The power of words in capital markets: SEC comment letters on foreign issuers and the impact of home country enforcement

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ABSTRACT: In this paper, we examine the language tone of comment letters issued to foreign firms listed on US stock exchanges and the impact of home country enforcement. We find that the tone of US Securities and Exchange Commission (SEC) reviews has capital market implications following the dissemination of comment letters. Using a textual analysis methodology, we gauge SEC linguistic nuance by creating a customized wordlist for the US regulatory context. We evaluate alternative measures of tone and present evidence that our discipline-specific tone measure outperforms the frequently-cited dictionaries employed in analyses of corporate narratives. We document that negative-tone regulatory language, in contrast to positive, produces significant investor reactions. We further demonstrate that negative market reactions are amplified relative to the strength of home country enforcement environments. We offer important implications for enforcement agencies, companies, lenders and investors.

Keywords: enforcement, SEC comment letters, textual analysis, tone, investor reaction.

JEL Classification: M48, K42, G14.

1 Introduction

In the international business literature, the importance of foreign firms, as well as their institutional disadvantage when operating in local markets, is widely acknowledged (Bell, Filatotchev, & Rasheed, 2012; Zaheer & Mosakowski, 1997). In the financial reporting realm, foreign firms listed on US stock exchanges account for a significant percentage of market capitalization (Securities and Exchange Commission (SEC), 2007a). Foreign firms are subject to home country enforcement settings in addition to the US regulatory oversight (Naughton, Rogo, Sunder, & Zhang, 2018). Although the SEC follows the same policy in applying enforcement sanctions on domestic and foreign registrants (SEC, 2007b), prior literature concludes that home country enforcement significantly influences various corporate choices and the overall financial reporting quality of foreign listers (Srinivasan, Wahid, & Yu, 2015). We extend this literature by investigating the influence of the tone of SEC's enforcement language on the market reaction and how this effect is mitigated or amplified according to the foreign issuer's level of home country enforcement. To this end, we consider SEC comment letters (CLs) as a proactive enforcement mechanism identifying potential reporting deficiencies (Gietzmann & Pettinicchio, 2013). Firms receiving a CL can remedy the relevant concerns by responding to the SEC reviewers' comments, initiating a correspondence thread which often contains multiple SEC questions and company responses until the final resolution of comments[1] (Heese, Khan, & Ramanna, 2017). To this end, the variation in the tone of the language employed within the CL conversations is more likely to be higher when compared to other formal enforcement orders.

Past research on financial disclosures has documented the power of language in influencing stock market activity. Relevant studies have emphasized the content tone employed by corporate

[1] Out of the 329 sample firms, only 11 received Accounting and Auditing Enforcement Releases (AAER) within the examined time period, in contrast to 3,491 CLs.

managers (Loughran & McDonald, 2011; Yekini, Wisniewski, & Millo, 2016), news media (Tetlock, 2007), and analysts (Huang, Zang, & Zheng, 2014a). In contrast to this producer-driven language, we consider the largely-unexplored area of the regulator's language in referring to the producers (Beattie, 2014). Since supervisory language is required to follow defined linguistic attributes, this imbalance in prior research could be a potential impediment to a better comprehension of the SEC's practices. Understanding SEC language tone is of particular importance to market participants due to the increased demand for additional qualitative information in corporate disclosures (Campbell & Abdul Rahman, 2010; SEC, 2016).

To measure the SEC's content tone, we employ a "bag-of-words" methodology (Henry & Leone, 2016). Since discipline-specific wordlists could efficiently address the problems of ambiguity/multiple meaning and effectively overcome the word-misclassification barrier, we create a customized negative and positive list of words designed specifically for the US regulator. We further test our customized wordlist against two domain-specific dictionaries (Henry (2008) and Loughran and McDonald (2011)) and sensitivity test for two general-purpose wordlists (General Inquirer and Diction 7) which are widely used within a financial disclosure setting. For a better understanding of the regulatory content tone, we account for both the SEC's overall tone and its breakdown into negative and positive tone measures. Thus, the first research question we address is: Does the regulatory tone wordlist have greater predictive power on cumulative abnormal returns relative to alternative wordlists at the release of CLs?

We next associate the power of home country settings with foreign regulatory actions. Prior studies provide strong evidence that enforcement leads to improved financial reporting (Chen & Zhang, 2010) and generates associated positive market reactions (Christensen, Hail, & Leuz, 2013; Palmrose, Richardson, & Scholz, 2004). Recent literature has also highlighted the paramount importance of enforcement in enhancing corporate accounting quality (De George, Li, & Shivakumar, 2016). Despite the recognition regarding the role of enforcement, there is a lack of evidence documenting the associations between local enforcement and foreign regulatory actions. Since home country enforcement settings could have an influential role on firms' financial reporting in the US markets (Srinivasan et al., 2015), we assess their impact upon SEC CL market reactions. Thus, our second research question: Is home country enforcement associated with cumulative abnormal returns upon the announcement of SEC CLs?

We employ a sample of foreign registrants of US stock exchanges for several reasons: First, it enables us to disentangle the effect of home country enforcement mechanisms on foreign firms' financial reporting in the US and, consequently, the impact on the SEC's CL releases. Second, it allows us to assess the effect of foreign firms' reporting quality on the US capital markets. Finally, US-listed foreign firms are economically significant since their market capitalization is on the increase; from 1996 to 2006 their market value had more than quadrupled (New York Stock Exchange (NYSE), 2006), while their number doubled from 1990 to 2014 (SEC, 2015b).

Against this background, we collect a sample of 1,323 CL reviews filed to 329 US-listed foreign firms and released through EDGAR between 2006 and 2014. Our sample relatively proportionally represents the country of origin and industry classification of foreign registrants and, thus, does not suffer from material biases of representation. We focus solely on SEC-initiated CLs and exclude any company responses. Using our word-frequency measures, we find that our domain-specific wordlist better explains the market reaction to CL releases compared with alternative wordlists. Consistent with the negativity bias hypothesis, we illustrate the significance of negative over positive information in equity prices. We conclude that there is scant incremental information within the positive-tone language of regulatory releases. We further test the influence of home country enforcement on market reactions and we find that investors react more negatively to the presence of CLs addressed to firms domiciled in countries with strong enforcement regimes. This suggests that SEC comments relating to these firms come as unexpected news.

