns*, Journal of Political Economy, 111 (2003), pp. 642–685.

[31] M. Petersen, *Estimating standard errors in finance panel data sets: Comparing approaches*, Review of Financial Studies, 22 (2009), pp. 435–480.

[32] R. ROLL, *A possible explanation of the small firm effect*, Journal of Finance, 36 (1981), pp. 879–888.

[33] R. J. Shiller, *From efficient markets theory to behavioral finance*, Journal of Economic Perspectives, 17 (2003), pp. 83–104.

[34] R. G. Sloan, *Do stock prices fully reflect information in accruals and cash flows about future earnings?*, Accounting Review, 71 (1996), pp. 289–315.

[35] D. Wu, *Shock spillover and financial response in supply chain networks: Evidence from firm-level data*, working paper, (2016).

[36] Y. Zhang, *Analyst responsiveness and the post-earnings-announcement drift*, Journal of Accounting Economics, 46 (2008), pp. 201–215.

Table 1.1: Summary Statistics of Trend Loading. This table reports the summary statistics of the trend loadings across LDA models with different topic numbers from 5 to 50. Mean is the average value; C/U ratio is the ratio between conditional mean and unconditional mean; Std Dev is standard deviation; 5th Pctl is the 5th percentile; 95th Pctl is the 95th percentile.

LDA Model	Mean	C/U Ratio	Std Dev	5th Pctl	Median	95th Pctl
5 topics	0.359	1.795	0.414	0	0.2	0.999
10 topics	0.216	2.16	0.31	0	0.051	0.926
15 topics	0.169	2.535	0.257	0	0.027	0.764
20 topics	0.141	2.82	0.226	0	0.011	0.666
25 topics	0.114	2.85	0.197	0	0.005	0.591
30 topics	0.101	3.03	0.176	0	0.004	0.508
40 topics	0.083	3.32	0.156	0	0.001	0.455
50 topics	0.072	3.6	0.139	0	0.001	0.402

Table 1.2: Summary Statistics of Performance-Scaled Trend Loading. This table reports the summary statistics of the performance-scaled trend loadings across LDA models with different topic numbers from 5 to 50.

LDA Model	Mean	Std Dev	5th Pctl	Median	95th Pctl
5 topics	0.026	0.110	-0.123	0.000	0.218
10 topics	0.019	0.076	-0.067	0.000	0.147
15 topics	0.017	0.063	-0.038	0.000	0.145
20 topics	0.008	0.051	-0.047	0.000	0.097
25 topics	0.007	0.043	-0.041	0.000	0.083
30 topics	0.005	0.042	-0.039	0.000	0.069
40 topics	0.006	0.036	-0.031	0.000	0.070
50 topics	0.004	0.030	-0.028	0.000	0.052

Table 1.3: Summary Statistics of Pooled-Industry Trend Loading. This table reports the summary statistics of the pooled-industry trend loadings across LDA models with different topic numbers from 5 to 50.

LDA Model	Mean	Std Dev	5th Pctl	Median	95th Pctl
5 topics	0.972	0.055	0.879	0.991	0.999
10 topics	0.966	0.058	0.873	0.985	0.998
15 topics	0.963	0.059	0.874	0.981	0.997
20 topics	0.959	0.062	0.862	0.977	0.996
25 topics	0.864	0.247	0.097	0.962	0.994
30 topics	0.842	0.260	0.043	0.951	0.993
40 topics	0.723	0.324	0.022	0.900	0.989
50 topics	0.617	0.360	0.000	0.779	0.982

Table 1.4: LDA Trend of the Manufacturing Industry. This table reports the LDA trend for the manufacturing sector from Fama-French 12 industries from year 1996 to year 2014. For each year, 3 interpretable words are chosen from the top 10 words of the trend.

Year	Top Ranked Words in Trend		
1996	pocket	beverage	enter
1997	concentrate	center	reincorporation
1998	payoff	cargo	eurodollar
1999	globe	player	clearance
2000	shipment	tonnage	indemnify
2001	aerospace	Shanghai	decommission
2002	trial	homeowner	revoke
2003	Shanghai	trade	utility
2004	domestic	machinery	silicon
2005	advantage	whole	port
2006	secondary	multiemployer	fluctuate
2007	deteriorate	kit	solvency
2008	embargo	statewide	rebuild
2009	unhedged	alarm	threat
2010	negotiation	unhedged	lose
2011	treaty	indebt	distribution
2012	local	upstream	commercial
2013	import	hourly	creation
2014	green	treaty	fraction

Table 1.5: Sorts of Excess Returns by 10-K Trend: Equal-Weighted. At the end of each year t over 1996 to 2014, stocks are allocated into deciles based on 10-K trend loadings with the 10-K released during the year t. Equal-weighted portfolios are formed based on 10-K trend loadings decile cutoffs. The portfolios are held for one year, from January of year $t+1$ to December of year $t+1$, and then rebalanced. LDA models with different number of topics are reported in each column of this table. Portfolio average annual returns for all deciles are reported, followed by the difference between the average return of the highest ranked decile and lowest ranked decile (10-1). I regress this 10-1 equal-weighted portfolio return against 3 risk models: CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF4). I report the CAPM alphas, FF3 alphas, and FF4 alphas with their respective T-stats (in parentheses). *, **, *** represent statistical significance at the ten percent, five percent, and one percent levels, respectively.

Trend Decile	5 topics	10 topics	15 topics	20 topics	25 topics	30 topics	40 topics	50 topics
1	0.204	0.201	0.195	0.192	0.241	0.238	0.239	0.199
2	0.168	0.218	0.170	0.208	0.163	0.171	0.168	0.223
3	0.147	0.170	0.162	0.155	0.159	0.167	0.168	0.180
4	0.168	0.164	0.170	0.134	0.165	0.176	0.165	0.157
5	0.131	0.147	0.143	0.205	0.158	0.168	0.144	0.179
6	0.219	0.195	0.196	0.163	0.161	0.134	0.180	0.126
7	0.175	0.173	0.172	0.186	0.180	0.227	0.172	0.215
8	0.179	0.151	0.156	0.164	0.184	0.149	0.167	0.158
9	0.180	0.168	0.224	0.169	0.165	0.180	0.166	0.156
10	0.187	0.162	0.162	0.180	0.177	0.151	0.179	0.170
10-1	-0.017	-0.039	-0.034	-0.012	-0.064	-0.087	-0.060	-0.029
10-1 CAPM Alpha	-0.019	-0.065**	-0.056***	-0.033	-0.064	-0.080*	0.059	-0.038**
t-stat	(-0.512)	(-2.587)	(-2.846)	(-1.334)	(-1.305)	(-1.786)	(-1.250)	(-1.830)
10-1 FF3 Alpha	-0.017	-0.053**	-0.054**	-0.037	-0.071	-0.078	-0.060	-0.039**
t-stat	(-0.427)	(-2.326)	(-2.552)	(-1.514)	(-1.317)	(-1.659)	(-1.210)	(-2.111)
10-1 FF4 Alpha	-0.084***	-0.056**	-0.042*	-0.021	-0.142***	-0.139***	-0.128***	-0.029
t-stat	(-4.642)	(-2.131)	(-1.840)	(-0.805)	(-3.314)	(-3.641)	(-3.383)	(-1.447)

Table 1.6: 15-Topic LDA Model. At the end of each year t over 1996 to 2014, stocks are allocated into deciles based on 10-K trend loadings of 15 LDA topics model with the 10-K released during the year t. EW column reports the results for equal-weighted portfolio; RW column reports the results for lag-return-weighted portfolio; Small EW column is for the equal-weighted portfolio for bottom quartile of the sample sorted on firm size; Median reports the middle half of the equal-weighted portfolio of the sample sorted on firm size; Large is the top quartile of the equal-weighted portfolio of the sample on firm size. Portfolio average annual returns for all deciles are reported, followed by the difference between the average return of the highest ranked decile and lowest ranked decile (10-1). I regress this 10-1 portfolio return against 3 risk models: CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF4). I report the CAPM alphas, FF3 alphas, and FF4 alphas with their respective T-stats (in parentheses). *, **, *** represent statistical significance at the ten percent, five percent, and one percent levels, respectively.

Trend Decile	EW	RW	Small EW	Medium EW	Large EW
1	0.195	0.142	0.341	0.193	0.126
2	0.170	0.197	0.240	0.166	0.108
3	0.162	0.118	0.230	0.133	0.150
4	0.170	0.212	0.275	0.166	0.132
5	0.143	0.110	0.180	0.161	0.104
6	0.196	0.079	0.242	0.240	0.140
7	0.172	0.177	0.310	0.107	0.143
8	0.156	0.141	0.201	0.148	0.112
9	0.224	0.129	0.278	0.339	0.136
10	0.162	0.104	0.259	0.133	0.130
10-1	-0.034	-0.038	-0.082	-0.060	0.004
10-1 CAPM Alpha	-0.056***	-0.063**	-0.106**	-0.062*	-0.047
t-stat	(-2.846)	(-2.186)	(-2.209)	(-1.800)	(-1.402)
10-1 FF3 Alpha	-0.054**	-0.059*	-0.101**	-0.070*	-0.030
t-stat	(-2.552)	(-1.878)	(-2.490)	(-1.841)	(-0.988)
10-1 FF4 Alpha	-0.042*	-0.077**	-0.067	-0.098**	-0.002
t-stat	(-1.840)	(-2.230)	(-1.623)	(-2.473)	(-0.071)

Table 1.7: Basic Sorts of Excess Returns by 10-K Performance-Scaled Trend Loading. Value-weighted portfolios are formed based on 10-K performance-scaled trend loadings decile cutoffs. The performance-scaled trend loading is trend loading multiplied by the average past 3-month average performance of the firms from the same sorted decile. The portfolios are held for one year, from January of year $t+1$ to December of year $t+1$, and then rebalanced. LDA models with different number of topics are reported in each column of this table. Portfolio average annual returns for all deciles are reported, followed by the difference between the average return of the highest ranked decile and lowest ranked decile (10-1). I regress this 10-1 equal-weighted portfolio return against 3 risk models: CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF4). I report the CAPM alphas, FF3 alphas, and FF4 alphas with their respective T-stats (in parentheses). *, **, *** represent statistical significance at the ten percent, five percent, and one percent levels, respectively.

Scaled Trend	5 topics	10 topics	15 topics	20 topics
1	0.083	0.108	0.119	0.127
2	0.121	0.154	0.109	0.135
3	0.107	0.085	0.114	0.103
4	0.112	0.043	0.050	0.057
5	0.051	0.065	0.083	0.099
6	0.100	0.112	0.118	0.101
7	0.111	0.064	0.116	0.061
8	0.094	0.093	0.078	0.130
9	0.109	0.139	0.097	0.099
10	0.092	0.082	0.085	0.074
10-1	0.009	-0.026	-0.033	-0.053
10-1 CAPM Alpha	-0.021	-0.068**	-0.067**	-0.067*
t-stat	(-1.056)	(-2.414)	(-2.196)	(-1.971)
10-1 FF3 Alpha	-0.021	-0.057*	-0.075**	-0.059
t-stat	(-0.992)	(-1.942)	(-2.272)	(-1.625)
10-1 FF4 Alpha	-0.031	-0.057*	-0.098**	-0.074*
t-stat	(-1.334)	(-1.682)	(-2.763)	(-1.824)

Table 1.8: Basic Sorts of Excess Returns by Pooled-Industry 10-K Trend Loading. Value weighted portfolios are formed based on 10-K pooled-industry trend loadings decile cutoffs. The pooled-industry scaled trend loading is trend loading calculated from the LDA model with the entire cross-section of the firms. The portfolios are held for one year, from January of year $t + 1$ to December of year $t + 1$, and then rebalanced. LDA models with different number of topics are reported in each column of this table. Portfolio average annual returns for all deciles are reported, followed by the difference between the average return of the highest ranked decile and lowest ranked decile (10-1). I regress this 10-1 equal-weighted portfolio return against 3 risk models: CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart four (FF4). I report the CAPM alphas, FF3 alphas, and FF4 alphas with their respective T-stats (in parentheses). *, **, *** represent statistical significance at the ten percent, five percent, and one percent levels, respectively.

