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Reading Between the Lines: CEO Temperament Measured by Textual Analysis and Firm Policy

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Abstract

Previous studies find associations between tone in financial disclosures and stock volatility, drift, and returns. These studies focus on language use in a broad sense, less concerned with precisely who said what. In this paper I target the words of the CEO as it relates to the kinds of policies their companies employ. The results of my research echo the impact of word choice uncovered by prior studies and shed light on the implications of CEO personality.

1. Introduction

The focus of my research is the textual analysis of financial documents. The topic of textual tone in financial text is interesting because it presents a new way of understanding a document. Previously, investors and analysts would solely read earnings reports, earnings calls transcripts, and other company disclosures to understand a business. With the emergence of textual analysis in the field of accounting and finance, outsiders to a firm now have another method they can utilize to paint a bigger picture. From anticipating fraud to predicting abnormal returns and trading volume after an earnings conference call in Larcker and Zakolyukina [2012] and Tetlock [2007], textual analysis proves to be a worthwhile concept to research in the business field.

In the present study I use the technique to analyze the words of CEOs in earnings conference calls and use those sentiment counts to determine the personality of the CEO. After assessing the temperament, I investigate the link between this CEO personality and the firm's policies and find a relationship between an aggressive personality and the debt to equity of the firm. Companies in my sample that have a CEO with an aggressive personality have higher debt to equity ratios, or riskier forms of financing. The age of the CEO and their tenure at the firm interestingly does not have any link to the firm policies they choose. Also, regardless of CEO and firm-level attributes, the R&D spending stays independent of these variables. The R&D spending varies on a case-by-case basis and the CEO's personality has no effect on this firm policy.

2. Literature

2.1. Personality and Social Psychology Studies

The relationship between word choice and personality is important to my research. One assumption I make in this study is that there exists a direct link between word choice and personality. The CEO's words represent the only measure of personality in my study, but there is scientific grounding that the words we choose are manifestations of our personality. After reviewing studies done on the subject, many researchers make similar findings in the field of psychology. As early as 1942 researchers explore the relationship between language use and personality. One such study is Sanford [1942]. In this study Fillmore Sanford employs two undergraduate volunteers and asks them to comment on a given stimulus. The first stimulus is prints of five paintings and the second is a stimulus card referred to as a "text-island" made up of three words. With the stimulus card the subjects are asked to create a narrative around those words. The speech from these exercises is separated into mechanical, grammatical, and lexical categories of oral speech, and used to describe the individual subjects. The first subject, named Merritt, has recording data that shows he is "complex, complete, uncoordinated, cautious, perseverative, deferent, and stimulus-bound" [Sanford, 1942]. The second subject, named Chatwell, is "colorful, confident, emphatic, direct, dynamic, progressive, well-coordinated, and independent from his recordings" [Sanford, 1942]. What is notable about these conclusions is the characterizations of the speech also appear to be characterizations of the persons according to Sanford [1942].

A more recent study on the link between linguistic style and personality is Pennebaker and King [1999]. This study consists of three phases where the researchers use daily diaries from 15 substance abuse inpatients, daily writing assignments from 34 students, and journals from 40 social psychologists to answer the question, "Can language use reflect personality style?" [Pennebaker and King, 1999]. The study's three phases of reliability, factor structure, and validity of written language are combined to tackle this question. Looking at phase one, or the reliability phase of their study, Pennebaker and King collect daily writing samples from 15 patients of a substance abuse treatment program in England. One aspect of the treatment program is the completion of a "significant event sheet" at the end of each day. This is essentially a diary entry about the most significant event of the day and its responses are due to the counseling staff each day. The second sample of phase one is the daily writings of a summer school health psychology class at Southern Methodist University in New Mexico. Of the 34 student volunteers, 5 are male and 29 are women, ranging in age from 18 to 67 years. The students throughout the course are given daily writing assignments with varying topics for this exercise. Lastly, for the third sample of the first phase, the researchers randomly select 40 social psychologists from the psychology organization SESP and journal publications in the PsycINFO database. For each psychologist, the 15 most recent journal abstracts are included in the study. Pennebaker and King then use the Linguistic Inquiry and Word Count (LIWC) computer software to analyze the writing samples. Their main finding in the study is that language use is a reliable individual difference. The word category usage in all the samples is very stable across time and with numerous writing topics supporting this reliability. In the other two phases of the study, the researchers find linguistic style strategy overlaps with projective tests. This is evident when the volunteers focus on another writing topic, and their characteristic speech patterns surface. An example from the study is a harsh person who claims they are not angry or upset, but still uses a lot of negative emotion words in their writing [Pennebaker and King, 1999]. This study along with Sanford [1942] are monumental studies in the field of personality and social psychology however they do suffer from small sample sizes. Sanford [1942] only has two male undergraduate students in the sample and Pennebaker and King [1999] has a combined sample size of 34 volunteers. Finding meaningful conclusions at these small sample sizes is still significant, but these results need to be tested on a broader scale.