There are concurrent and complementary studies to ours in the literature (Cassell, Cunningham, & Lisic, 2019; Ryans, in press). However, our study significantly differs from previous works in a number of ways. While Cassell et al. (2019) document an inverse relation between the readability of firms' response to SEC CLs response time as well as the filing review outcome, we examine the language tone of CLs and the impact of foreign firms' home country enforcement. Thus, our study significantly differs as we focus on the linguistic content of SEC-generated disclosures by developing and testing our own domain-specific dictionary, rather than on companies' responses to SEC comments as in Cassell et al. (2019). Our study differs from Ryans (in press) in several important aspects. First, our textual analysis tests are focused on the linguistic content and not the statistical text classification of the CLs. Specifically, while Ryans (in press) classifies CLs as important or not based on the magnitude of negative abnormal returns, we examine the tone of the words expressed by the SEC staff. Second, our approach considers and analyzes every CL disclosure within our sample, rather than employing a limited number of training documents. Third, we generate our own domain-specific regulatory dictionary amenable to replication. By employing predefined tone wordlists, we circumvent the "black box" problem (Loughran & McDonald, 2016). Finally, we differ from both studies by employing a sample of US-listed foreign companies and demonstrate that negative market reactions to SEC CLs are amplified relative to the strength of home country enforcement environments.

Our research contributes to several streams of literature. First, we enhance the growing body of literature on financial reporting enforcement, where the US regulatory agency considers its filing review process to be a potent instrument for promoting trust in financial markets. We complement this research stream by demonstrating that the tone of words employed in regulatory reviews and the strength of local enforcement regimes are associated with significant reductions in equity value. Second, we expand current understandings on investor perceptions of regulatory releases, suggesting that investors do pay attention to the valence of SEC reviews, a fact that elicits stronger stock-price responses to the negative-tone content of CLs. In this vein, our results complement relevant psychology literature on impression formation by suggesting that investors place more weight on negative rather than positive language tone. Third, our study extends content-analysis literature by introducing a unique, domain-specific dictionary for SEC regulatory language. On this basis, we evaluate the frequently-cited dictionaries employed as language-tone measures in capital market research and conclude that our customized wordlist outperforms them. We argue that the application of our wordlist can be valuable in an analysis of additional SEC enforcement orders (i.e., AAERs) and other actions issued by monitoring agencies that have the authority to display regulatory releases within the business realm (e.g., Public Company Accountability Oversight Board (PCAOB), Federal Reserve (FED), Internal Revenue Service (IRS)).

The remainder of the paper is organized as follows: Section 2 reviews the related literature and develops our hypotheses. Section 3 describes the data and language-measures methodology. In Section 4, we present the research design and in Section 5 we discuss our main results. Section 6 discusses the results of the sensitivity analysis and Section 7 concludes the study.

2 Literature review and hypotheses development

2.1 SEC filing review process

Under Section 408 of the 2002 Sarbanes-Oxley Act, the SEC's Division of Corporation Finance (hereafter DCF) reviews firms' disclosures at least once every three years (SEC, 2015a). If the filing review process identifies potential deficiencies or questions, a CL is issued. CL reviews are enforcement tools which occur more frequently than any other SEC enforcement instrument. In general, SEC comments are considered leads or trigger events of AAERs (Heese et al., 2017; Kedia & Rajgopal, 2011). Moreover, since SEC comments require a shorter time to be resolved, they are considered timely regulatory indicators of poor financial reporting quality (Lawrence, Minutti-Meza, & Vyas, 2018) and, thus, valuable to investors. Generally, CLs consist of qualitative information devoid of statistics, attributes that make them ideal for textual analysis purposes.

The SEC's DCF files a letter only in cases where a deficiency was identified following the completion of a review. Throughout the process, CLs[2] and follow-up letters are issued until the final resolution of the respective issues. After completion of the CL process, the SEC staff thorough EDGAR releases CLs (form type: upload) and the relevant firm-response letters (form type: corresp).

Prior research has demonstrated some important dimensions of SEC comments. Accordingly, SEC comments are dependent on firm size, profitability, complexity and quality of corporate governance (Cassell, Dreher, & Myers, 2013; Ertimur & Nondorf, 2006; Ettredge, Johnstone, Stone, & Wang, 2011; Robinson, Yanfeng, & Yong, 2011). They appear to improve the quality of: a) financial reporting (Bozanic, Dietrich, & Johnson, 2017); b) corporate disclosure

[2] "Comment letters" may also indicate letters submitted to the SEC in response to releases or proposals. In our study, we focus solely on SEC-generated comments filed to US registrants.

(Hennes & Schenck, 2014; Wang, 2016); c) peer filings (Brown, Tian, & Tucker, 2018); and d) tax compliance (Kubick, Lynch, Mayberry, & Omer, 2016). They also mitigate information asymmetry (Johnston & Petacchi, 2017). However, CLs are related to considerable costs, as they are an instrument of insider trading (Dechow, Lawrence, & Ryans, 2016), increase audit fees (Gietzmann & Pettinicchio, 2013), and contribute to changes in institutional holdings (Gietzmann & Isidro, 2013). Related to content analysis, Cassell et al. (2019) suggest that more easily-readable corporate responses to CLs result in fewer follow-up SEC comments and restatements. Condie (2017) documents that misreporting firms provide more readable and more negative-tone CL responses, relative to non-misreporting firms. More pertinent to our study, Ryans (in press) examines the effect of important CLs on firm value and suggests that the information content associated with important comment reviews could predict returns only when the CLs were viewed on EDGAR.

2.2 SEC comment letters and qualitative information

CLs principally include negative information regarding firms' financial reporting quality (Lawrence et al., 2018). Thus, as opposed to voluntary corporate filings (Davis, Piger, & Sedor, 2012; Henry & Leone, 2016), regulatory disclosures are expected to employ largely negative words so as to communicate concerns regarding accounting practices.