Trend Decile	5 topics	10 topics	15 topics	20 topics
1	0.123	0.121	0.113	0.109
2	0.096	0.104	0.081	0.088
3	0.092	0.067	0.101	0.088
4	0.142	0.098	0.092	0.086
5	0.091	0.144	0.122	0.119
6	0.106	0.073	0.106	0.097
7	0.091	0.087	0.125	0.130
8	0.106	0.102	0.078	0.100
9	0.064	0.101	0.091	0.085
10	0.08	0.110	0.083	0.102
10 - 1	-0.043	-0.011	-0.030	-0.008
10-1 CAPM Alpha	-0.082***	-0.051**	-0.057	-0.052**
t-stat	(-3.838)	(-2.534)	(-1.917)	(-2.188)
10-1 FF3 Alpha	-0.075***	-0.046*	-0.062*	-0.060**
t-stat	(-3.264)	(-2.095)	(-2.062)	(-2.325)
10-1 FF4 Alpha	-0.062**	-0.034	-0.073**	-0.059*
t-stat	(-2.445)	(-1.406)	(-2.145)	(-1.994)

Table 1.9: Difference in Fundamentals after the 10-K Release. This table reports the change in return of assets at and two years after the release of 10-K, $\Delta ROA = ROA_{t+2} - ROA_t$. Panel A reports the unconditional difference of the whole sample and the T-stats of the test which examines whether the difference equals to zero. Panel B reports the conditional difference of the difference between the highest and lowest trend loading sorted decile samples. The T-stats is also reported for the test of whether difference in difference equals to zero.

Panel A. Unconditional difference	
ΔROA	-0.00092
t-value	(-0.60)
Panel B. Conditional difference between high minus low trend deciles	
$\Delta ROA_H - \Delta ROA_L$	-0.00694
t-value	(-1.21)

*$\Delta ROA = ROA_{t+2} - ROA_t$.

Table 1.10: Cross-Sectional Test of the Difference in Fundamentals. This table reports the cross-sectional regression of difference between return on assets at and two years after the release of 10-K, $\Delta ROA = ROA_{t+2} - ROA_t$, on a trend loading, Trendvar, and a set of firm characteristics. The firm characteristics include BM (book-to-market), EP (earning-to-price), leverage, cash flow, accruals, market value (size), sales growth, asset growth, and net investment. Firm fixed effect and year fixed effect are also controlled and exhibited in the results in each columns. *, **, *** represent statistical significance at the ten percent, five percent, and one percent levels, respectively.

	ΔROA			
Intercept	-0.010***	-0.023***	0.055	0.057
	(-3.440)	(-3.040)	(0.380)	(0.400)
Trendvar	0.011	0.007	0.007	0.003
	(1.610)	(1.010)	(1.150)	(0.490)
BM	0.005**	0.004**	-0.004*	-0.006***
	(2.460)	(2.040)	(-1.780)	(-2.770)
EP	-0.486***	-0.480***	-0.402***	-0.394***
	(-11.470)	(-11.370)	(-8.810)	(-8.670)
Leverage	0.029***	0.028***	-0.202***	-0.203***
	(4.310)	(4.120)	(-19.580)	(-19.680)
Cash Flow	-0.363***	-0.363***	-0.716***	-0.715***
	(-63.980)	(-64.130)	(-92.160)	(-92.220)
Accruals	0.000*	0.000	0.000	0.000
	(-1.680)	(-1.270)	(-1.060)	(-0.580)
Size	0.000	0.000	0.000	0.000
	(1.440)	(1.610)	(-1.150)	(-0.810)
Sales Growth	0.000	0.000	0.000	0.000
	(-0.240)	(0.110)	(-0.180)	(0.100)
Asset Growth	-0.003***	-0.002***	-0.001	-0.001
	(-3.140)	(-2.910)	(-1.230)	(-0.980)
Net Investment	0.002	0.002	0.000	0.000
	(1.960)	(2.080)	(-0.450)	(-0.060)
Firm Fixed Effect	**No**	**No**	**Yes**	**Yes**
Year Fixed Effect	**No**	**Yes**	**No**	**Yes**

*$\Delta ROA = ROA_{t+2} - ROA_t$.

Table 1.11: 15-Topic LDA Trend Loading Cross-Sectional Regression. This table reports the cross-sectional regression of stock returns with different timespans on 10-K trend loading and other asset pricing anomaly variables. For the dependent variables, RET is the next calendar year return; RET3 is the 3-month aggregate return after the release of 10-K; RET6 is the 6-month aggregate return; RET12 is the 12-month aggregate return; RET13_24 is the aggregate return from 13th month to 24th month; RET7_18 is the aggregate return from 7th month to 18th month; RET13_36 is the aggregate return from 13th month to 36th month. For the independent variables, TREND is the 10-Ks trend loading; LAGRET6 is the lagged 6 month return before the release of 10-K; LAGRET36 is the lagged 36 month return before the release of 10-K; B/M is book value of equity divided by market value of equity as in Fama and French (2008); MV is the market value when 10-K releases; ASSETG is the asset growth defined as the percentage change in total assets; ACCRUALS is from Sloan (1996); ROA is return on asset; EP is earnings-to-price ratio; NETINVEST is capital expenditures less depreciation sorted into quintiles each fiscal year; L2ASSETG is the lagged asset growth; CASHFLOW is defined as in Titman, Wei, and Xie (2004); SALES is COMPUSTAT Item 12; SALESG is the yearly growth rate in sales (Item 12). Fama-French-Carhart 4 factors for corresponding timespan are also controlled. Panel A reports OLS regression; Panel B reports panel regression with clustered standard errors by firm; Panel C reports panel regression with clustered standard errors by year. *, **, *** represent statistical significance at the ten percent, five percent, and one percent levels, respectively.

Panel A: OLS Pooled Regression							
	RET	RET3	RET6	RET12	RET13_24	RET7_18	RET13_36
Intercept	0.118***	0.044***	0.05***	0.144***	0.145***	0.148***	0.256***
	(5.67)	(10.93)	(7.89)	(14.41)	(11.41)	(16.74)	(15.26)
TREND	-0.052	-0.004	0.035*	0.075***	-0.065*	-0.049**	-0.099**
	(-0.95)	(-0.35)	(2.01)	(2.77)	(-1.88)	(-2.02)	(-2.19)
LAGRET6	-0.08***	-0.031***	-0.059***	-0.072***	-0.11***	-0.049***	-0.146***
	(-3.37)	(-6.92)	(-7.87)	(-6.03)	(-7.37)	(-4.64)	(-7.51)
LAGRET36	-0.003	-0.003**	-0.008***	-0.015***	-0.004	0	-0.014***
	(-0.5)	(-2.31)	(-4.3)	(-4.84)	(-1.02)	(0.02)	(-2.88)
B/M	0	0	0	0	0	0	0
	(0.09)	(-0.18)	(-0.51)	(-0.87)	(0.27)	(-0.08)	(0.6)
MV	0	0	0*	0***	0	0**	0
	(-1.06)	(-1.27)	(-1.83)	(-2.75)	(-0.92)	(-2.31)	(-1.01)
ASSETG	-0.004	-0.002	-0.004**	-0.009***	-0.001	-0.005**	-0.005
	(-0.6)	(-1.43)	(-2)	(-2.98)	(-0.14)	(-2)	(-1)
ACCRULS	-0.115	-0.076***	-0.152***	-0.33***	-0.14*	-0.109**	-0.175*
	(-0.95)	(-3.28)	(-3.92)	(-5.45)	(-1.82)	(-2.02)	(-1.74)
ROA	-0.003	-0.006	-0.032	-0.045	-0.045	0.043	0.032
	(-0.03)	(-0.36)	(-1.14)	(-1.01)	(-0.81)	(1.11)	(0.43)
EP	-0.128	0.003	0.101	-0.021	-0.09	-0.475***	-0.736**
	(-0.34)	(0.05)	(0.83)	(-0.11)	(-0.37)	(-2.8)	(-2.32)
NETINVEST	0.006	0.001	0	0.008**	0.001	0.007**	0.005
	(0.9)	(0.42)	(0.12)	(2.26)	(0.24)	(2.51)	(0.94)
L2ASSETG	-0.001	0	-0.001	-0.001	-0.001	-0.001	0
	(-0.26)	(-0.32)	(-0.55)	(-0.48)	(-0.73)	(-0.49)	(-0.08)
CASHFLOW	0.013	0.004	-0.025	-0.071***	0.062	0.004	0.067
	(0.16)	(0.23)	(-0.97)	(-1.72)	(1.18)	(0.11)	(0.99)
SALES	0	0	0	0*	0	0	0
	(0.07)	(0.22)	(0.9)	(1.71)	(-0.29)	(0.89)	(-1.09)
SALESG	0	0	0	0	0	0	0
	(0.1)	(0.31)	(-0.01)	(-1.49)	(0.27)	(-0.64)	(-0.25)

Table 1.11 Continued.

Panel B: Cross-Sectional Regression with Standard Error Clustered by Firms.

	RET	RET3	RET6	RET12	RET13_24	RET7_18	RET13_36
Intercept	0.112***	0.044***	0.062***	0.165***	0.154***	0.155***	0.284***
	(4.39)	(9.12)	(8.51)	(15.82)	(15.37)	(19.03)	(17.72)
TREND	-0.053**	-0.003	0.042***	0.073***	-0.034	-0.039*	-0.077**
	(-2.01)	(-0.36)	(2.8)	(2.89)	(-1.33)	(-1.72)	(-2.22)
LAGRET6	-0.081***	-0.031***	-0.062***	-0.099***	-0.114***	-0.058***	-0.136***
	(-2.59)	(-4.04)	(-4.11)	(-5.56)	(-4.83)	(-6.11)	(-5.92)
LAGRET36	-0.002	-0.003**	-0.01***	-0.018***	-0.005**	-0.001	-0.018***
	(-0.53)	(-2.01)	(-4.53)	(-5.02)	(-1.99)	(-0.56)	(-3.81)
B/M	0*	0**	0***	0***	0***	0	0***
	(1.78)	(-2.35)	(-3.18)	(-8.56)	(4.47)	(-0.52)	(8.2)
MV	0***	0***	0***	0***	0**	0***	0*
	(-3.04)	(-3.06)	(-2.79)	(-3.3)	(-2.18)	(-2.94)	(-1.85)
ASSETG	-0.004	-0.002*	-0.005*	-0.01*	-0.001	-0.006	-0.007
	(-1.16)	(-1.89)	(-1.76)	(-1.83)	(-0.38)	(-1.54)	(-1.39)
ACCRULS	-0.181**	-0.072**	-0.143***	-0.334***	-0.167**	-0.269**	-0.183*
	(-2.04)	(-2.05)	(-2.81)	(-3.22)	(-2.03)	(-2.27)	(-1.85)
ROA	-0.038	-0.007	-0.027	-0.004	-0.07	0.012	0.003
	(-0.93)	(-0.43)	(-0.69)	(-0.05)	(-1.63)	(0.33)	(0.06)
EP	-0.095	0.016	-0.149	-0.464	-0.009	-0.466	-0.383
	(-0.59)	(0.2)	(-0.72)	(-1.47)	(-0.07)	(-1.64)	(-1.19)
NETINVEST	0	0	0	0.007**	-0.001	0.003	0.005
	(-0.02)	(0.39)	(-0.14)	(2.06)	(-0.16)	(0.99)	(0.98)
L2ASSETG	-0.001	0	-0.001	-0.002	-0.001***	0	0
	(-1.13)	(-1.09)	(-1.53)	(-1.32)	(-2.7)	(-0.44)	(-0.4)
CASHFLOW	0.011	0.004	-0.034	-0.118	0.069*	-0.001	0.1
	(0.28)	(0.27)	(-1.09)	(-1.56)	(1.76)	(-0.03)	(1.51)
SALES	0	0	0	0**	0	0	0
	(-0.54)	(0.47)	(1.32)	(2.39)	(-0.2)	(1.18)	(-1.01)
SALESG	0	0	0	0**	0	0	0
	(0.35)	(0.98)	(-0.34)	(-2.54)	(0.57)	(-1.23)	(-0.1)

Table 1.11 Continued.