A study with James W. Pennebaker and a larger sample size is Mehl, Gosling, and Pennebaker [2006]. The study seeks to provide an investigation into the personality ramifications of daily life through tracking participants for two days with the Electronically Activated Recorder (EAR) that captures sounds in the participants' environments. In addition to the EAR data, the researchers also have "judges" who listen to the EAR recordings and give their impressions of the personality. The feedback from the judges is reviewed with the preliminary personal responses from the volunteers to test for any correlations. Their results show there is a significant correlation between the judge's impression and the self-reports of personality. This finding is interesting because the judges are presented only with the EAR recordings of the volunteers' tone of voice and their word choices. Another finding is that some personalities are more evident through word choice than others. The traits of extraversion and subsequently the big five personality traits, are usually expressed in the participants' daily interactions and language usage in Mehl, Gosling, and Pennebaker [2006].

A more recent study on the same topic is Fast and Funder [2008]. This paper looks at categories of word use relevant to personality based on data from interviewees and their close friends or "acquaintances," as referred to in the study. There are 181 target participants (90 women, 91 men) and 330 acquaintances from the University of California that participate in the study [Fast and Funder, 2008]. The acquaintances of the target participants are either nonromantic friends, romantic partners, family members, friends from work, or other. The researchers had the target participants fill out take-home questionnaires and participate in recorded group interactions to code their behavior. The volunteers' acquaintances are paid to provide personality judgements of the subjects. In their study, Fast and Funder analyze the take-home responses and correlate those with the accounts of the acquaintances and group interactions. They find many word categories like optimism, negative emotion, anxiety, certainty, and leisure related to the self and acquaintance ratings of personality. Out of the 6,600 correlations computed in the study, 1,042 correlations are significant between the word categories and the self-ratings of personality, and 1,056 correlations are significant between the word categories and the acquaintance ratings [Fast and Funder, 2008]. The findings are interesting because the large number of self-rating correlates implies self-reports are more linked to word use than previously thought. The other unexpected result is the large number of significant acquaintance correlates. The acquaintances are not given access to the target participants' self-reports and only go off their intuition.

Another study on personality and word choice is Hirsh and Peterson [2009]. This paper looks at the big five personalities like the previous studies, but also extends its scope to the lower-level aspects of personality traits. The researchers have 94 undergraduate students from the University of Toronto first fill out personality questionnaires and then complete two writing assignments. The first assignment is to write about their past experiences and the second is to write about their future goals. After, the researchers use the LIWC software from Pennebaker, Francis, and Booth [2007] to analyze the word frequencies in the writing assignments consisting on average of 16,448 words. Hirsh and Peterson find word choice in the writing assignments to be significantly correlated with the big five personalities and the lower-level aspects. The study notes that one limitation of using the LIWC software is it only looks at word use and not the context in which the words are nested in. Given this limitation, the study points to a relationship between word usage and personality in this study, as seen in the previously mentioned studies that also use this software. Overall, the listed research suggests that word choice plays a larger role than expected in personality manifestations. Evidence of this can be seen in the psychological studies of varying sample size and method, across many decades.

2.2. Textual Analysis Studies in Finance and Accounting

The LIWC software mentioned previously, and others like it, are not limited to the field of psychology. They are part of a broader research method known by some as textual analysis. The technique of textual analysis is used across many disciplines to extract meaning from text and is often referred to as content analysis, computational linguistics, information retrieval, or natural language processing. These terms all may seem unrelated but are essentially different ways of saying the same thing. Sociologists, geographers, historians, psychologists, and media studies researchers find textual analysis to be beneficial to their respective fields, yet the concept of parsing text is still relatively new to the field of accounting and finance. The following research offers a glimpse of the concept's capabilities and explains why textual analysis has drawn considerable attention in business applications.