One of the most robust findings in the psychology of judgment is that, when forming impressions, people react asymmetrically to negative information compared with positive (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). As bad news has a greater impact on impressions, humans have the tendency to place more weight on it, thus, highlighting the more efficacious nature of bad news over good news. The principle explaining this greater sensitivity to negative events, traits, perceptions, or interactions is known as negativity bias hypothesis[3] (Baumeister et al., 2001; Kanouse & Hanson, 1972) and holds for a wide range of disciplines (Rozin & Royzman, 2001), including the accounting and finance domains (Loughran & McDonald, 2016).

Prior literature assessing the market implications of the negative information incorporated into regulatory financial disclosures provides evidence of adverse capital market reactions. Specifically, SEC AAERs (Feroz, Kyungjoo, & Pastena, 1991; Leng, Feroz, Cao, & Davalos, 2011), accounting misstatements (Dechow, Sloan, & Sweeney, 1996), litigation releases (Nourayi, 1994), PCAOB enforcement orders against auditors (Dee, Lulseged, & Zhang, 2011), and CL conversations (Dechow et al., 2016; Ryans, in press) all incur negative stock returns upon their announcement. Prior studies (Engelberg, 2008; Huang et al., 2014a; Tetlock, 2007) also document that investors place little weight on positive narratives and they ignore, or at least materially discount, positive language in business disclosures, while they give significant weight to negative information. Thereby, negative-tone language is expected to be more salient, have greater impact, and generate stronger reactions compared with positive-tone language.

Considering the negativity bias and prior research on investor reactions to qualitative corporate financial disclosures, we expect the financial tone measures to significantly impact upon stock market activity around financial events (Henry & Leone, 2016; Huang, Teoh, & Zhang, 2014b; Kothari, Li, & Short, 2009; Loughran & McDonald, 2011; Tetlock, 2007). Thus, we employ computational linguistics to illustrate the explanatory value of linguistic content on stock returns surrounding the announcement of CL disclosures. Hence, if qualitative information acts as a predictor of market reactions (Henry & Leone, 2016; Loughran & McDonald, 2011; Yekini et

[3] Negative bias is considered a "built-in predisposition" (Rozin & Royzman, 2001). Since people more thoroughly process and give weight to negative rather than positive or neutral information, negativity could certainly affect their decision making.

al., 2016), we anticipate that disclosing negative-tone language in CL filings can convey negative connotations. This in turn will attract stronger investor attention and, thus, stimulate more negative shareholder-wealth effects. Concomitantly, examining CL valence with respect to the deconstruction of language tone into two separate measures (negativity and positivity scores), we assume an asymmetric market reaction (Loughran & McDonald, 2011; Tetlock, 2007) and expect the negative tone to asymmetrically contain more information than the positive tone (Henry & Leone, 2016; Kothari et al., 2009).

For the evaluation of tone measures, we consider two customized wordlists employed in capital market research, and we further test the robustness of our findings using another two frequently-cited general wordlists. Our customized wordlist (CL wordlist – CW) is designed specifically for the SEC regulatory setting, wherein the US supervisory authority conducts reviews and issues comments on deficient corporate filings. The respective wordlist is intended to mitigate ambiguity and multiple meaning, since various words used in general dictionaries[4] have different meanings within a financial reporting setting. At a first glance, domain-specific dictionaries (Henry, 2006, 2008; Loughran & McDonald, 2011) may seem appropriate for explaining the tone of language used in financial narratives, especially when the national regulator addresses questions regarding possible corporate misconduct or requires further financial clarifications. However, such wordlists usually refer only to the language generated by the firm's managers (i.e., preparers of financial statements and receivers of SEC reviews), without taking into account the particular characteristics of the language used by a national public authority. The vocabulary employed by the SEC is expected to be characterized by different linguistic attributes than those of corporate filings. Indeed, since the SEC implemented the Plain Writing Act, we expect its own documents

[4] In our computational-linguistic context, we make no distinction between the terms "wordlist" and "dictionary".

to employ clear and comprehensible language (Senate and House of Representatives of the U.S.A, 2010). Consequently, SEC staff language is expected to be less biased, compared with the word choices of other sources, and to be free of corporate tactics such as impression management (Beattie & Jones, 2000), report obfuscation (Courtis, 2004), and positivizing negative news (Bloomfield, 2002). The more objective language of the SEC, devoid of obfuscation and ambiguity practices, highlights the need for a discipline-specific wordlist that differs from previously-developed dictionaries. Hence, in cases of corporate improprieties and relative to both general and financial wordlists, a SEC-oriented wordlist is expected to have greater predictive ability and improved accuracy in explaining negative market reactions (Henry & Leone, 2016) to CL releases. Thus, we hypothesize that:

H1: The customized comment letter wordlist has superior predictive ability on cumulative abnormal returns to comment letter correspondence, compared with alternative wordlists.

2.3 Home country enforcement of foreign firms listed in the US

We further examine the role of home country enforcement on capital market reactions related to the language tone of SEC CL reviews. Foreign companies listed on US markets are subject to financial reporting regulation set out by the SEC (SEC, 2013). Using a sample consisting of US-listed foreign firms from all over the world enables us to examine market responses to the release of SEC comments for filers which face US levels of scrutiny and oversight but which operate under different enforcement characteristics (Srinivasan et al., 2015). Thus, we test whether and how the market reaction to US enforcement-activity outcomes, expressed by CL filings, is associated with those firms' home country enforcement contexts.

Prior studies demonstrate the influence of home country characteristics on firms' financial reporting in the US markets (Leuz, 2006; Srinivasan et al., 2015), highlighting the influential role of local enforcement on corporate financial reporting (Lang, Smith Raedy, & Wilson, 2006). In particular, prior literature concludes that country-level enforcement is influential to the: a) level of compliance with foreign regulations (Leuz, 2006); b) frequency of restatements (Srinivasan et al., 2015); c) degree of earnings management (Lang et al., 2006); d) timely recognition of economic income (Ball, Robin, & Wu, 2003); and e) overall reliability (Leuz, Nanda, & Wysocki, 2003) and value relevance of financial reporting (Lang et al., 2006). With respect to the relation of CLs to disclosure quality (Lawrence et al., 2018; SEC, 2015a), and based on prior evidence, we anticipate that local enforcement has an impact on corporate filing quality, which is then further reflected in the SEC review and comment process.