Panel C: Cross-Sectional Regression with Standard Error Clustered by Years.

	RET	RET3	RET6	RET12	RET13_24	RET7_18	RET13_36
Intercept	0.112***	0.044*	0.062	0.165**	0.154**	0.155***	0.284***
	(3.08)	(2.09)	(1.45)	(2.32)	(2.46)	(3.11)	(2.88)
TREND	-0.053**	-0.003	0.042	0.073*	-0.034	-0.039	-0.077*
	(-2.11)	(-0.29)	(1.53)	(1.94)	(-1.22)	(-1.64)	(-1.75)
LAGRET6	-0.081	-0.031	-0.062	-0.099	-0.114*	-0.058**	-0.136**
	(-1.5)	(-1.04)	(-1.19)	(-1.44)	(-1.82)	(-2.75)	(-2.17)
LAGRET36	-0.002	-0.003	-0.01*	-0.018*	-0.005	-0.001	-0.018
	(-0.19)	(-1.29)	(-1.74)	(-1.83)	(-0.57)	(-0.18)	(-1.26)
B/M	0**	0**	0***	0***	0**	0	0***
	(2.45)	(-2.19)	(-4.15)	(-9.61)	(2.83)	(-0.47)	(5.04)
MV	0***	0***	0*	0***	0**	0***	0**
	(-3.39)	(-3.67)	(-2.02)	(-3.99)	(-2.44)	(-3.87)	(-2.48)
ASSETG	-0.004	-0.002	-0.005	-0.01	-0.001	-0.006	-0.007
	(-1.41)	(-1.65)	(-1.43)	(-1.69)	(-0.35)	(-1.62)	(-1.16)
ACCRULS	-0.181	-0.072**	-0.143***	-0.334**	-0.167	-0.269	-0.183
	(-1.61)	(-2.14)	(-3.39)	(-2.39)	(-1.27)	(-1.39)	(-1.43)
ROA	-0.038	-0.007	-0.027	-0.004	-0.07	0.012	0.003
	(-0.49)	(-0.24)	(-0.45)	(-0.05)	(-0.8)	(0.18)	(0.04)
EP	-0.095	0.016	-0.149	-0.464	-0.009	-0.466**	-0.383
	(-0.85)	(0.19)	(-0.72)	(-1.31)	(-0.09)	(-2.2)	(-1.14)
NETINVEST	0	0	0	0.007	-0.001	0.003	0.005
	(-0.01)	(0.32)	(-0.08)	(1.42)	(-0.12)	(0.56)	(0.66)
L2ASSETG	-0.001	0	-0.001	-0.002	-0.001**	0	0
	(-0.99)	(-1.33)	(-1.3)	(-1.16)	(-2.17)	(-0.39)	(-0.35)
CASHFLOW	0.011	0.004	-0.034	-0.118	0.069	-0.001	0.1
	(0.32)	(0.19)	(-1.12)	(-1.38)	(1.31)	(-0.03)	(1.42)
SALES	0	0	0	0	0	0	0
	(-0.35)	(0.25)	(0.63)	(1.21)	(-0.13)	(0.72)	(-0.78)
SALESG	0	0	0	0*	0	0	0
	(0.31)	(0.52)	(-0.22)	(-1.86)	(0.4)	(-1)	(-0.09)

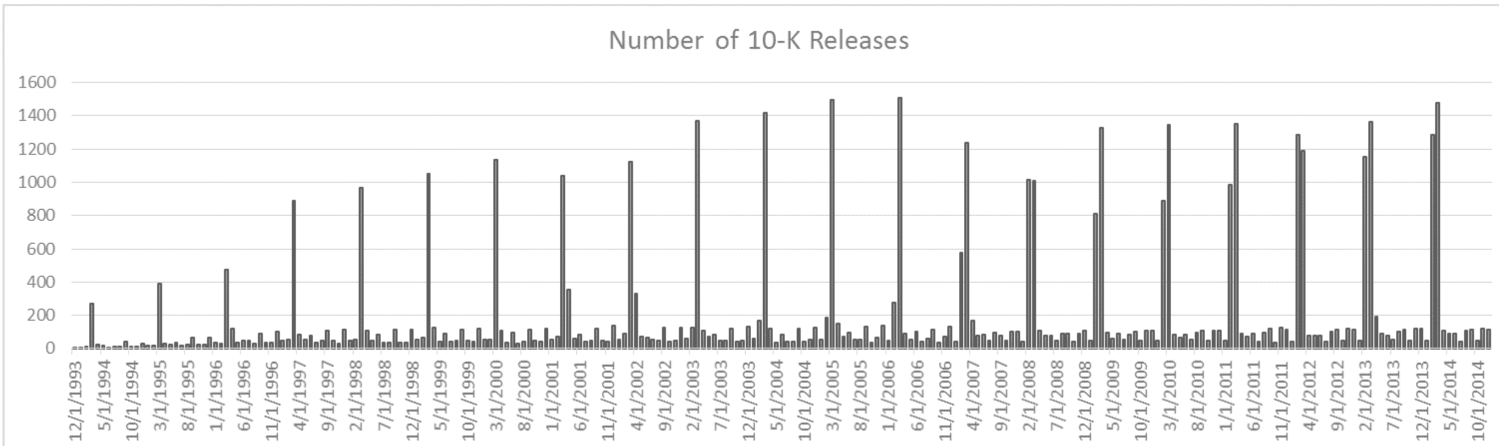

Figure 1.1: Aggregate Monthly Releases of 10-K Date

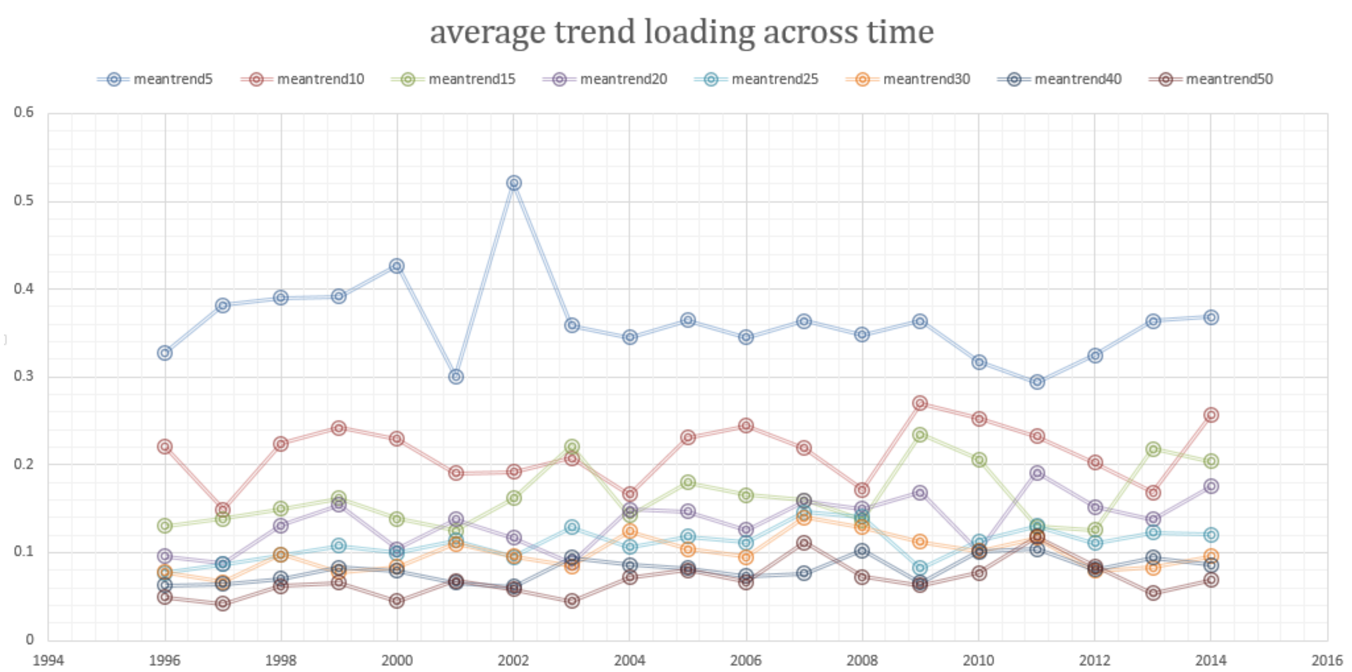

Figure 1.2: Average Trend Loading across Years

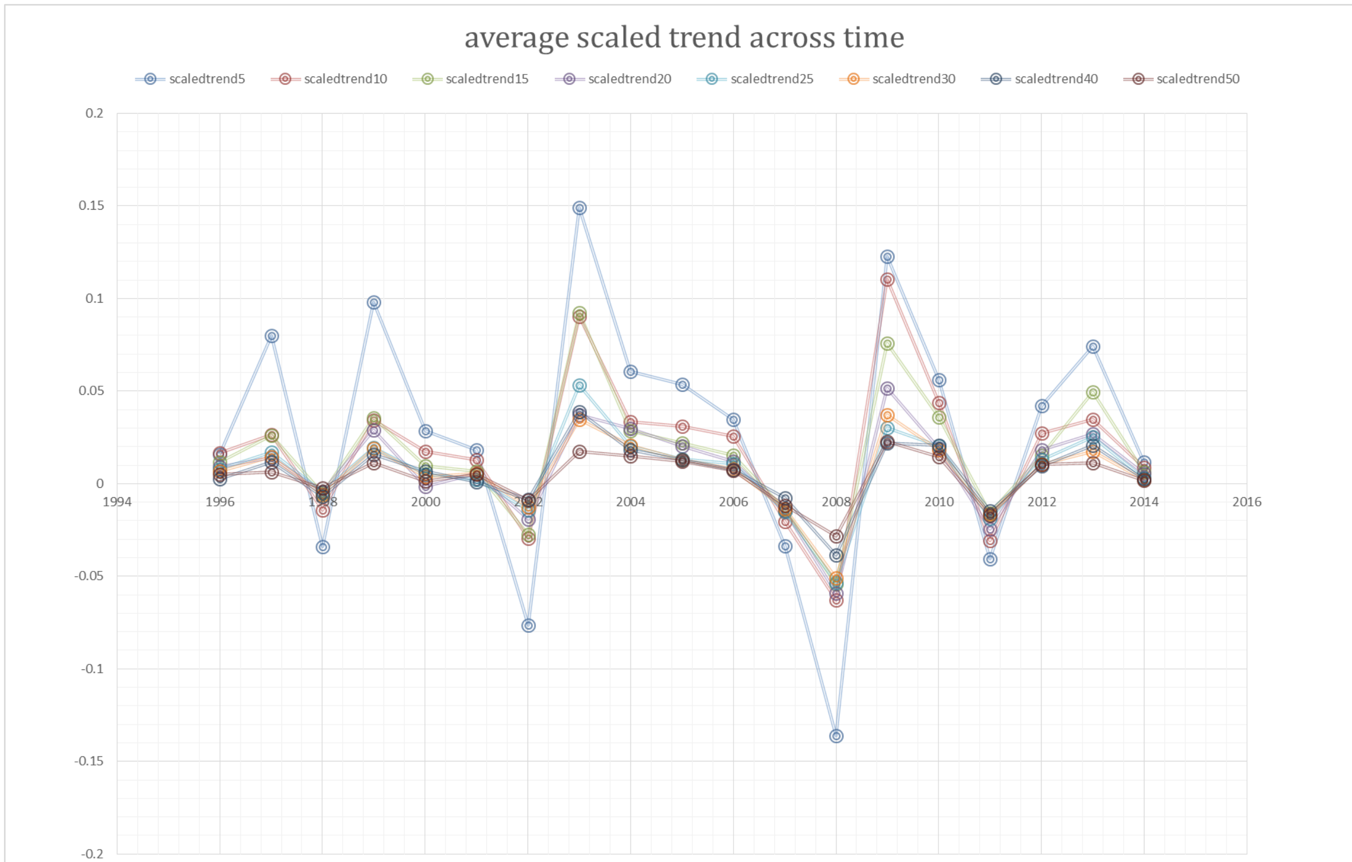

Figure 1.3: Average Performance-Scaled Trend Loading across Years

CHAPTER 2

EARNINGS MANAGEMENT, ANALYSTS' FORECAST ERRORS, AND 10-K TREND LOADING

Chapter 1 uses the machine learning method LDA (Latent Direchlet Allocation) to measure how trendy each firm's 10-K file is and terms this measure "trend loading". This chapter disentangles the relations between three firm information characteristics: firm 10-K trend loading, earnings management, and analysts' forecast errors during the 10-K release. I find that 10-K trend loading contains incremental information beyond earnings management; I also provide evidence suggesting that analysts can learn from the 10-K trend loading, contrary to the former literature indicating that analysts contribute to market inefficiency. This paper further demonstrates that analysts can make forecast errors contrary to the level of 10-K trend loading and partially correct market underreactions.