One of the pioneering papers on the subject is Li [2008]. This paper is important because it finds a link between firm performance and annual report readability, a very simple application of textual analysis. Readability is the ease with which a reader can understand a written text and is concerned with the composition and structure of a document. Since textual analysis focuses on finding meaning in text, the ability of the reader to first comprehend the text is of great importance. There are multiple ways to measure readability, but Li [2008] uses the Fog Index in his study. This is a function that consists of two variables: average sentence length, and the complex words (defined as the percentage of words with more than two syllables) in the text. The sample for Li's study consists of 55,719 firm-years of 10-K annual reports from filing dates 1994 to 2004. After using the Fog Index on the annual reports, Li also analyzes the length of the documents to capture the reports' readability. Li assesses the length of the 10-K because longer documents tend to be more difficult to read and potentially contain hidden adverse information. The main findings in Li [2008] are that firms with lower reported earnings tend to have 10-Ks that are harder to read and firms that report profits in the annual report are easier to read. Li [2008] concludes that evidence from his study points to managers purposely structuring the annual reports to hide bad information from investors.

Tetlock [2007] also quantitatively measures business text but focuses on the sentiment of the media in the daily Wall Street Journal column, *Abreast of The Market*. What separates this paper from Li [2008] is its use of the "bag-of-words" approach. "Bag-of-words" is another method of textual analysis that measures the frequency of each word in a text. An example would be a parsing computer program that counted the number of negative words relative to the total word count to test for an overarching negative tone. Tetlock [2007] uses the Harvard General Inquirer (GI) and Diction word lists in his study to measure the magnitude of the positive and negative words in the WSJ column over the 16-year period of 1984-1999 as a gauge of the tone of the articles.[1] Tetlock [2007] explores the link between this measure of media pessimism and the stock market using regressions. The influential paper finds that high media pessimism produces downward pressure on market prices, and unusually high or low levels of pessimism lead to high market trading volume for short periods [Tetlock, 2007]. Another interesting finding in this study

[1] The Harvard GI is a well-known content analysis program that returns sentiment counts of a given text.

is that pessimism is not related to decreases in risk. This debunks a common theory that the media is a either a source of new financial information, cause of volatility, or just a noise.

Balakrishnan, Qiu, and Srinivasan [2010] follow a similar path as other studies in the field of finance and accounting but focus on the method of text classification, which is essentially putting documents or words into predefined categories. Their sample consists of 4,755 annual reports and these documents are analyzed to explore the link if any with market returns. The other part of their methodology involves creating equally-weighted portfolios based on either an out-perform, average, or under-perform prediction on a hold-out sample. Balakrishnan, Qiu, and Srinivasan [2010] find that a portfolio based on the model's predictions earns positive size-adjusted returns. The researchers explain the advantages of text classification are its capability to conduct large-scale text mining of annual reports and predict future accounting and market performance [Balakrishnan, Qiu, and Srinivasan, 2010].

It is hard to research textual analysis in the field of finance and accounting and not come across Tim Loughran and Bill McDonald. These researchers are both professors at Notre Dame and have written many papers on textual analysis in finance. One such paper, Loughran and McDonald [2011], brings to light the limitations of using the Harvard General Inquirer (GI) and Diction word lists Tetlock [2007] and others use with the "bag-of-words" method. They contend that the Harvard word lists are made for the field of psychology and are not a good match for financial documents. According to Loughran and McDonald [2011], 75% of the negative words in the Harvard word lists do not have a negative meaning in a business context. Words like tax, liability, board, and depreciation are considered to have a pessimistic meaning under the General Inquirer word lists but are all normal terms in a financial report and do not constitute a negative connotation. Presented with the shortcomings of the current word lists, Loughran and McDonald create their own word lists. In Loughran and McDonald [2011], the two create 6 comprehensive word lists with language that are specific to business and the context of a 10-K report. The custom word lists lead to more accurate sentiment measures when parsing financial documents, and as a result, further adapt textual analysis to the field finance.