The oversight regulatory scrutiny of strong-enforcement countries is expected to mitigate material corporate financial reporting weakness or fraud, which is likely to be discounted by financial markets. Equally, markets might expect the SEC to issue CLs to firms located in regimes with less efficient oversight-regulatory authorities. Both these factors could suggest that the negativity of the SEC regarding accounting practices, as expressed by the language tone used in CLs, is interpreted as more serious "breaking news" for filers from strong-enforcement environments. Thus, our second hypothesis is as follows:

H2: There is a greater negative cumulative abnormal return at the release of comment letter correspondence for firms from countries with stronger home country enforcement regimes.

3 Data and language measure collection

3.1 Sample construction

Our sample consists of CLs issued to foreign firms cross-listed on major US stock exchanges. Since the SEC began publicly releasing CL reviews in 2005 for filings made after August 1, 2004, our CL sample period begins in 2005 (SEC, 2004). We obtain SEC-originated CL filings from the SEC File Transfer Protocol (FTP) and CL information from the Audit Analytics CL database. According to the premise that SEC reviews predominantly refer to annual report filings (Dechow et al., 2016), we focus on CLs which relate to annual financial statements and their corresponding amendments. We then link CL firms to Compustat for fundamental variables and to Bloomberg for daily stock prices.

Table 1 shows how the original sample was shaped by our filters and data requirements. Specifically, our sample consists of all foreign companies included in the SEC's annual list of "Foreign companies registered and reporting with the US Securities and Exchange Commission" from 2005 to 2014 (SEC, 2015b). We then require foreign firms to be cross-listed in the US and to be a member of a major, organized stock exchange for our sample period. We include both American Depository Receipts and companies directly listed on US stock markets. We exclude firms trading over-the-counter (OTC) as they are not required to register with the SEC and they are exempt from the 2002 Sarbanes-Oxley Act (Doidge, 2004). We further exclude firms that merely issue debt, with no trading equity securities. We also remove SEC registrants without any CL conversation identified by Audit Analytics. Finally, we drop the year 2005 from our analysis[5], since there was only one CL conversation in this particular year. These selection criteria provide us with a final sample of 329 foreign firms and 3,491 CLs filed to SEC registrants, and it covers the period from 2006 to 2014[6].

[Insert Table 1 about here]

Since multiple correspondences are possible between the SEC staff and the filer until the completion of the process, we identify a CL conversation as the thread of uploads and

[5] Our inferences remain unchanged if we maintain this observation.

[6] The end date of 2014 results from the use of the SEC (2015b) list of foreign registrants as of December 31, 2014. The list of foreign registrants is not updated by the SEC for the years after 2015, throughout the period this paper was submitted and under revision.

correspondence filings under the same unique numeric key provided by Audit Analytics (Conversation ID). As our focus is on the impact of the tone content of SEC reviews, we exclusively consider the series of comments initiated by the DCF which are related to an initial CL (further analysis of SEC CLs is detailed in Appendix A). Thereby, we do not include firm responses.

Table 2 outlines the sample distribution by country, industry, and year. Panel A tabulates the firm and CL filing frequency according to the country of incorporation. Most firms are domiciled in Canada (32.52%), Israel (9.73%), and the United Kingdom (7.29%). Table 2, Panel B reports the distribution across the 17 Fama-French industry groupings, indicating that more than half of the sample is concentrated in either "Other[7]" (23.94%), "Banks, insurance companies, and other financials" (16.36%), or "Mining and minerals" (15.45%) industries. Within this framework, country and industry representation appear to be reasonably proportional to that reported by the SEC's DCF, with the exception of some slight over- or under-representations. Finally, Table 2, Panel C, reports the distribution across the years 2006 to 2014.

[Insert Table 2 about here]

3.2 Data cleansing and parsing comment letters

We process CL filings using a customized program to estimate document tone measures. We first convert all filings into searchable text files to facilitate text parsing. Similar to Loughran and McDonald (2011) textual analysis approach, we remove markup tags, SEC headers, and other information irrelevant to our content analysis purposes, such as addresses and the names and

[7] The "Other" Fama-French industry group includes services, wholesale, hotels, telephone/telegraph communications, radio-TV broadcasters, computer systems, power producers, irrigation systems, air conditioning supplies, sanitary services, advertising specialty, alarm and signaling products, ophthalmic goods, training equipment and simulators, guidance systems, trucks, tractors, trailers, lighting equipment, mineral products, pottery, glass and paper products, office furniture and fixtures, leather goods, tires and inner tubes, plastic and petroleum products, *in-vivo* diagnostics, biological products, and commercial printing and publishing.

positions of the SEC staff conducting the review. We focus on the main body of the CL document, given that it is characterized by a certain text structure. More specifically, the CL's main text begins with the word "Dear" and ends with the word "Sincerely"[8]. Similar to Henry and Leone (2016) and Loughran and McDonald (2011), the remaining texts are free of graphics, tables, exhibits, and tagged segments.

To evaluate the implications of CL valence, we generate a domain-specific dictionary (CW wordlist) especially for the SEC's regulatory purposes by employing one of the most widely-acceptable textual analysis methods, i.e., the "bag-of-words" approach. This method requires the parsing of CL documents into vectors of words and word counts (Henry & Leone, 2016; Kothari et al., 2009; Loughran & McDonald, 2011). Thus, we transform the narrative information into countable values representing the valence of SEC staff comments. More specifically, through Wordsmith Tools 6 lexical-analysis software (Scott, 2012), we obtain summary information for each token[9] employed by SEC staff when addressing comments to companies. In our analysis, we convert all characters to lowercase; while common stop words[10] (Henry, 2008), single character words, and numbers (Davis et al., 2012) are excluded from the analysis, as they provide little to no discriminatory power in the information retrieval. In addition, we remove names, abbreviations, word elongations, acronyms, and punctuation marks. We consider different word inflections as separate words. Thus, we do not include any stems[11] since, in certain contexts, not all the forms of a given word would convey an equally negative or positive connotation (Henry & Leone, 2016).