2.1 Introduction

Corporate business descriptions are supposed to convey information about firm prospects, and the choice of words in business descriptions can attract investment zeitgeist. In Chapter 1, I examine the market reaction to the trendiness of a firm's choice of language in its business descriptions. Using the machine learning method LDA (Latent Direchlet Allocation), I extract the hottest topic (which I define as the overall "trend") of the cross-section of 10-K files and each firm's loading on the trend (which I define as the firm's "trend loading"). Thereafter, a firm's trend loading reflects how trendy this firm's business description sounds to the investors. I further show that investors underreact to firm trend loading in the short run but overreact to it in the long run, consistent with the model of Hong and Stein [18], which predicts the short-run continuation and long-run reversal of stock returns with respect to news.

Earlier literature shows systematic evidence of similar market inefficiencies around the time of corporate information disclosures. Stylized facts related to this phenomenon include firstly, investor underreaction to earnings announcements, which results in so-called post-earnings announcement drifts of stock prices (Ball and Brown [5]; Bernard and Thomas [7]; Chan et al. [10]) and secondly, investor overreaction to company IPOs and SEOs because IPO and SEO stocks significantly underperform a size- and industry-matched sample of seasoned firms (Ritter [27]; Loughran and Ritter [21]; Spiess and Affleck-Graves [29]).

Later studies identify earnings management as well as analysts' forecast errors as possible sources for this market inefficiency. Teoh, Welch, and Wong [31, 32] find that the extent of market overreactions to IPOs and SEOs increases alongside earnings management, indicating that investors naively extrapolate pre-issue earnings; Teoh and Wong (2002) [33] further argue that analysts' forecast errors can be predicted by accruals and that analyst credulity about accruals management generally contributes to market inefficiency around the time of IPOs and SEOs.

The adjustment of 10-K trend loading comes with a lower cost when compared to earnings management, although both the discretionary accruals and 10-K trend loading are chosen by the firm. Hence, it is natural to pose the question whether both earnings management and 10-K trend loading convey the same information to the investors. Furthermore, since the 10-K releases are accompanied with earnings management and analysts' forecasts and the market seems to underreact to the 10-K trend loading in the short run, it is also interesting to examine whether earnings management and analyst credulity will accelerate or dampen the market underreaction to 10-K trend loading. This paper therefore tries to answer these questions by disentangling the relations between earnings management, analysts' forecast errors, and the 10-K trendiness measurement.

The results of this paper find that 10-K trend loading includes information beyond earnings management, analysts aggregate information from 10-K trendiness in addition to earnings management, and analysts make forecast errors contrary to 10-K trend loading and subsequently partially correct market underreactions.

The contribution of this paper is three-fold. First, this is the first work that incorporates the textual information of 10-K trendiness into the existing framework among analysts' forecast errors, earnings management, and stock prices. Second, this paper shows that this novel 10-K trendiness measure introduces extra, if not completely separate, information to investors, in addition to earnings management and analysts' forecast errors. Third, this paper provides evidence against analyst credulity—analysts can learn from 10-K trend loading and facilitate market efficiency.

The rest of the paper proceeds as follows: Section 2.2 introduces the literature; Section 2.3 describes the data used in this work; Section 2.4 presents the empirical tests and findings; some concluding remarks are offered in the final section.

2.2 Literature Review

This paper belongs to a large body of literature on investor reactions to 10-K releases. Early research finds evidence of investor response around 10-K and 10-Q filings dates after the adoption of the EDGAR (Electronic Data Gathering, Analysis, and Retrieval) system[1]. For example, Griffin [16] shows that the excess returns are significantly greater during the 10-K EDGAR release days than during nonrelease days; You and Zhang [35] find strong evidence of underreaction to 10-K releases and that abnormal price movements predict future profitability, indicating that 10-Ks contain useful information about future firm performance; Asthana et al. [4] examine small and large trades around 10-K releases and posit that 10-K releases increase small trading activities. In a previous study, I show that investors underreact to the trend loading of 10-K business description topics in the short run and overreact to it in the long run. This finding further contributes to the voluminous literature of investor mispricing behaviors around corporate events including 10-K releases by introducing a potential source of market inefficiency—the 10-K trendiness.

In the meantime, previous papers point out that earnings announcements and analysts' forecast errors also affect investor comprehension of information released during corporate events such as IPOs and SEOs. On one hand, Teoh, Welch, and Wong [31, 32] find that earnings management influences investors' perceptions around IPOs and SEOs. Managers can report unusually high earnings if they adopt discretionary accounting accrual adjustments that give a raised value of reported earnings compared with the actual cash flows. If investors are guided by the inflated earnings numbers but are unaware of the fact that

[1] The advent of EDGAR fundamentally changed the cost of investors to obtain 10-Ks. Before EDGAR adoption, research documents little evidence of market reaction to 10-K filings (Stice [30]; Easton and Zmijewski [13])

there is a discrepancy between the real cash flow and reported earnings, then they pay a higher price than the underlying value based on these misleading prior beliefs. After the managed earnings are gradually proven to be biased due to other information, including analyst reports and financial media coverage, the investors will update their beliefs about the underlying cash flow thus push the price downwards. Ceteris paribus, the higher the scale of the managed earnings is, the larger the extent of the stock inefficiency to the earnings announcement should be in the long run. However, since the earnings and 10-K textual information are perceived almost simultaneously by the investors[2], it is important to differentiate the influence from 10-K trend loading and earnings management on the stock returns.

On the other hand, analysts' forecast errors also play a crucial part in investors' perceptions about stock prices. Teoh and Wong [33] argue that analysts are credulous about earnings accruals and contribute to market inefficiency. There is further evidence of analysts being inefficient in using information to predict the earnings. Analysts are found to both overreact (De Bondt and Thaler [8]; La Porta [26]; Frankel and Lee [15]), and underreact (Mendenhall [23]; Lys and Sohn [22]; Abarbanell and Bernard [1]) to corporate events. However, there are other theories against analyst inefficiency that provide systematic evidence: Gu and Wu [17] argue that earnings distribution is skewed and if the analysts' objective function is to minimize the average absolute forecast error, then earnings skewness explains a significant amount of the variation in analysts' forecast bias across firms and time; Keane and Runckle [20], using GMM framework, assume the existence of correlations in the analysts' forecasts within the same industry and the discretionary asset write-downs. These authors fail to reject the hypothesis of rationality of analysts; Basu and Markov [6] argue that analysts likely face linear loss function, rather than the quadratic loss function, and try to minimize the absolute forecast errors. By conducting the least absolute deviation regression with linear loss function, they find no evidence of forecast inefficiency in future earnings, making the results of both under- and overreactions (De Bondt and Thaler [8]; Abarbanell and Bernard [1]) much weaker as compared to the OLS (ordinary least square) results. Hence, it is not clear that analysts are indeed inefficient or

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[2] You and Zhang [34] show that, from January of 1995 to December of 2005, the average time gap between firm earnings announcement and 10-K release is approximately 42 days.

misleading.

Therefore, the trendiness of 10-K, earnings management, and analysts' forecast errors may together play significant roles in the process of how firms influence the perception of the investors and how investors correct this perception while making the stock price efficient. Thus, it is important to investigate how these information characteristics together form the market reactions after the 10-K releases. Different from former literature which only examines earnings management alongside analysts' forecasts, this paper provides additional textual 10-K trendiness information. In this paper, I disentangle the relations between these three firm information characteristics and stock returns by examining both long-run and short-run stock behaviors. To the best of my knowledge, this is the first paper that compares the 10-K textual trendiness information with earnings management and analyst forecast errors. Since both earnings management and the trendiness of 10-K are perceived by investors almost simultaneously, I also provide evidence that they contain different information. In addition, this paper implies that the analysts improve market efficiency.

2.3 DATA

2.3.1 Sample Selection and 10-K trends

I collect the universe of 10-K files which have corresponding Central Index Key (CIK) in Compustat using python package "SECEdgar". I download a total number of 65986 10-Ks from the year 1994 to 2016. I remove HTML tags from the data and extract Item 1, the "Business" description. I get 56566 cleaned 10-K files, 8139 10-KA files, and 243 10-K405 files, which add up to 64948 files out of a total of 65986 files (98.5%).

To calculate 10-K trend loading, I apply the machine learning algorithm LDA (Latent Dirichlet allocation) to the extracted 10-K Item 1. Given the number of topics, LDA returns a probability distribution on each topic for every document. For the year t, I run LDA in a 3-year rolling window $[t-2, t-1, t]$ for each Fama-French 12 industry. I then choose the topic with highest aggregate topic loadings for firms in year t and the same industry as the "hottest" topic. I define each firm's loading on this "hottest" topic as the "trend loading". I then pool the results from different industries of the same year together.

Out of the total 56566 10-K's in the data sample, 95% (after the year 1995) have specific release date of the 10-K to the public. According to SEC regulation, firms have up to 90 days to file the 10-K. Consequently, for the 10-K which doesn't specify its release date, I define the release date as 90 days plus the end of the financial year from Compustat database (datadate). For the whole sample, I aggregate the 10-K's for each calendar year based on this release date despite its fiscal year. For instance, firm A's 1998 fiscal year ends at April, 1999, while firm B's 1999 fiscal year ends at September, 1999, so I count them both releasing the 10-K's at the calendar year 1999.

2.3.2 Analysts' Forecast Errors

Teoh and Wong [33] report analysts' forecast errors are predictable by past accounting accruals and the predicted forecast error from accruals significantly accounts for the long-term stock mispricing after IPO and SEO. They further argue that analysts systematically misuse the accounting information and analysts' credulity about accruals management contributes to market inefficiency to a further extent.

Consistent with Teoh and Wong [33], I construct the measure of analysts' forecast from the median consensus forecast for each firm in the annual forecast horizon. In IBES, I select median consensus forecast for the annual earnings from the 6th month before the 10-K release data minus the reported earning and denote it as the analysts' forecast error before the report (AFE_{-1}). Similarly, I construct the analyst earnings error after the report using the 6th month median consensus forecast after the 10-K release date minus the next annual earnings number and denote it as the analysts' forecast error after the report (AFE_{+1}). The reason I require a minimum of 6-month gap between an analyst' forecast and corresponding 10-K release is to ensure that the analysts have information from past accruals, which usually comes out 3 to 4 months after the fiscal year end.