A study that uses the Loughran and McDonald [2011] word list and customizes it is Allee and DeAngelis [2015]. This study uses the word lists to analyze the tone dispersion, or the degree to which the tone is spread out evenly throughout a text. Using the average reduced frequency (ARF) as a measure of tone dispersion, the researchers apply the Perl software to parse through 73,201 conference call transcripts between 2004 and 2014. Allee and DeAngelis [2015] find that tone dispersion is significantly associated with firm performance. The two other big findings from the study are that tone dispersion is associated with managers' reporting choices and there are strategic motivations for tone dispersion by management.

Another method of sentiment analysis in the finance field is the Naïve Bayes. The Naïve Bays method is essentially a way of identifying and weighting sentiment words through machine learning. The key assumption of the Naïve Bayes method is that words in a text are independent of each other. A prominent paper using this approach is Antweiler and Frank [2004]. This paper looks at 1.5 million stock message postings from Yahoo! Finance and Raging Bull to measure the sentiment. The paper finds that a positive shock to the message board leads to negative returns on the next day of trading. This phenomenon has not been reported by any other studies and provides an insight into the enigma of market fluctuations. Antweiler and Frank [2004] also find higher disagreements among the postings correlates with higher subsequent trading volume. Ultimately the evidence in the study points to the talk surrounding the stock market being more than just noise, but relevant to predicting trading volume and volatility. Another paper using the same method, Das and Chen [2007], also finds the sentiment in message board postings related to stock market levels, trading volume, and volatility. The Naïve Bayes algorithm they use first needs to be trained with a small number of pre-classified messages before it can be used on a larger sample. The algorithm learns from the pre-classified messages and this training aspect leads to improved precision in extracting sentiment. One result they find with their algorithm is the stock price leads the sentiment index they created. This result points to small investor sentiment on message boards being reactive rather than predictive [Das and Chen, 2007]. The researchers conclude that their software program could be beneficial to regulators and firms to monitor message boards for manipulation or general investor sentiment.

The applications of textual analysis also extend to predicting fraud. In Larcker and Zakolyukina [2011], a total of 29,663 conference call transcripts are analyzed using a text parsing software program to explore the degree to which financial statements are intentionally misstated or manipulated. The study is built upon prior work in the fields of linguistics and psychology which finds that the language in truthful texts differs from that of false texts [Larcker and Zakolyukina, 2011]. The theory behind this is executives who manipulate information feel guilty and are afraid to be caught for it. These negative emotions are embodied by negative comments and negative affect, and the deceiver will often speak in general terms and not refer to themselves. The study looks at financial restatements and determines if one is deceptive by looking for a disclosure of material weakness, an auditor change, late file, form 8-K filing or a formal SEC investigation that leads to an Accounting and Auditing Enforcement Release (AAER). Since the study looks at financial restatements from 2003 to 2007, the researchers know which ones are deceptive and can back-check the conference calls to see if the language forecasts this narrative. Larcker and Zakolyukina [2011] find deceptive CEOs use extreme positive emotion and fewer anxiety words, and deceptive CFOs use more negation words and extreme negative emotion words and even swear words in the cases with SEC involvement. The researchers also find that an investment portfolio consisting of the studies' highest deception numbers from CFO narratives produces an annualized alpha of between -4% and -11% [Larcker and Zakolyukina, 2011]. Collectively, the study finds that the words of CEOs and CFOs in conference calls can be used to predict financial statement manipulation. Regardless of the method in use, textual analysis has provided researchers with a wealth of new information on financial documents benefitting institutional and individual investors, along buy- and sell-side analysts.

3. Methods

My methodology is separated into three segments. The first segment is gathering and scrubbing text to analyze, and the second segment is using a software to parse the text and return sentiment counts. The third segment is running multiple regressions to explore the relationship between the sentiment counts and the firm policies. To conduct textual analysis, there must first be text to feed into a parsing software. When determining specifically what text to use, my selection gravitates towards public companies because information about the firm's performance is readily available. Given earnings conference calls, 10-Ks, proxy statements, and Form 8-Ks, I look at the earnings conference calls because they contain words from the CEO on the firm's performance and outlook as well as a Q & A section that contains impromptu responses to analysts' questions. The less rehearsed Q & A part of the conference call gives a clearer picture of the CEO's temperament especially when presented with an unexpected question. With earnings conference calls designated as the text for my investigation, the next part of my research involves choosing companies to analyze. The sample in this study consists of fifty companies of varying market capitalizations from the machinery industry. The machinery industry, a subset of the industrials sector, is ideal because it is a very mature industry and not subject to a lot of regulations like the financial or oil and gas industries. For each company I collect the four most recent quarterly earnings call transcripts from fiscal years 2018 and 2019 off of the investing website SeekingAlpha which has these transcripts readily available for publicly traded companies. Before the transcripts can be read by a parsing program, I must first scrub the text to remove inapplicable data.