[8] Minor exceptions exist, where instead of using "Sincerely" to close, SEC staff used the word "Regards" or the phrase "Very truly yours". Such cases were treated manually.
[9] The act of breaking up a sequence of strings into pieces such as words, keywords, phrases, symbols, and other elements called tokens. Tokens can be individual words, phrases, or even whole sentences, and they serve as inputs in other processes like parsing and text mining.
[10] "Stop words" are words which appear very often within the examined context. Our study employs Henry's (2008) brief stop-word list comprised of the following words: *a*, *an*, *and*, *as*, *at*, *by*, *for*, *in*, *of*, *on*, *or*, *that*, *the*, *this*, and *to.*
[11] In content analysis, the "stem" is considered the morphological root of a word form, i.e. *argu* is the stem of *argue, argues, and arguing.*

Directional words (words with ambiguity of tone, e.g., decrease) are also included in our analysis. Based on the context of word occurrences (Henry, 2008), we develop a custom-made dictionary consisting of words appearing in at least 1% of the CL filings (consistent words).

Overall, the lexical-analysis software identified more than 1,900 consistent, distinct words that occur over 1,400,000 times within the CL conversations. Similar to Loughran and McDonald (2011), each of the consistent words was examined separately and characterized as negative, positive, or neutral whenever the majority of its occurrences indicated a negative, positive, or neutral connotation. Next, a tailor-made program was created to generate the relative negative and positive word counts. The confirmation of characterization of the consistent words was also made in relation to the other frequently-cited dictionaries. Our final dictionary is symmetrical as it consists of 67 words with a negative connotation and 65 words with a positive connotation. Table 3 presents the respective negative and positive words found within the CL context.

[Insert Table 3 about here]

We also account for simple negation words in our positive wordlist[12]. Thus, we consider a word with a positive connotation as positive only when a simple negation word does not occur within the three words preceding our positive word. Since we do not expect negation preceding negative words, we do not take into consideration negation for the negative wordlist (Loughran & McDonald, 2011).

Following the parsing into tokens, we create word counts and calculate the tone measures according to the relative frequency of the predefined negative and positive lists of words. We then select the weighting scheme in the vector space model, representing the weights assigned to each of the negative and positive words within the wordlists. We adopt an equal-weighting scheme

[12] *No, not, none, neither, never* and *nobody* (Loughran & McDonald, 2011).

(similar to Davis et al., 2012; Henry, 2008; Kothari et al., 2009; Tetlock, 2007) according to the premise that, in the context of financial narratives, equal-weighted tone measures are more intuitive, are more amenable to replication, and are equally as powerful as alternative weighting methods (Henry & Leone, 2016). The development of a dictionary designed specifically for the purposes of regulatory language precludes the use of machine-learning probabilistic classifiers, such as the Naïve Bayesian algorithm and alternative approaches based on vector distance (Henry & Leone, 2016).

For the evaluation of the language-tone measures, we consider three different wordlists, while we further test our inferences using two alternative dictionaries (see Section 6.1). The first is our customized wordlist (CW). The other two wordlists are previously-developed, frequently-cited dictionaries, namely the Loughran and McDonald (2011) (LM) positive and negative dictionary developed for 10-K analysis and the Henry (2006) and Henry (2008) (HL) wordlist, as used in the Henry and Leone (2016) study on earnings press releases. Since neither the LM nor HL dictionaries are based on SEC-generated narratives, word misclassification is likely, i.e., many words could be classified incorrectly within our context (Loughran & McDonald, 2011).

To further assess the power of our domain-specific dictionary, we examine the composition of the respective negative- and positive-tone wordlists by documenting the tone words with the highest document frequency (see Appendix B).

4 Research design

Our objective is to determine the most appropriate language-tone measure. This process includes comparing alternative dictionaries based on their relative effectiveness in capturing the tone of the CL correspondence, and evaluating the association between home country enforcement and shareholder wealth effects.

4.1 Event study

Our primary tests examine cumulative abnormal returns relative to SEC CL releases. We employ the market-adjusted model so as to avoid contamination of the estimation window in cases of multiple CL conversation releases within a relatively short time-span. In order to ascertain how the CL conversation announcement is reflected in the filer's stock price, we employ a short-window event study so as to capture immediate investor reactions to the newly-publicized disclosures. The cumulative abnormal return is measured as the sum of the 3-day period abnormal returns over days 0 through +2. In all cases, the abnormal return refers to the firm's stock return minus the Standard & Poor's (S&P) 500 market-index return over the 3-day event window[13].

4.2 Variable construction for language-tone measures

Similar to prior studies estimating the tone content of financial documents (Henry & Leone, 2016; Loughran & McDonald, 2011), we measure the net language tone by determining the relative equal-weighted frequencies of negative and positive words within the CL narratives. Our viewpoint differs from past approaches in the extent to which it does not focus solely on disclosures expressing positive/optimistic sentiments (Davis et al., 2012; Engelberg, 2008; Henry, 2008; Henry & Leone, 2016). Contrarily, in our study it is negative-tone words which exercise the dominant influence on CLs. Thus, we differentiate from Davis et al. (2012) and subtract the percentage of positive words employed in a CL conversation from the respective percentage of negative words. We calculate the language-tone measures as follows:

$$TONE_{i,j} = NEG_{i.j} - POS_{i,j} \quad (1)$$

[13] To examine the appropriateness of the event window, we follow prior literature and estimate market reactions for alternative event windows (Loughran & McDonald, 2011). Specifically, we assess the post-announcement market reactions for every event window from [0, 1] to [0, 10]. The [0, 2] window exhibits the highest t-statistic of all the alternative windows.

Where: $TONE_{i,j}$ is the language-tone measure for CL conversation *i*, based on the wordlist *j* (CW_TONE$_i$, LM_TONE$_i$, and HL_TONE$_i$[14]); $NEG_{i.j}$ is the percentage of negative words in wordlist *j* found in the CL conversation *i*; and $POS_{i,j}$ is the percentage of positive words for the CL conversation *i*, based on wordlist *j*.