2.3.3 Earnings Management

Following Teoh Welch, and Wong [31], I construct 4 measures of accruals from COMPUSTAT database: discretionary current accruals (DCA), non-discretionary current accruals (NDCA), discretionary total accruals (DTAC), and non-discretionary total accruals (NDTAC). All of these four variables are components of total accruals (TAC), as calculated from COMPUSTAT variables:

$$\begin{aligned}\text{TAC (Total Accruals)} &= \text{CA (Current Accruals) + LA (Long-term Accruals)}\\ &= \text{Net Income(172)} - \text{Cash Flow from Operations (308)}\end{aligned}$$

The current accrual is defined as the change of current assets minus the change of operating current liabilities:

$$\begin{aligned}\text{CA (Current Accruals)} = &\ \Delta[\text{Current Assets(4) - Cash(1)}]\\ &- \Delta[\text{Current Liabilities(5)}\\ &- \text{Current maturity of long-term debt(44)}]\end{aligned}$$

I apply cross-sectional regression of the Jones [19] model to construct measures of annual discretionary and non-discretionary accruals. I regress annual current accruals on the change in sales within the sample of all firms of the same 2-digit SIC industry code. To be consistent with Teoh Welch, and Wong [31] and accounting literature to avoid potential influence of heteroskedasticity, when I run this cross-sectional regression, I also scale all of the variables with last fiscal year end total assets. For firm j belonging to the same two-digits SIC code reporting 10-K at year t, $TA_{j,t-1}$ standing for total assets for firm j and year $t-1$, $CA_{j,t}$ representing current accrual in year t for firm j, and $\Delta SALES_{j,t}$ denoting firm j's change in sales in year t, we have:

$$\frac{CA_{j,t}}{TA_{j,t-1}} = a_0 \frac{1}{TA_{j,t-1}} + a_1 \frac{\Delta SALES_{j,t}}{TA_{j,t-1}} + \xi_{j,t}$$

The non-discretionary current accruals (deflated by total assets) are generally considered to be the portion of current accruals caused by sales grows, and are orthogonal to managerial manipulation. Consequently, it is calculated by:

$$NDCA_{j,t} = \hat{a_0} \frac{1}{TA_{j,t-1}} + \hat{a_1} \frac{\Delta SALES_{j,t} - \Delta A/R_{j,t}}{TA_{j,t-1}}$$

where $\Delta A/R_{j,t}$ is the change in trade receivable for firm j in year t. Dechow et al. [24] argue that there are possibilities that credit sales can be manipulated by the firm, thus I follow the accounting literature and adjust the sales growth by cutting off the change in trade receivable.

After teasing out the predicted or non-discretionary current accruals from the current accruals, the remaining portion of current accruals can be viewed as "manipulated" or discretionary part of the current accruals, because this part is orthogonal to the part which is not manipulable by the management. It is hence computed as:

$$DCA_{j,t} = \frac{CA_{j,t}}{TA_{j,t-1}} - NDCA_{j,t}$$

I use a similar equation of the current accruals to estimate the total accruals. Similar to the previous regression equation for the decomposition of the current accruals, I regress total accruals on change in sales, alongside with an extra regression variable, "property, plant, and equipment" and scale every variable including intercept with the total asset from last fiscal year end. The reason I put in this adjustment variable is that total accruals are influenced by the long-run assets. The estimation regression equation within each 2-digit SIC industry subgroup is as follows:

$$\frac{TAC_{j,t}}{TA_{j,t-1}} = b_0 \frac{1}{TA_{j,t-1}} + b_1 \frac{\Delta SALES_{j,t}}{TA_{j,t-1}} + b_2 \frac{PPE_{j,t}}{TA_{j,t-1}} + \xi_{j,t} \tag{2.1}$$

where firm j's are from the same 2-digit SIC industry, $TAC_{j,t}$ is the total accrual for firm j in year t, and $PPE_{j,t}$ is the gross property, plant, and equipment for firm j in year t (COMPUSTAT item 7).

Therefore, with the similar intuition from the calculation of non-discretionary and discretionary current accruals, the non-discretionary total accruals for year t and firm j ($NDTAC_{j,t}$) are defined as:

$$NDTAC_{j,t} = \hat{b_0} \frac{1}{TA_{j,t-1}} + \hat{b_1} \frac{\Delta SALES_{j,t} - \Delta A/R_{j,t}}{TA_{j,t-1}} + \hat{b_2} \frac{PPE_{j,t}}{TA_{j,t-1}} \tag{2.2}$$

where $\hat{b_0}$, $\hat{b_1}$, and $\hat{b_2}$ are the regresssion estimates from Eq.(2.1); the discretionary total accruals for year t and firm j ($DTAC_{j,t}$) is defined by subtracting the predicted portion of the total accruals from itself:

$$DTCA_{j,t} = \frac{TAC_{j,t}}{TA_{j,t-1}} - NDTAC_{j,t}$$

As in the previous regression equation, when I calculate the non-discretionary total accruals ($NDTAC_{j,t}$), I subtract changes in accounts receivable ($\Delta AR_{j,t}$) from the sales change to avoid the influence from credit sales manipulation of the management.

In this study, I emphasize discretionary current accruals and discretionary total accruals, hence the key variables are DCA and $DTAC$. Since managers have greater flexibility and control on current accruals over the long-term accruals, I follow Teoh Welch, and Wong [31] and apply only current and total accruals (the sum of current and long-term accruals) as test variables. I also provide discretionary current accruals and discretionary total accruals from last year's 10-K report, DCA_{-1}, and $DTAC_{-1}$ for later regression tests.

2.3.4 Summary Statistics

In Table 2.1, I report the summary statistics for variables for later empirical tests with their mean, median, standard deviation, 5th and 95th percentiles. The average post-10-K analysts' forecast error is $0.42 and the average pre-10-K analysts' forecast error is $0.40. The average trend loading is 0.169, with 90th percentile equal to 0.615. The average discretionary current accrual is $0.005 while the average discretionary total accrual is $0.065. The average log of market value is $6.35 million. Finally, the dummy variable DY, which equals 1 if the calendar year end equals fiscal year end, has a mean 0.592, indicating that in the sample, 59.2% of the firms choose calendar year to be their fiscal year.

2.4 Empirical Test

2.4.1 Motivation and Hypothesis Development

In this subsection, I investigate the relations between three firm information characteristics (earnings management, analysts' forecast, and 10-K trend loading) and their influences on total stock returns.

Literature indicates that investors have been constantly misled by earnings management and hence they price the financial asset with biased expectations. Sloan [28] investigates the relation between stock returns and accruals, and finds that investors are "fixated" on earnings and thus fail to adjust for the accruals. Teoh, Welch, and Wong [31] provide evidence that high level of earnings management has incremental influence on market inefficiency after the firm's IPO. Teoh, Welch, and Wong [32] show further evidence that investors naively extrapolate pre-SEO earnings without fully adjusting earnings management.

Meanwhile, my previous study suggests investors underreact to the 10-K trendiness in the short run, consistent with Cooper, Dimitrov, and Rau [11] and Cooper et al. [12]. Since both accruals and 10-K trendiness are perceived by the investors almost simultaneously and they both contribute to investor mispricing, I examine whether they contain different misinformation.

Furthermore, literature also suggests analysts' forecast errors are correlated with cross-section of returns. Frankel and Lee [15] show that analysts' forecast errors are predictable and these errors help investors to correct their beliefs on prices predicted by the analysts' forecasts themselves. Teoh and Wong [33] report that accruals predict analysts' forecast errors. Due to the fact that 10-K trend loading is also information disseminated by the mangers, it is natural to ask if 10-K trend loading also predicts analysts' forecast error, and if analysts correct or amplify the influence of 10-K trend loading on stock prices. Due to the novelty of the 10-K trendiness measurement, whether the predictability of analysts' forecast errors from earnings management will be substituted by the predictability of analysts' forecast errors from 10-K trend loading remains questionable.

I test the above hypotheses in the following steps. First, I take a correlation test between variables of interests. Second, I examine the relation between two pieces of information released by the management: discretionary accruals (earnings management) and 10-K trend loadings (the 10-K trendiness measure). Third, I investigate the lead-and-lag relation between analysts' forecast errors and the other two 10-K information characteristics (discretionary accruals and trend loadings). Fourth, I test the investors' reactions to firm information characteristics. Fifth, I launch two-stage regression to examine the substitution effects between firm information characteristics. In the end, I offer a 3-day event study of the market reactions to the 10-K release.

2.4.2 Correlation Test

The key variables of interest in the information dissemination process during the 10-K releases include pre- and post-10-K analysts' forecast errors (AFE_{-1} and AFE_{+1}), discretionary current accruals (DCA), discretionary total accruals (DTAC), 10-K trend loading, and 12-month buy-and-hold stock return. I report the Pearson correlation tests among these variables in Table 2.2.

From Table 2.2, 10-K trend loading is positively and significantly correlated with 12-month buy-and-hold return with a P-value less than 0.0001. This is consistent with my previous findings that the market underreacts to 10-K trend in the short run. 10-K trend loading is also positively correlated with discretionary current accruals and discretionary total accruals, but not with either of the pre- or post-10-K analysts' forecast errors. Pre-10-K analysts' forecast error is positively correlated with post-10-K analysts' forecast, indicating that analysts' forecast errors are auto-correlated and "stagnant". It is also significantly and negatively correlated with discretionary total accruals, suggesting earnings management tends to correct the error of analysts' forecast. Post-10-K analysts' forecast error is not correlated with either of the earnings management measures, indicating that analysts don't update their posterior beliefs about the firms' fundamentals from the accruals. It is interesting that pre-10-K analysts' forecast error is positively correlated with 12-month buy-and-hold stock return, but the post-10-K analysts' forecast errors are negatively correlated with the returns. This suggests that analysts may contribute to the stock underreactions to the 10-K releases, but they then correct their prior prediction by forecasting next period's earnings with an extra amount contrary to the stock price movement. Finally, discretionary current accruals and discretionary totally accruals are highly correlated. However, neither of them has significant correlation with the 12-month buy-and-hold returns.

2.4.3 Earnings Management and 10-K Trend Loading

Since both earnings management and the 10-K trend loadings are extracted from the same 10-K files, it is natural to ask whether they contain the same information. Teoh, Welch, and Wong [31] show that stock underperformance after IPO is higher when earnings management is stronger. Sloan [28] argues that accruals can explain the cross-sectional variation of stock returns. In a previous work, I show that the stock returns after 10-K are positively correlated with 10-K trend loading within a year, indicating that the investors are underreacting to the 10-K trendiness. If both earnings management and choice of trendy words are managers' options to alter investors' beliefs about the firm's fundamental, then it is of great interest to find out whether these two variables are correlated.

To find out the answer for the above question, I regress measures of discretionary accruals on the 10-K trend loading and a set of control variables. The first model I test is:

$$\begin{aligned} DCA_{j,t} = b_0 + \Sigma_{i=1}^{12} b_{1,i} DI_i + b_2 DY + b_3 Trend_{j,t} + b_4 AFE_{-1} \\ + b_5 AFE_{+1} + b_6 log(MVE) + b_7 DCA_{j,t-1} + \xi_{j,t} \end{aligned} \tag{2.3}$$

where DI_i is the Fama-French 12 industries dummy variable which equals to 1 if the firm belongs to industry i, DY is a dummy variable which equals to 1 if fiscal year end is the calendar year end, $Trend_{j,t}$ is the 10-K 15 topics model trend loading for firm j at year t, AFE_{-1} is the analysts' forecast error 6 months before the release date of 10-K, AFE_{+1} is the analysts' forecast error 6 months after the release date of 10-K, $log(MVE)$ is the natural log of market value of the firm, and $DCA_{j,t-1}$ is the lagged discretionary current accruals from last 10-K.

I report the estimates in column 1 of Table 2.3. The coefficient of $Trend_{j,t}$ is positive but not significant, indicating that there is no correlation between earnings management and 10-K trend after controlling for other variables. Not surprisingly, lagged DCA is correlated with DCA, showing a continuation pattern of DCAs. However, the coefficients of both AFE_{-1} and AFE_{+1} are not significant after controlling for the 10-K trend, which is inconsistent with the negative correlation between analysts' forecast errors and discretionary accruals reported in Teoh and Wong [33].

Further, to examine if there is potential correlation between 10-K trend and lagged discretionary current accruals, I run model 2:

$$\begin{aligned} DCA_{j,t-1} = b_0 + \Sigma_{i=1}^{12} b_{1,i} DI_i + b_2 DY + b_3 Trend_{j,t} + b_4 AFE_{-1} \\ + b_5 AFE_{+1} + b_6 log(MVE) + b_7 DCA_{j,t} + \xi_{j,t} \end{aligned} \tag{2.4}$$

and report the results in column 2 of Table 2.3. The coefficient of 10-K trend loading is non-significant, implying there is no correlation between the information from the 10-K trend loadings and the information from previous earnings management after controlling for variables including firm size. The coefficients of both pre- and post-10-K analysts' forecast errors are still non-significant, suggesting that analysts don't influence accounting accruals.