The earnings call transcripts initially contain words from other executives of the firm besides the CEO. In addition to the company executives, the transcripts also include questions from the analysts or the operator facilitating the conference call. Once all four transcripts are collected for each company, I scrub the files so only the CEO's words are remaining. This is to prevent a misrepresentation of the CEO's words and promote accurate parsing.

The software I use in my research is a Python program from the Notre Dame Software Repository for Accounting and Finance.[2] This is a website set up by Tim Loughran and Bill McDonald who use these programs in their 2011 study mentioned earlier in this paper. The files I use in conducting my textual analysis are two Python programs and a master dictionary .csv file. The first Python program is a generic parser program, one that generates sentiment counts for all files within a specified folder. The sentiment counts are based on the Loughran-McDonald dictionary in the master dictionary file. The second is a program that needs to be downloaded to load the master dictionary file. In Loughran and McDonald [2011], the two create their own word list that is in the dictionary file that is available on the repository. The Loughran-McDonald

[2] Loughran, T., and B. McDonald. "Software Repository for Accounting and Finance." Last modified (n.d.), Accessed on April 5, 2019.

dictionary is a very comprehensive word list with classifications such as negative, positive, uncertainty, litigious, constraining, superfluous, interesting, and modal words. Along with these classifications the file also contains the number of syllables and a metric to measure the rarity of each word. The word list however is intended for analyzing formal business documents like 10 – K annual reports containing industry lingo. For the present study I replace the Loughran-McDonald word list with the Harvard General Inquirer word list because of its regular use in the field of psychology. Since the objective of my research is to investigate the personalities of CEOs, the Harvard GI word list seems more appropriate. For this reason, I use the *Hostile* category of words from the Harvard GI word list. This a list of 833 words that indicate attitude or concern with hostility or aggressiveness. It is a subset of the broader *Ngtv* word list that contains 1,160 negative words.

With the desired dictionary in order, I begin putting each companies' conference calls through the parsing program. Each time the program is run it outputs a .csv file with data on the linked text. It outputs the number of words in the text as well as the percentage of negative words, positive words, etc. For the present study the focus is on the percentage of hostile words, or the percentage of words in the conference call that also appear in the Harvard GI *hostile* word list. This is the main independent variable of my research because it is my way of assessing the aggressiveness of a given CEO. Along with the percentage of hostile words, the other independent variables relating to the CEO are the CEO's age and tenure. The firm-level independent variables are the firm's market cap, log of total assets, firm age, and the size of the board.

The dependent variables are measures of firm policy like R&D spending, capital expenditures, and the debt to equity ratio. R&D and capital expenditure data is from fiscal year 2018 10-K reports of each company and then scaled by total assets of the firm. The debt to equity ratio has no modifications and is taken from the investment research website Morningstar. Once all the variable data is in one Excel spreadsheet, multiple regressions are run to explore the relationships between the independent and dependent variables.

4. Descriptive Statistics

4.1. Conference Call Statistics

As mentioned in the previous section, the texts that are ran through the Python program are the earnings conference calls. The length of each conference call varies by the extent of the CEO's remarks during the call. Several CEOs in my sample have other executives do most of the talking on the call and only participate during the Q & A when prompted by an analyst. In other cases, the CEO does most of the speaking throughout the call. This variance among the CEOs is evident when looking at the data for the conference calls. Within my sample, the maximum number of words in a conference call is 6,891 words and the minimum is 304 words. The average number of words is 3,334.88 words and the 25th and 75th percentiles are 2,345 and 4,210 respectively. Some other interesting statistics with the conference calls that are returned by the parsing software are the number of numbers, syllables, and average word lengths. The average number of numbers is 69.89 in a conference call and the average syllables per word is 1.55. Lastly, the average word length is 4.73 letters. The language of the CEOs reflects their educational and professional credentials in the way they use more complex words and numbers to communicate the company's earnings and future.