Since the alternative dictionaries were conceptualized within different contexts, they do not include an equal number of negative and positive words[15]. For this reason, we further consider negativity $(NEG_{i.j})$ and positivity $\left(POS_{i,j}\right)$ scores separately. Hence, we are able to address possible asymmetric market reactions around the CL disseminations. We estimate the negativity and positivity scores as follows:

$$NEG_{i,j} = \frac{Number\ of\ negative\ words_{i,j}}{Total\ number\ of\ words_i} * 100 \tag{2}$$

$$POS_{i,j} = \frac{Number\ of\ positive\ words_{i,j}}{Total\ number\ of\ words_i} * 100 \tag{3}$$

Where: $NEG_{i,j}$ and $POS_{i,j}$ represent the frequency count of negative and positive words scaled by the count of total words in a CL correspondence *i*, based on the CW, LM and HL wordlists.

4.3 Empirical models

4.3.1 Benchmark equation

Building on prior work, we develop our benchmark model to investigate the influence of language-tone measures on investor behavior. To test our hypotheses, we employ regressions in

[14] CW_TONE$_i$, LM_TONE$_i$ and HL_TONE$_i$ represent the language-tone measures based on the CW, LM and HL wordlists respectively. In a similar vein, CW_NEG, LM_NEG and HL_NEG, and CW_POS, LM_POS, and HL_POS indicate the negativity and positivity scores of the respective dictionaries.

[15] The LM wordlist contains 2,329 negative and 354 positive words and the HL includes 85 negative and 104 positive words.

which the dependent variable is the cumulative abnormal returns (CAR) from day 0 to day +2 following the CL conversation announcement dates. In the following and all subsequent model specifications, we estimate robust standard errors (Knoeber & Walker, 2013) including year, country, industry, and firm-fixed effects, to control for unobservable time, country, industry, and cross-sectional factors, respectively. Our model is as follows (omitting firm observation subscripts and fixed effects):

$$\begin{aligned} CAR = {} & \beta_0 + \beta_1 TONE\_MEASURE + \beta_2 ISSUES + \beta_3 CL\_SIZE + \beta_4 MULT\_CONV \\ & + \beta_5 SIZE + \beta_6 LARGE\_FILER + \beta_7 ROA + \beta_8 LEVERAGE \\ & + \beta_9 PRICE\_BOOK + \beta_{10} DISTRESS + \beta_{11} UEPS + \beta_{12} EVENT \\ & + \beta_{13} NASDAQ + \varepsilon \end{aligned} \tag{4}$$

We estimate our benchmark model for each of the three dictionaries and evaluate the relative power of the different measures according to the significance level, magnitude of the respective language coefficients, and the R-squared value (Henry & Leone, 2016). The vector TONE_MEASURE represents the key variables of interest of the respective tone measures of the CL filings, namely the language-tone score (TONE), the negativity (NEG), and positivity (POS) scores. All definitions for the variables employed in the benchmark and subsequent models, along with the data sources of the variables, are in Table 4.

[Insert Table 4 about here]

Disclosures employing higher proportions of negative words (NEG) are expected to express greater problems regarding a firm's financial reporting quality and to generate stronger market reactions (Loughran & McDonald, 2011) around CL conversation release dates. The presence of positive words (POS) is expected to signal positive news and attenuate negative market reactions. However, considering the bias towards negative information, we anticipate a lower magnitude of the POS coefficient relative to NEG. Therefore, we expect the negativity score to generate a stronger investor reaction and the positivity measure to mitigate negative reactions.

4.3.2 Comment letter control variables

We include in our model control variables and elaborate on their expected relationship with CAR. Thus, we consider the severity of CL conversations, since the significance of CLs varies according to the issues addressed (Dechow et al., 2016). As accounting-related comments are expected to be more salient compared with non-accounting comments in terms of remediation cost (Cassell et al., 2013), we include a proxy for the number of accounting issues[16] (ISSUES) raised by the DCF within the SEC-firm correspondence. We expect the CAR to be more negative in cases of a greater number of accounting issues raised by the SEC staff.

We also include the CL file size (CL_SIZE), estimated by the file size in kilobytes of the SEC EDGAR "complete submission text file". Loughran and McDonald (2014) relate annual report file-size with document readability. Given that file-size readability indicates the ability of the narrative to convey firm-relevant information in a concise manner, we expect larger CL files to contain greater and more relevant information about the firm's filings; thus, reducing the possibility of any unexpected information. Therefore, we expect a positive association between CAR and file size. Since multiple CL correspondence announcements may occur within a year, we also include in our model an indicator variable set equal to 1 if there is more than one CL conversation (MULT_CONV) released for a company within a given year. Seeing as the presence of multiple threads in a given year could reduce investor reactions, we assume a positive relation between MULT_CONV and CAR.

[16] According to Audit Analytics classification, accounting-related topics include various accounting-rule and disclosure-type issues such as accounts receivable, cash-reporting issues, acquisitions, mergers, and business combinations.

4.3.3 *Firm-specific control variables*

In line with prior literature, we include proxies for company characteristics. We control for company size (SIZE) and the type of SEC filer (LARGE_FILER). Large firm size is usually associated with greater financial reporting quality (Doyle, Ge, & McVay, 2007) and at the same time is linked to a more efficient use of managerial and monetary resources when dealing with SEC comments (Cassell et al., 2013). In this vein, accelerated and large accelerated filers[17] are characterized by a greater disclosure transparency (Deloitte, 2012), which may affect investor behavior. Thus, we include an indicator variable equal to 1 if the reviewed firm is an accelerated or large filer (LARGE_FILER).

We further employ several control variables that could influence CAR (Henry & Leone, 2016; Loughran & McDonald, 2011; Piotroski, 2000). Hence, we consider return on assets (ROA), leverage (LEVERAGE), price-to-book ratio (PRICE_BOOK), and a proxy for financially-distressed firms (DISTRESS). Similar to Henry and Leone (2016) and Johnston and Petacchi (2017), we also consider unexpected earnings per share (UEPS) as a proxy for earnings surprise. In accordance with event-study analysis, we also include an indicator variable (EVENT) equal to 1 whenever the event window in question contains a firm-confounding event[18]. Following Loughran and McDonald (2011), we also adjust for different stock-trading behaviors and microstructures, including a NASDAQ dummy (NASDAQ).