I further examine the same tests with discretionary total accruals as the dependent variable and report the results in column 3 and 4 in Table 2.3. The estimates remain the similar pattern as in the previous tests. Both lagged and contemporaneous discretionary total accruals have insignificant correlations with 10-K trend loading, showing the information between two sources of management is irrelevant after taking in the consideration of the firm size. Only model 3 reports a significant estimate of the correlation between discretionary total accruals and the current AFE. The other 3 coefficients between lagged DTAC and both AFE measures are insignificant, consistent with column 1 and 2 of Table

2.3, suggesting that after controlling 10-K trend loading, the negative relation (as reported by Teoh and Wong, 2002) between analysts' forecast errors and earnings management is not significant anymore.

Consequently, the findings in Table 2.3 suggest a different, if not orthogonal, relation between management discretionary accruals and 10-K trend loadings. When firm sizes and industry effects are taken into consideration, the 10-K trend loading has no correlation for lagged and contemporaneous discretionary total and current accruals.

2.4.4 Analysts' Forecast Errors and 10-K Information

As key characteristics of firms' information environment, analysts' reports relate to the information asymmetry between insiders and outsiders. Ideally, the information from analysts' forecasts should predict stock returns and limit the insiders' ability to benefit from private information. Frankel and Lee [15] report that IBES consensus forecasts predict cross-sectional returns after controlling for market risk, B/P ratio, and total market value. Zhang [36] argues that not only the precision of analysts' forecasts matters, responsiveness of analysts' forecast also plays an important part. He finds that with responsive forecast revision, the market reacts more in the event window and less in the drift window, implying that analyst responsiveness reduces the post-earnings-announcement drift and improves market efficiency.

In this subsection, I test formally whether analysts can correctly discount the information of discretionary total/current accruals and the information from the 10-K trend loadings simultaneously. In model 1, I use a multivariate OLS regression for each firm i:

$$\begin{aligned} AFE_{-1} = b_0 + \Sigma_{i=1}^{12} b_{1,i} DI_i + b_2 DY + b_3 Trend_{j,t} + b_4 AFE_{+1} \\ + b_5 AFE_{-1} * Trend + b_6 log(MVE) + \xi_{j,t} \end{aligned} \tag{2.5}$$

where AFE_{+1} is the median consensus analyst forecast error 6 months after the release of 10-K for year t and firm j, AFE_{-1} is the median consensus AFE 6 months before the release of 10-K for year t and firm j, DI_i is the dummy variable that equals to 1 if firm j belongs to industry i, and DY is the dummy that equals to 1 if fiscal year end is calendar year end. Brown et al. [9] and Ali [3] document the variation of AFE with firm size, so the natural log of market value of firm, $log(MVE)$, is also included.

I report the estimates of above regression in column 1 of Table 2.4. The coefficient of the 10-K trend loading, *Trend*, is insignificant, suggesting analysts' forecast error does not influence the manager's choice of words and perceptions of topic trend in the later 10-K reports. I add a further set of variables in model 2:

$$\begin{aligned} AFE_{-1} = b_0 &+ \Sigma_{i=1}^{12} b_{1,i} DI_i + b_2 DY + b_3 Trend_{j,t} + b_4 AFE_{+1} \\ &+ b_5 AFE_{-1} * Trend + b_6 log(MVE) + b_7 DCA_{j,t} + b_8 DCA_{j,t} * Trend \\ &+ b_9 DTAC_{j,t} + b_{10} DTAC_{j,t} * Trend + \xi_{j,t} \end{aligned} \tag{2.6}$$

where I add discretionary current and total accruals for firm j and year t, $DCA_{j,t}$ and $DTAC_{j,t}$ and their intersections with 10-K trend loading. Again, the coefficient of 10-K trend loading on past analysts' forecast error is insignificant, but the coefficient of discretionary total accruals is significantly negative, indicating that management takes into consideration of analysts' forecast errors and construct the discretionary accruals in a contrary direction.

In model 3 and 4, I choose analysts' forecast error after 10-K (AFE_{+1}) to be the dependent variable and test a similar set of variables. Reported in column 3 and 4 of Table 2.4, the coefficients of *Trend* are negative in both models 3 and 4, after controlling for discretionary current/total accruals and lagged AFE. According to model 4, 50% of trend loading increment leads to 12 cents of deduction of analyst's choice in forecasting next year's earning, while neither of the coefficients of discretionary accruals is significant (but partically consistent with the findings of Teoh and Wong [33], the coefficients of accruals are negative). This implies that analysts learn from past 10-K trend loadings instead of the discretionary accruals, and update their prediction opposite to the trendiness of 10-K. The interaction terms between discretionary accruals and 10-K trend loading are also insignificant, further positing that discretionary accruals do not contain incremental information as compared with the 10-K trendiness.

2.4.5 Long-Run Return and Firm Characteristics

So far the evidence from previous subsections suggests that the information from 10-K trendiness is different, if not orthogonal, from the information abstracted from earnings management, and the former substitutes for the latter when predicting the analysts' forecast errors after the 10-K release. Accounting literature implies that naive investors can't correctly discount the accruals from the earnings report and hence earnings accruals can explain the cross-sectional variance of stock returns (Sloan [28]). With the new evidence from the previous subsection of the partial substitution effect of 10-K trendiness on discretionary accruals, a potential explanation of the return predictability of the earnings accruals is that it partially comes from the textual information in the self-description of the firm as measured by the 10-K trend loadings. Investors are more likely to underreact, in the short run, to the direct perceptions from words chosen by managers, rather than to the abstract discretionary accrual information.

In this subsection, I test the market reaction to the release of 10-K and examine whether the stock performance is consistent with above hypotheses. To differentiate the influences from 10-K trend loading and earnings management on stock returns, I run the following cross-sectional regressions in model 1 to model 4 in Table 2.5:

$$\begin{aligned} Ret_{bh12} = {} & b_0 + \Sigma_{i=1}^{12} b_{1,i} DI_i + b_2 DY + b_3 Trend_{j,t} + b_4 AFE_{+1} \\ & + b_5 AFE_{+1} * Trend + b_6 AFE_{-1} + b_7 AFE_{-1} * Trend \\ & + b_8 log(MVE) + b_9 DCA_{j,t} + b_{10} DCA_{j,t} * Trend \\ & + b_{11} DTAC_{j,t} + b_{12} DTAC_{j,t} * Trend + b_{13}(MKT_t - Rf_t) \\ & + b_{14} HML_t + b_{15} SMB_t + b_{16} UMD_t + \xi_{j,t} \end{aligned} \tag{2.7}$$

Following Petersen [25], I control for the clustered standard error by firms. Petersen [25] comments that, for panel data, when there are only a few clusters in one dimension, clustering by the more frequent cluster yields results that are almost identical to clustering by both firm and time. In this paper's data panel, the year dimension is much smaller compared to the firm dimension, hence the panel regression is less biased by clustering standard error only by firms.

Overall, the coefficients on 10-K trend loading are significantly positive after controlling for industry fixed effects and all controlled variables with clustered standard errors by firms. Both pre- and post-10-K analysts' forecast errors have significant influences on stock returns, but the pre-10-K AFE has positive effect on stock returns while the post-10-K AFE has negative effect. This is actually consistent with our previous findings: the analyst seems to learn from 10-K trendiness and reacts contrary to the trend loading. Because the trend loading induces stock return continuation and moves in the opposite direction of the post-10-K AFE, stock returns hence are negatively correlated with the post-10-K

AFE. Furthermore, the interaction term between trend loading and post-10-K AFE is also negative. Thus for each firm, the higher trend loading has incremental effect for the negative influence from AFE to the market—the higher the 10-K trend loading is, the stronger the effort that analysts exert to correct the influence from the trendiness of 10-K. Such effort from analysts corresponds to a further correction on the stock returns contrary to the trendiness. Consistent with the accounting literature (Sloan [28]; Allen, Larson, and Sloan [14]), after controlling for 10-K trend loading, both the discretionary current and total accruals are negatively correlated with the future stock returns. The interaction terms between discretionary accruals and trend loading are insignificant. This further demonstrates that the information from these two sources is not overlapping with each other, since investors don't interpret the intersection of them with extra scale of stock returns.

2.4.6 Two-Stage Regressions of Information Substitution

The evidence so far suggests that the measure of 10-K trend loading is correlated with the stock underreaction, and that the post-10-K analysts' forecast errors are negatively correlated with 10-K trend loading, implying that the analyst reacts more to the choice of words in 10-K business description than the discretionary accruals discounted from the footnotes of the 10-Ks. Furthermore, I show that the correlation between both measures of discretionary accruals and 10-K trend is insignificant after controlling for firm size and the analysts' forecast errors do not seem to react to earnings management information controlling for 10-K trend loading. Hence we have systematic evidence of the nonoverlapping between trend and earnings management, and analysts accept 10-K as the prior information source to update their beliefs on the firm's fundamentals.

To further provide robust evidence on above findings, I deliver a two-stage cross-sectional regression as in Teoh and Wong [33]. For the first model, I test whether 10-K trend loading has additional information beyond the scope of earnings management to investors. If investors interpret accruals correctly with the existence of 10-K trendiness, then the predicted component of the 10-K trend loading by accruals should have no explanatory power to the further stock returns. Even if investors are over-pessimist, as long as this over-pessimism is uncorrelated with the accruals, this result will still hold. However, if such over-pessimism as a reaction to 10-K trend loading is from earnings management's failure to adjust for the 10-K trend loading, then such predictable component of 10-K trend loading will be correlated with the stock underreaction. In the first stage regression of Model 1, 10-K trend loading is regressed on both current and total accruals:

$$Trend = a_0 + a_1 DCA + a_2 DTAC + \epsilon = \widehat{Trend} + \epsilon(Trend) \tag{2.8}$$

The residual 10-K trend loading, $\epsilon(Trend)$, is the difference between the 10-K trend loading and its predicted components from DCA and $DTAC$. I thereafter run a cross-sectional regression, as in Teoh and Wong (2002), of the 12-month buy-and-hold return on the predicted and residual components of 10-K trend loading alongside a set of control variables:

$$\begin{aligned} Ret_{bh12} = b_0 + \Sigma_{i=1}^{12} b_{1,i} DI_i + b_2 DY + b_3 \widehat{Trend} + b_4 \epsilon(Trend) \\ + b_{13}(MKT_t - Rf_t) + b_{14} HML_t + b_{15} SMB_t + b_{16} UMD_t + \epsilon \end{aligned} \tag{2.9}$$

where DI_i is the dummy variable that equals to 1 if firm j belongs to industry i, and DY is the dummy that equals to 1 if fiscal year end is calendar year end, $MKT_t - Rf_t$ is the 12-month market return net of risk free rate, HML_t, SMB_t, and UMD_t are corresponding growth, size, and momentum factors downloaded from Ken French's website.

Column 1 of Table 2.6 reports the second stage of model 1, and we can observe that both of the coefficients of predicted trend loading and residual trend loading are positively significant. This indicates that the market refuses to interpret the information from earnings management as a perfect substitution to the information perceived from 10-K trendiness, but the 10-K trend loading does share some common information with discretionary accruals, contributing to part of the market underreactions. I add both before- and after-10-K trend AFEs to model 2 and report its results in Column 2 of Table 2.6. The result remains similar for the both predicted and residual components of 10-K trend loading, while the AFE_{-1} is negatively and AFE_{+1} is positively correlated with stock returns, consistent with the previous section's findings.