4.2. CEO and Company Statistics

Table I reports the descriptive statistics for the companies in my sample. There are several CEO statistics and firm-level statistics in the present study that make up the independent variables. The average age of the fifty machinery companies is 86 years, which is expected given the maturity of the industry. The youngest company is 3 years old and an outlier in the data set with the 25th percentile at 33 years. The companies can be characterized as mid-cap with the average market capitalization at $8.8 billion, with eleven of the companies considered to be large-cap. The size of the board of directors of the sample is on par with board size standards across all industries. The average board size for the present study is 9.86 and according to a Corporate Library study, the average board size across industries is 9.2 members.[3] The average percentage of hostile words from the CEOs in the sample is 0.267% and the median is 0.232%. The 25th and 75th percentiles for this variable are 0.184% and 0.289% respectively. Most of the data for this variable sits close to the mean and median, however the top 25th percentile has CEO hostile word usage around the maximum of 0.732%.

For this study there are two other variables related to the CEO. They are the CEO's age and the CEO's tenure at the company. These variables help give a better understanding of who the CEO's are beside the words they use in their conference calls. The average tenure for the sample is 6.9 years with the median at 5 years. The 25th and 75th percentiles are 3 years and 9 years respectively and these numbers also align with the tenure most CEOs experience at their companies. One CEO had a tenure of 27 years in the sample, but this is a clear outlier given the percentiles for this variable. Many CEOs have tenures of less than one year or have spent time as the CEO of other machinery companies. The age of these CEOs is on average 56.6 years and the median age is 57 years. Most of the CEOs have an age between 53 and 61 years with the maximum age of 72. These numbers are on par with the CEO average age for this sector and is expected due

[3] McNamara, Carter. "Overview of Roles and Responsibilities of Corporate Board of Directors." (Free Management Library). Accessed on April 29, 2019.

to the industry's maturity and prerequisite experience of the CEOs. Many of the CEOs have decades of experience in the machinery industry and most have engineering degrees.

Like the CEOs in other industries, the CEOs in the machinery industry are predominantly male. Out of the fifty CEOs in the sample there are only three female CEOs. For the CEO variables the present study looks at the CEO's words, age, and tenure, but not the gender. This is due to the small number of female CEO's in my sample and there would need to be many more to include this characteristic in the regressions.

5. Results

The regression results for the variables can be seen in Table II. When these variables are put through three regressions, the results are significant for the debt to equity variable, but not for the R&D and capital expenditure dependent variables. For each of the three regressions with debt to equity and the independent variables, there is a significant result between the percentage of hostile words and the debt to equity variable. Each regression, the percentage of hostile words variable has a p-value of less than 0.05 and a t-statistic above 2. The coefficients are all above 3 while the r-squared is low at 0.08, 0.126, and 0.192 for the three regressions. The other independent variables do not have a significant p-value except for the Log of TA variable significant at the 90% level on the third regression. For the other dependent variables of R&D and capital expenditures, both produce low coefficients and no p-values at a significant level.

The R&D regression results show there is no compelling relationship between the CEO personality and the research and development spending of the firm. The coefficients are very low and there are no significant p-values for these regressions. As with the debt to equity results, the r-squared is very low for the regressions. With each subsequent regression the r-squared values increase due to the increase of variables from the sample but remain low below the 0.20 level. The

Capex results are like the R&D results and characterized by high p-values and low coefficients. The r-squared numbers are slightly better than the R&D numbers but follow the trend of the other dependent variables for this statistic.

6. Discussion

In the present study I apply the software used in Loughran and McDonald [2011] for 10-K analysis and adapt it to gauge CEO personality in a conference call. Regressions of the conference call sentiment and the firm's policies evidence a relationship with the debt to equity ratio. While there are no significant results with the other firm-level dependent variables, there is a compelling result with the debt to equity variable. Looking at the regression statistics it can be concluded that the use of hostile words by the CEO has a big influence on the debt to equity ratio of the firm. Earlier in the paper I reference multiple studies done in the field of psychology that find a link between personality and word choice. Building off these studies, the results from the present study support my hypothesis that aggressive CEO pursue aggressive firm policies. After analyzing the percentage of hostile words data and the debt to equity ratios of each company, the companies with higher ratios also have a higher percentage of hostile words by the CEO.