4.3.4 *Home country enforcement model*

We test our second hypothesis specifying the following model:

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[17] Accelerated filers are firms with more than $75 million but less than $700 million worldwide market value, while large accelerated filers are defined as firms with more than $700 million market value.
[18] Such events include earnings releases, dividend announcements, stock splits, M&A, and equity offerings.

$$\begin{aligned}\mathrm{CAR} = {} & \beta_0 + \beta_1\mathrm{TONE\_MEASURE} + \beta_2\mathrm{ENFORCEMENT\_MEASURES} + \beta_3\mathrm{DISTANCE} \\ & + \beta_4\mathrm{ISSUES} + \beta_5\mathrm{CL\_SIZE} + \beta_6\mathrm{MULT\_CONV} + \beta_7\mathrm{SIZE} + \beta_8\mathrm{ROA} \\ & + \beta_9\mathrm{LEVERAGE} + \beta_{10}\mathrm{PRICE\_BOOK} + \beta_{11}\mathrm{DISTRESS} + \beta_{12}\mathrm{UEPS} \\ & + \beta_{13}\mathrm{EVENT} + \beta_{14}\mathrm{NASDAQ} + \varepsilon\end{aligned} \tag{5}$$

The dependent variable and control variables are defined similarly to baseline equation (4). The vector ENFORCEMENT_MEASURES represents our measures of financial reporting enforcement at home country level. We consider the following alternative proxies in order to capture the multiple dimensions of enforcement activity. First, we include rule of law (RoL), measuring the extent of a country's compliance with rules and regulations (Kaufmann & Kraay, 2017). Second, following Leuz et al. (2003), we employ the overall measure of a country's enforcement strength (ENFORCE_INDEX), calculated as the mean score of: a) efficiency of judicial system, b) rule of law, and c) degree of government corruption as defined by La Porta, Lopez-De-Silanes, Shleifer, and Vishny (1998). Third, we include the audit and enforcement index (AUDIT_ENF), measuring the effectiveness of a country's accounting and auditing enforcement (Brown, Preiato, & Tarca, 2014).

Fourth, we consider the legal environment and the level of corruption of the home country. Legal origin is shown to be related to investor protection, to an independent judiciary and, thus, to proxy enforcement (La Porta, Lopez-De-Silanes, & Shleifer, 2008). We incorporated a common law (C_LAW) dummy variable as a proxy for legal institution (La Porta et al., 1998). Firms from countries with legal systems closer to the US system are less likely to (mistakenly) break the law, as they are more accustomed to the US setting (Knoeber & Walker, 2013) and more aware of the increased SEC scrutiny (Coffee, 2002). Thereby, an investor may face less information asymmetry from firms from common law regimes, as their familiarization with US reporting rules is expected to curtail infringement and provide more relevant information to investors. However, firms from common law countries could more effectively react to the tough US oversight. Their familiarization with US regulations suggests a particular firm infrastructure which would make it easier to confront strong regulatory enforcement (Knoeber & Walker, 2013) and protect investors (Djankov, La Porta, Lopez-de-Silanes, & Shleifer, 2008). For this reason, these firms could potentially mitigate any negative reactions. Thus, we do not make a prediction for the association of C_LAW with CAR.

In addition to legal origin, we control for the home country's level of corruption (CORRUPTION) (Transparency International, 2013). To facilitate interpretation, we multiply the original corruption index with (-1), so that higher values denote greater corruption. Firms domiciled in highly-corrupt countries generally operate in weaker enforcement environments (Healy & Serafeim, 2016), thus, indicating disclosures of lower quality and value relevance. So, we anticipate firms from highly-corrupt regimes would be associated with lower financial reporting quality and would, therefore, elicit less of a negative investor reaction.

We further augment our baseline equation to account for a (DISTANCE) variable to measure the geographical proximity of the firm's home country with the US (Leventis, 2018). Since physical distance to SEC offices is used as a proxy for informational advantages (Uysal, Kedia, & Panchapagesan, 2008), we use the natural log of the bilateral great circle distance between the capital city of the firm's home country and Washington DC (Erel, Liao, & Weisbach, 2012). Low geographic proximity could indicate a lower level of familiarization compared with countries closer to the US (Bris, Cantale, Hrnjić, & Nishiotis, 2012; Chen, Hope, Li, & Wang, 2018). However, it could also suggest a greater information disadvantage in terms of lack of access to the firm's operation or unavailability of information (Chen et al., 2018).

5 Empirical results

5.1 Univariate analysis

In Table 5, we present descriptive statistics for the variables used in our analysis. The negative sign of the market reaction to CLs, mean -0.072 (median = -0.111), indicates the negative anticipation of the market towards the issuance of CLs. These results are in line with reactions to revenue-recognition CLs (Dechow et al., 2016) and other SEC enforcement actions (Feroz et al., 1991; Leng et al., 2011). The mean (1.255) and median (1.244) tone score of the CW_TONE is higher than the LM_TONE (mean = 0.813 and median = 0.764) and the HL_TONE (mean = -0.059 and median = -0.047). The positive sign of the CW and LM tone measures suggest the dominant use of negative words in regulatory disclosures, highlighting the different context in which the HL wordlist was developed. This pattern is corroborated by the greater value of the CW and LM negativity measures relative to the positivity ones.

[Insert Table 5 about here]

The mean (median) of RoL 1.069 (1.543) shows that sample firms are, on average, domiciled in quite strong enforcement countries. We conclude the same when we take into consideration the ENFORCE_INDEX (mean = 8.268 and median = 9.167) and the AUDIT_ENF (mean = 40.93 and median = 46). Regarding legal origin, the majority of the sample firms are located within a common law system. Further, on average our sample firms receive 4 (median = 3) comments related to their accounting practices, have an average natural logarithm of total assets of 9.453 (median = 9.628), and receive comments with an average file size of 162kB (median = 130kB).

Table 6 presents the correlation matrix. Comparing the tone scores, we find that CAR has a significant negative correlation with CW measures. Regarding the enforcement variables, we notice that RoL, ENFORCE_INDEX, AUDIT_ENF, and CORRUPTION are highly correlated; hence, we include them in separate models. Further, the DISTANCE and LARGE_FILER variables exhibit a moderately high coefficient (0.64). Other inferences suggest that multicollinearity is not a serious problem. To mitigate potential concerns, we further report the variance inflation factors (VIF) under each model, which are all lower than the conservative cut-off value of 5 (e.g., Studenmund, 2016), implying no multicollinearity.