Teoh and Wong [33] argue that analysts' forecast mistakenly interprets the accruals and market further overreacts to such information. To test such setting, I regress AFE_{+1} on accruals in the first stage regression in model 3:

$$AFE_{+1} = a_0 + a_1 DCA + a_2 DTAC + \epsilon = \widehat{AFE_{+1}} + \epsilon(AFE_{+1}) \tag{2.10}$$

where $\widehat{AFE_{+1}}$ is the predicted AFE by 10-K trend and $\epsilon(AFE_{+1})$ is the regression error term. Similar to model 1 and 2 in this session, the second stage is regression is:

$$\begin{aligned} Ret_{bh12} = b_0 + \Sigma_{i=1}^{12} b_{1,i} DI_i + b_2 DY + b_3 \widehat{AFE_{+1}} + b_4 \epsilon(AFE_{+1}) + b_5 trend \\ + b_{13}(MKT_t - Rf_t) + b_{14} HML_t + b_{15} SMB_t + b_{16} UMD_t + \epsilon \end{aligned} \tag{2.11}$$

and the result is listed in Column 3 of Table 2.6. After controlling for 10-K trend loading, the predictable and residual components of AFE_{+1} are still both significantly negative. This implies that investors react negatively not only to the earnings management information contained in AFE_{+1}, but also to the part of AFE_{+1} which cannot be explained by accruals. I add the interaction between trend loading and two components of AFE_{+1} and AFE_{-1} to model 4, and the major estimates remain the same.

In this section, I provide further evidence on the existence of incremental information from 10-K trend loading and analysts' forecast errors on discretionary accruals for the investors. The finding is consistent with former sections' results that the market underreacts to 10-K trendiness, but the price gets partially corrected by analysts' forecast errors which goes in the contrary direction of the 10-K trendiness, and that the earnings accruals plays a minor role in this process.

Together, these results suggest a following possible scenario: when the earnings report releases, investors gradually learn information contained in 10-Ks. They overreact to earnings accruals (Sloan [28]) but underreact to 10-K trendiness in the short run. The information of earnings management and 10-K trend loading is not completely overlapped. Later, the analysts learn from 10-K trendiness and try to correct the biased prior of the investors by making forecasts with errors contrary to the 10-K trendiness and the market indeed responds to such effort of corrections.

2.4.7 Short-Run Event Study

In this subsection, I provide a short-term event study test to the market reaction within in the 3-day window around the 10-K release date.

I divide the data into two subgroups: high trend subgroup and low trend subgroup based on top and bottom 50% sorted 10-K trend loadings. To further examine the interactions between 10-K trend and related variables, I sort each above subsample into two subgroups based on that variable.

Early studies (Aharony and Swary [2]) argue that information of earnings announcements is often coupled with dividend announcements, hence the information can be convoluted together. To separate confounding influences from dividend announcements to 10-K trend loading, I divide the sample into clean and dirty test groups.

I collect data of dividend announcements of firms from the CRSP event file. I label a 10-K report as "dirty" if there is a dividend announcement date within the $[-7, 7]$ days window surrounding the 10-K release date. In my final data sample, there are 37640 clean events and 3449 dirty events.

I calculate the cumulative abnormal return for the 3-day $[-1, 1]$ window around the event date. The daily abnormal return is estimated from the market model, which uses the time series daily data from the months $[-12, -2]$. CAR is calculated as the summation of the 3 abnormal returns from the 3 testing days $[-3, 3]$.

I report the simple two-group t-tests between high and low trendy groups across different conditioning variables in Table 2.7. Panel A of Table 2.7 compares the difference in high/low trend loading CAR across large (top half) and small (bottom half) firm size data sample. Overall, for the large firms, high trend loading stocks underperform the low trend loading stocks with a significant 3-day 0.04% return in difference. For the small firms, the pattern is opposite. Low trend loading underperforms high trend loading firm by 0.037%, but it is insignificant. When it comes to comparison between dirty vs. clean samples, this finding is mainly from the clean sample, not the dirty sample. Hence, this finding implies that the market tends to react positively to large firms with more trendy 10-Ks while negatively with large firms with less trendy 10-K's. For the large firms, a trendy 10-K seems to produce short-term benefits for the shareholders.

In Panel B of Table 2.7, I compare the difference in CAR between high/low trendy firms across high (top thirtile) vs. low (bottom thirtile) analysts' forecast errors, AFE_{+1}. I find for high AFE_{+1} firms, high trend loading firms overperform low trend loading firms by 0.078%. This pattern mainly comes from the clean sample and indicates that analysts tend to give higher afterwards valuation to firms with positive market reaction to high trend loading and negative reaction to low trend loading.

In Panel C of Table 2.7, I compare the difference in CAR between high/low trendy firms across high (top thirtile) vs. low (bottom thirtile) discretionary total accruals. For the low accruals sample, high trend loading firm overperforms low trend firm by 0.325%, while for the high accruals sample, the direction is opposite but insignificant. Unlike the pattern for size and AFE, the comparison is significant only within the dirty sample. This findings implies that when double sorting the short-term market reaction to the 10-K on both trend loading and earnings management, the meanings of market reaction is not direct. There is only a significant relation between earnings management and trend when the event is confounded with dividend payment. Together, this implies that the market's reaction doesn't really show a perfect correlation between the information of discretionary accruals and 10-K trend loading.

In sum, this section gives further evidence of the market's reaction to 10-K trend loading across different variables of interest. I find that the market's interpretability of the information from 10-K trend loading does differ across firm size and post-10-K analysts' forecast errors, but not with the accruals. This short-run finding further supports the claim of the difference between two aspects of 10-K files (choice of words vs. choice of accruals) in terms of their information content and influences to the market.

2.5 Conclusion

In this paper, I disentangle the relations between three firms information characteristics: discretionary accruals, analyst forecast errors, and a novel textual-based 10-K trendiness measure (10-K trend loading). I test the correlations between each of them and the market's reaction to them. Additionally, I report a short-term 3-day event study to provide further evidence of the relationships found between these variables. I find that the textual-based information (10-K trend loading) has incremental information beyond the scope of discretionary accruals. Analysts react mostly to the 10-K trend loading rather than earnings management after the release of 10-K. Consistent with Sloan [28], the market reacts negatively to the discretionary accruals, but positively to the 10-K trend loading without any incremental influence from the interaction between these two information characteristics.

Overall, the contribution of this work is three-fold: first, this is the first work that incorporates the textual information of 10-K trend into the existing framework among analysts' forecast errors, earnings management, and stock prices; second, since both textual trend loading and accruals are reported from 10-K, this paper tries to differentiate their influences and shows that 10-K trend loading includes information different from earnings management; third, by adding 10-K trend loading to the analysis, this work provides contrary evidence to the traditional impression that analyst forecasts are misleading—analysts actually do play a role in making market to be more efficient.

This paper sheds light on future studies of managerial perception manipulation with textual disclosures. The findings of this study imply that managers have textual information channels, in addition to earnings management, to influence the investors' perceptions of stock prices. This paper focuses on the SEC 10-Ks to identify such channels, but one can find other likely managerial disclosure files. Therefore, a broader set of similar textual information, such as 10-Qs, 8-Ks, and newswires, can potentially provides more details about the mechanism of managerial perception manipulation. Finally, qualitative features of these disclosure files, including trend loading, can pose novel approaches to examine existing research puzzles.

2.6 References

[1] J. Abarbanell and V. Bernard, *Test of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior*, Journal of Finance, 47 (1992), pp. 1181–1207.

[2] J. Aharony and I. Swary, *Quarterly dividend and earnings announcements and stockholders' returns: An empirical analysis*, Journal of Finance, 35 (1980), pp. 1–12.

[3] A. Ali, *Bias in analysts earnings forecasts as an explanation for the long-run underperformance of stocks following equity offerings*, working paper, (1996).

[4] S. Asthana, S. Balsam, and S. Sankaraguruswamy, *Differential response of small versus large investors to 10-k filings on edgar*, Accounting Review, 79 (2004), pp. 571–589.

[5] R. Ball and P. Brown, *An empirical evaluation of accounting income numbers*, Journal of Accounting Research, 6 (1968), pp. 159–178.

[6] S. Basu and S. Markov, *Loss function assumptions in rational expectations tests on financial analysts earnings forecasts*, Journal of Accounting Economics, 38 (2004), pp. 171–203.

[7] V. L. Bernard and J. K. Thomas, *Post-earnings-announcement drift: delayed price response or risk premium?*, Journal of Accounting Research, 27 (1989).

[8] W. F. M. D. Bondt and R. Thaler, *Do security analysts overreact?*, 80 (1990), pp. 52–57.

[9] R. Bowen, D. Burgstahler, and L. Daley, *Evidence on the relationships between earnings and various measures of cash flow*, Accounting Review, 61 (1986), pp. 713–725.

[10] L. K. C. CHAN, N. JEGADEESH, AND J. LAKONISHOK, *Momentum strategies*, Journal of Finance, 51 (1996), pp. 1681–1713.

[11] M. J. COOPER, O. DIMITROV, AND P. R. RAU, *A rose.com by any other name*, Journal of Finance, 56 (2001), pp. 2371–2388.

[12] M. J. COOPER, H. GULEN, AND P. R. RAU, *Changing names with style: Mutual fund name changes and their effects on fund flows*, Journal of Finance, 60 (2005), pp. 2825–2858.

[13] P. D. EASTON AND M. E. ZMIJEWSKI, *Sec form 10k/10q reports and annual reports to shareholders: Reporting lags and squared market model prediction errors.*, Journal of Accounting Research, 31 (1993), pp. 113–129.

[14] A. ERIC, C. LARSON, AND R. SLOAN, *Accrual reversals, earnings, and stock returns*, Journal of Accounting Economics, 56 (2013), pp. 113–129.

[15] R. FRANKEL AND C. M. LEE, *Accounting valuation, market expectation, and cross-sectional stock returns*, Journal of Accounting Economics, 25 (1998), pp. 283–319.

[16] P. A. GRIFFIN, *Got information? investor response to form 10-k and form 10-q edgar filings*, Review of Accuouting Studies, 8 (2003), pp. 433–460.

[17] Z. GU AND J. S. WU, *Earnings skewness and analyst forecast bias*, Journal of Accounting Economics, 35 (2003), pp. 5–29.

[18] H. HONG AND J. C. STEIN, *A unified theory of underreaction, momentum trading, and overreaction in asset markets*, Journal of Finance, 54 (1999), pp. 2143–2184.

[19] J. J. JONES, *Earnings management during import relief investigations*, Journal of Accounting Research, 29 (1993), pp. 193–228.

[20] M. P. KEANE AND D. E. RUNKLE, *Are financial analysts' forecasts of corporate profits rational?*, Journal of Political Economy, 106 (1998), pp. 768–805.

[21] T. LOUGHRAN AND J. R. RITTER, *The new issues puzzle*, Journal of Finance, 50 (1995), pp. 23–51.

[22] T. LYS AND S. SOHN, *The association between revisions of financial analysts' earnings forecasts and security-price changes*, Journal of Accounting Economics, 13 (1990), pp. 341–363.

[23] R. MENDENHALL, *Evidence on the possible underweighting of earnings-related information*, Journal of Accounting Research, 29 (1991), pp. 170–179.

[24] A. P. S. PATRICIA M. DECHOW, RICHARD G. SLOAN, *Detecting earnings management*, Accounting Review, 70 (1995), pp. 193–225.

[25] M. PETERSEN, *Estimating standard errors in finance panel data sets: Comparing approaches*, Review of Financial Studies, 22 (2009), pp. 435–480.

[26] R. L. PORTA, *Expectations and the cross-section of stock returns*, Journal of Finance, 51 (1996), pp. 1715–1742.

[27] J. R. RITTER, *The long-run performance of initial public offerings*, Journal of Finance, 46 (1991), pp. 3–27.

[28] R. G. SLOAN, *Do stock prices fully reflect information in accruals and cash flows about future earnings?*, Accounting Review, 71 (1996), pp. 289–315.

[29] D. SPIESS AND J. AFFLECK-GRAVES, *Underperformance in long-run stock returns following seasoned equity offerings*, Journal of Financial Economics, 38 (1995), pp. 243–267.

[30] E. K. STICE, *The market reaction to 10-k and 10-q filings and to subsequent wall street journal earnings announcements.*, Accounting Review, 66 (1988), pp. 1119–1151.

[31] S. H. TEOH, I. WELCH, AND T. J. WONG, *Earnings management and the long-term market performance of initial public offerings*, Journal of Finance, 53 (1998), pp. 1935–1974.