Interestingly, the age of the CEO and their tenure at the firm does not have any link to the firm policies they choose. There are no significant relationships between these variables and the firm policies and going into the research I expected to find a more conservative firm policy for a seasoned CEO. Another finding is regardless of CEO and firm-level attributes, the R&D spending of the company remains unaffected by these variables. It varies on a company-by-company basis and the CEO's personality has no effect on this firm policy.

For future studies it would be interesting to look at other personalities and how they relate to the firm's policies. For this study I only focus on an aggressive personality but extending my method to the big five personality traits and less common personalities would be worth a look. Using a different way of determining personality would also add something new to the field of finance and accounting. Research looking at the words of company executives and their confirmed big five personality compared to the firm policies could lead to more precise results with that second layer of verification. Another future study would be to look at the stock market implications of an aggressive CEO personality. The study could look at the stock returns and the standard deviations of those returns after an earnings conference call and examine the impact of an aggressive personality or any of the big five personalities. There is also the option of exploring how CEO gender would play into my research. For the present study, there are only three female CEOs in my sample, so I didn't include this characteristic in the regressions to avoid an unrepresentative sample. It would be interesting to see if there were any differences in the firm policies given an aggressive male CEO and an aggressive female CEO.

It would also be constructive to adapt the textual analysis software from the present study and others to include the context of the word usage. The Python software I use merely counts the number of words in the conference calls that also appear in the Harvard GI word list. The phrases or verbal cues in the executives' words get lost in the parsing process and leave a fragment of the document unexamined. Additionally, the words used in the analysis could be extended to other executives at the firm besides the CEO. The CEO holds the highest position, but the CFO might have more impact on the firm policies the company strategizes. The present study is limited to the CEO and their responses on the publicly available conference calls. It's important to keep in mind that the message the CEO conveys in the conference call may differ when compared against the real life narrative and it is very difficult to know for sure what the CEO says behind closed doors.

While limited by the information readily available, this same study could be furthered by analyzing the executives' tone of voice or facial expressions in public appearances.

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Table I:

Descriptive Statistics

Variable	N	Mean	Median	Max	Min	25th Percentile	75th Percentile
% of Hostile Words	50	0.267	0.232	0.732	0.118	0.184	0.289
CEO Age	50	56.60	57.0	72.0	40.0	53.0	61.0
CEO Tenure	50	6.90	5.0	27.0	1.0	3.0	9.0
Market Cap	50	8.80	4.50	74.10	1.10	3.00	7.70
Log of TA	50	8.41	8.33	11.27	6.43	7.67	8.93
Firm Age	50	86.26	99.50	176.00	3.00	33.00	119.25
Board Size	50	9.86	10.00	16.00	4.00	9.00	11.00

Notes:
Market Cap is in billions, Log of TA is in millions, and Firm Age, CEO Age, and CEO Tenure are in years.

Table II:

Regression Results

	Debt to Equity			R&D			Capex		
Constant	0.291	-1.143	-5.484	0.019	-0.004	0.019	0.198	0.043	0.186
	(0.459)	(2.054)	(3.277)	(0.005)	(0.022)	(0.036)	(0.040)	(0.175)	(0.286)
% of Hostile Words	3.158**	3.243**	4.075**	0.001	0.001	-0.004	-0.122	-0.130	-0.105
	(1.548)	(1.543)	(1.659)	(0.016)	(0.017)	(0.018)	(0.133)	(0.132)	(0.145)
CEO Age		0.033	0.040		0.0004	0.0004		0.002	0.003
		(0.038)	(0.040)		(0.0004)	(0.0004)		(0.003)	(0.004)
CEO Tenure		-0.069	-0.077		-0.0003	-0.0002		0.004	0.003
		(0.044)	(0.046)		(0.0005)	(0.0005)		(0.004)	(0.004)
Market Cap			-0.041			0.0002			0.0003
			(0.025)			(0.0003)			(0.002)
Log of TA			0.541*			-0.003			-0.011
			(0.316)			(0.003)			(0.028)
Firm Age			0.002			0.00004			0.00008
			(0.004)			(0.00005)			(0.0004)
Board Size			-0.054			0.0006			-0.009
			(0.114)			(0.001)			(0.010)
Observations	50	50	50	50	50	50	50	50	50
R-Squared	0.080	0.126	0.192	0.00003	0.025	0.046	0.017	0.082	0.111

Standard errors are reported in parenthesis.

*, **, *** indicates significance at the 90%, 95%, and 99% level, respectively.