[32] ——, *Earnings management and the underperformance of seasoned equity offerings*, Journal of Financial Economics, 50 (1998), pp. 63–99.

[33] S. H. TEOH AND T. J. WONG, *Why new issues and high-accrual firms underperform: The role of analysts credulity*, Review of Financial Studies, 15 (2002), pp. 869–900.

[34] H. YOU AND X. ZHANG., *Investor under-reaction to earnings announcement and 10-k report*, working paper, (2007).

[35] ——, *Financial reporting complexity and investor underreaction to 10-k information*, 14 (2009), pp. 559–586.

[36] Y. ZHANG, *Analyst responsiveness and the post-earnings-announcement drift*, Journal of Accounting Economics, 46 (2008), pp. 201–215.

Table 2.1: Summary Statistics. *Trend* is from 10-K trend loading. DCA is the discretionary current accruals. $DTAC$ is the discretionary total accruals. AFE is the analyst forecast error calculated using the median consensus forecast 6 months prior to the fiscal year end minus annually reported earnings per share. AFE_{+1} is the analyst forecast error 6 months after the fiscal year end. $log(Mv)$ is the log of market value of the release date of the firm. DY is the dummy variable which equals to 1 if the firm chose calendar year as their fiscal year.

Variable	Mean	Median	Std Dev	10th Pctl	90th Pctl
AFE_{+1}	0.422	0.185	2.584	-0.509	1.520
AFE	0.409	0.180	2.914	-0.490	1.502
Trend	0.169	0.027	0.257	0.000	0.615
DCA	0.005	-0.002	0.807	-0.095	0.097
$DTAC$	0.065	0.060	1.354	-0.208	0.192
$log(Mv)$	6.347	6.318	1.981	3.796	8.949
DY	0.592	1.000	0.492	0.000	1.000

Table 2.2: Pearson Correlation between 10-K Trend Loadings, Analysts' Forecast Errors, Discretionary Accruals, and 12-month Buy-and-hold Returns. AFE is the analyst forecast error calculated using the median consensus forecast 6 months prior to the fiscal year end minus annually reported earnings per share. AFE_{+1} is the analyst forecast error 6 months after the fiscal year end. DCA is the discretionary current accruals. DTAC is the discretionary total accruals. Trend is 10-K topic trend. Ret_{bh12} is the 12-month buy-and-hold return after the release of 10-K file. P-values are reported in the parentheses.

	AFE	AFE_{+1}	DCA	$DTAC$	Ret_{bh12}
Trend	0.006	-0.007	0.013	0.013	0.026
	(0.29)	(0.233)	(0.023)	(0.019)	(<.0001)
AFE		0.065	0.001	-0.013	0.051
		(<.0001)	(0.893)	(0.034)	(<.0001)
AFE_{+1}		-0.005	-0.004	-0.031	
			(0.415)	(0.492)	(<.0001)
DCA				0.885	-0.001
				(<.0001)	(0.882)
$DTAC$					-0.001
					(0.93)

Table 2.3: Cross-sectional Regression of Pre- and Post-10-K Analyst Forecast Error on the 10-K Trend Loading and Discretionary Accruals. This table reports the cross-sectional regressions of the pre- and post-10-K analysts' forecast errors of annual primary earnings per share (AFE_{-1}, AFE_{+1}) on a set of variables: log of market value of the release date of the firm ($log(Mv)$), firm 10-K trend loading (*Trend*), discretionary current accruals (DCA), discretionary total accruals ($DTAC$) and their intersection with the 10-K trend loading, and dummy variables of year and Fama-French 12 industries (DYs and DIs). t-stats are reported in the parameter estimates.

	AFE_{-1}		AFE_{+1}	
$log(Mv)$	-0.009	-0.012	0.031***	0.031***
	(-0.94)	(-1.26)	(-3.35)	(-3.26)
Trend	-0.033	-0.04	-0.221***	-0.223***
	(-0.51)	(-0.62)	(-3.36)	(-3.39)
AFE_{+1}	0.079***	0.079***		
	(-10.9)	(-10.87)		
$AFE_{+1} * Trend$	0.238***	0.239***		
	(-7.49)	(-7.51)		
DCA		-0.026		-0.15
		(-0.27)		(-1.56)
$DCA * Trend$		0.034		0.521
		(-0.09)		(-1.42)
$DTAC$		-0.202***		-0.04
		(-3.02)		(-0.60)
$DTAC * Trend$		0.213		0.128
		(-1.27)		(-1.42)
AFE_{-1}			0.083***	0.083***
			(-11.38)	(-11.35)
$AFE_{-1} * Trend$			0.200***	0.200***
			(-6.64)	(-6.65)
DYs	**Yes**	**Yes**	**Yes**	**Yes**
DIs	**Yes**	**Yes**	**Yes**	**Yes**

Table 2.4: Cross-sectional Regression of Discretionary Accruals on 10-K Trend Loading and Analysts' Forecast Errors. DCA is the discretionary current accruals. DTAC is the discretionary total accruals. Trend is 10-K topic trend. DCA_{-1} is the discretionary current accrual from last fiscal year end. $DTAC_{-1}$ is the discretionary total accruals from last fiscal year end. AFE is the analyst forecast error calculated using the median consensus forecast 6 months prior to the fiscal year end minus annually reported earnings per share. AFE_{+1} is the analyst forecast error 6 months after the fiscal year end. $Log(Mv)$ is the log of the market value of the firm. DIs are the Fama-French 12 industries dummy variables. DY is the dummy variable of weather the fiscal year end is the calendar year end.

	DCA	DCA_{-1}	DTAC	$DTAC_{-1}$
Intercept	0.017**	0.021***	0.147***	0.118***
	(2.50)	(2.85)	(15.49)	(7.84)
Trend	0.004	0.006	0.006	0.000
	(0.85)	(1.01)	(0.86)	(0.02)
AFE_{-1}	0.000	-0.001	-0.002***	-0.001
	(0.82)	(-1.30)	(-3.00)	(-0.42)
AFE_{+1}	0.000	0.000	0.000	0.000
	(-0.40)	(-0.31)	(-0.01)	(0.06)
Log(Mv)	-0.003***	-0.003***	-0.013***	-0.012***
	(-4.40)	(-3.80)	(-11.80)	(-7.06)
DCA_{-1}	0.059***			
	(9.36)			
DCA		0.072***		
		(9.36)		
$DTAC_{-1}$			0.168***	
			(39.44)	
$DTAC$				0.420***
				(39.44)
DIs	YES	YES	YES	YES
DYs	YES	YES	YES	YES

Table 2.5: Cross-Sectional Regression of 12-Month Buy-and-hold Stock Return on 10-K Trend Loading, Analysts' Forecast Errors, and Discretionary Accruals with Standard Error Clustered by Firms. DCA is the discretionary current accruals. DTAC is the discretionary total accruals. Trend is 10-K topic trend. AFE is the analyst forecast error calculated using the median consensus forecast 6 months prior to the fiscal year end minus annually reported earnings per share. AFE_post is the analyst forecast error 6 months after the fiscal year end. Logmve is the log of the market value of the firm. DIs are the Fama-French 12 industries dummy variables. DY is the dummy variable of weather the fiscal year end is the calendar year end. The dependent variable is the 12-month buy-and-hold firm stock return after the release date of 10-K.

Intercept	0.389***	0.388***	0.389***	0.452***
	(17.79	(15.92)	(15.91)	(15.26)
Logmve	-0.05***	-0.048***	-0.048***	-0.055***
	(-16.43	(-14.33)	(-14.32)	(-14.22)
Trend	0.076***	0.069***	0.061***	0.086***
	(4.56	(3.78)	(3.43)	(3.96)
AFE_post		-0.011***	-0.01***	-0.01***
		(-4.64)	(-3.97)	(-3.72)
AFE		0.015***	0.013***	0.017***
		(3.81)	(3.11)	(2.53)
AFE_post*Trend			-0.005	-0.006
			(-0.6)	(-0.63)
AFE*Trend			0.021*	0.028*
			(1.71)	(1.77)
DCA				-0.059*
				(-1.73)
DCA*Trend				0.093*
				(0.23)
DTAC				-0.099***
				(-3.92)
DTAC*Trend				0.035
				(1.26)
DY	Yes	Yes	Yes	Yes
DI	Yes	Yes	Yes	Yes
FF 4 Factors	Yes	Yes	Yes	Yes

Table 2.6: Two-Stage Cross-Sectional Regression. The first stage for model 1 and 2 is: $Trend = a_0 + a_1 DCA + a_2 DTAC + \epsilon$; The first stage for model 3 and 4 is: $AFE_{+1} = a_0 + a_1 DCA + a_2 DTAC + \epsilon$. In the second stage regressions, both predictable and residual components of above dependent variables are included together with control variables. DIs are the Fama-French 12 industries dummy variables. DY is the dummy variable of weather the fiscal year end is the calendar year end. Fama-French 4 factors are downloaded from Ken Frenchs website.

Intercept	0.074***	0.072***	0.075***	0.071***
	(4.27)	(4.16)	(4.50)	(4.25)
Trend			0.095***	0.089***
			(4.84)	(4.31)
$\widehat{Trend}$	0.081**	0.078**		
	(2.33)	(2.25)		
$\epsilon(Trend)$	0.103***	0.1***		
	(4.34)	(4.23)		
AFE_{+1}		-0.011***		
		(-5.76)		
$\widehat{AFE_{+1}}$			-0.008**	-0.01**
			(-2.38)	(-2.48)
$\epsilon(AFE_{+1})$			-0.01***	-0.01***
			(-4.32)	(-4.01)
$\widehat{AFE_{+1}} * Trend$				-0.022
				(-1.48)
$\epsilon(AFE_{+1}) * Trend$				-0.003
				(-0.30)
AFE_{-1}		0.018***		0.015***
		(9.62)		(7.18)
$AFE_{-1} * Trend$				0.001***
				(3.29)
DY	Yes	Yes	Yes	Yes
DI	Yes	Yes	Yes	Yes
FF 4 Factors	Yes	Yes	Yes	Yes

Table 2.7: Short-Run Event Studies. CAR is calculated for the 3-day window around the release date of 10-K, using CAPM model estimated from month -12 to month -2. Large firm is the top half of the same, while small firm is the bottom half. High/Low Post afe group are from sorted on tertiles on post 10-K analyst forecast errors. High/Low dtac group are from sorted on tertiles on discernable total accruals.

Panel A. Double sorting by 10-K trend loading and firm size.				
	low trend	high trend	diff	p-value
Whole sample				
large firm	-0.00032	0.000094	-0.00041	0.0497**
small firm	0.000195	-0.00017	0.00037	0.1935
Dirty				
large firm	-0.00009	-0.00006	-0.00003	0.4837
small firm	0.00063	0.00023	0.0004	0.3451
Clean				
large firm	-0.00036	0.000119	-0.00048	0.0367*
small firm	0.000063	0.0002	0.000266	0.2771

Table 2.7 Continued.

Panel B. Double sorting by 10-K trend loading and AFE_{+1}

	low trend	high trend	diff	p-value
Whole sample				
large	-0.00029	0.000464	-0.00075	0.0603*
small	0.000086	-0.00005	0.00014	0.373
Dirty				
large	0.00108	0.00121	-0.00013	0.4565
small	0.00154	0.000493	0.00104	0.183
Clean				
large	-0.00041	0.000371	-0.00078	0.0657*
small	-0.00005	-0.00004	-0.00001	0.4909

Panel C. Double sorting by 10-K trend loading and DTAC.

	low trend	high trend	diff	p-value
Whole sample				
large DTAC	-0.00068	-0.00044	-0.00025	0.3273
small DTAC	0.000177	-0.00065	0.000828	0.0585*
Dirty				
large DTAC	0.000842	0.000239	0.000603	0.3158
small DTAC	-0.00252	0.000733	0.00325	0.0124**
Clean				
large DTAC	-0.00077	-0.0005	-0.00027	0.3187
small DTAC	0.000012	-0.00064	0.000652	0.1205