[Insert Table 6 about here]

5.2 Tone measures

Table 7 presents the results from the analysis of the effect of the regulatory language-tone measures on CAR. Columns (1) to (3) represent the language-tone scores for the CW, LM, and HL wordlists, while Column (4) includes all tone measures. Consistent with our expectations, the coefficient estimated for the CW is negative, indicative of the stronger investor reactions around CL dissemination. Overall, the greater predictive ability of our domain-specific measure is suggested by the significance of the CW tone-score coefficient ($p < 0.05$) combined with the coefficient's magnitude and the higher adjusted R-squared value relative to the lower respective values of the LM and HL wordlists.[19] More specifically, in our CW model the adjusted R-squared takes the value of 4.10%, higher than the corresponding value of 2.52% reported in Loughran and McDonald (2011).

[Insert Table 7 about here]

[19] We also conducted formal tests (i.e., Wald tests) for the difference in coefficients between the CW tone-score and LM and HL wordlists. Untabulated results indicate that the difference in pairwise estimated coefficients of language tone measures is statistically significant at 5% (the same results are obtained when comparing the positive and negative score measures between the three wordlists). This demonstrates that our customized CL wordlist has superior predictive ability on cumulative abnormal returns to CL correspondence, compared with alternative wordlists.

We next test the negativity and positivity scores separately. The right-hand side of Table 7 presents the results of the association of negativity and positivity scores on CAR. Columns (5) to (7) of Table 7 refer to the three different wordlists, while Column (8) includes all scores. The negativity and positivity scores of CW have the expected direction, conforming to the negativity bias hypothesis. NEG only has a significant negative coefficient (t-statistic of -2.36) for the CW wordlist. Thus, higher proportions of negative words, as measured by the CW wordlist, indicate greater problems in a firm's financial reporting quality and generate lower abnormal returns. As expected, in the CW and HL wordlists, positivity score coefficients are lower relative to their respective negativity scores. In all cases, positivity score coefficients are not significant, suggesting that investors place less value on positive narratives since they generally disregard, or at least discount, positive-tone language in business disclosures (Engelberg, 2008; Henry & Leone, 2016; Tetlock, 2007). The significance and the magnitude of the NEG coefficient, in combination with a higher adjusted R-squared value, indicate the greater explanatory value of the CW dictionary for CL market reactions.

With respect to the rest of the control variables, the negative coefficient of the accounting-related issues addressed by the SEC staff ($p < 0.01$) suggests that companies receiving a greater number of accounting comments are associated with more negative CAR. We also find that investors are sensitive to CL file-size ($p < 0.05$), with a positive sign, illustrating a more negative tone in larger documents. Our results further indicate a positive, though weak, association between CAR and firm size ($p < 0.10$); and a negative, but weak, relationship between CAR and unexpected earnings per share ($p < 0.10$). Overall, the results suggest that the negative-tone language employed in SEC regulatory comments generates more negative investor reactions and that our discipline-specific CL wordlist outperforms alternative dictionaries. Thus, we accept Hypothesis 1.

5.3 Home country enforcement effect

We further examine the impact of home country enforcement regimes on CAR. The results from estimating Model (5) are tabulated in Table 8; where each Column represents a different country characteristic. The coefficients of the dominant tone (CW_TONE) and negativity (CW_NEG) measures are negative and statistically significant ($p < 0.05$). The coefficients of all three enforcement measures (RoL, ENFORCE_INDEX, and AUDIT_ENF – see Columns 1 & 5, 2 & 6, and 3 & 7, respectively) are negative and statistically significant at the 1% level, suggesting that investors react more negatively to CLs addressed to firms from stronger enforcement regimes. In other words, companies from strong-enforcement countries are expected to produce more reliable and useful financial information and, thus, SEC regulatory comments are less expected. This probably makes the regulatory comments more informative to investors. In Columns (4) and (8) the results indicate that market reactions are more moderate for companies operating within common law systems ($p < 0.01$). Conversely, firms from highly-corrupt countries produce less trustworthy disclosures ($p < 0.05$ for the language-tone and $p < 0.01$ for the negativity and positivity score models), which is reflected in the positive association between negative CAR and the corruption index. Regarding geographical proximity, we find both a negative and positive coefficient, suggesting that distance could be presumed to be a factor that provides an information disadvantage to investors or could indicate a lower level of interest in firms located further from the US.

[Insert Table 8 about here]

With respect to other company and CL characteristics, we evidence a negative and significant coefficient for accounting-related issues. The positive and significant coefficient for

CL file-size suggests that larger CLs are more informative, similar to Loughran and McDonald (2014).

6 Sensitivity analysis

6.1 Alternative dictionaries

Beyond the two domain-specific dictionaries (LM and HL), we also assess the superior predictive ability of our customized CL wordlist against two general-purpose dictionaries which are widely used within a financial disclosure setting (e.g., Huang et al., 2014b; Loughran & McDonald, 2011). These are the General Inquirer Harvard IV-4[20] (GI) wordlist, based on psychology, and the Diction 7[21] (DICTION) wordlist, prepared for sociology and political science purposes. Untabulated results indicate that the coefficients estimated for the GI and DICTION dictionaries are not significant, while the corresponding explanatory power of these dictionaries (captured by adjusted R-square) is lower than the CW wordlist. Our main inferences remain unchanged when jointly including in the model LM, HL, GI, DICTION, and CW measures, as only the CW_TONE and CW_NEG attain negative and statistically significant coefficients ($p < 0.05$). Thus, we affirm the greater explanatory value of the CW dictionary for CL market reactions.

6.2 Other tests

We probe the sensitivity of our results by employing a number of alternative textual-analysis specifications and sample differences. First, we re-estimate our regressions and control for the type of the annual report (i.e., include indicators to capture 20-F, 40-F, and 10-K filers), so as to mitigate any effect arising from variations in the length of reporting periods and the use of

[20] General Inquirer was developed by Stone Philip and is available at: http://www.wjh.harvard.edu/~inquirer/ (Accessed November 8, 2020).
[21] Available at: http://www.dictionsoftware.com/ (Accessed November 8, 2020).

different accountings standards. For example, forms 40-F and 20-F should be submitted within six months of fiscal year end, while this period varies from 60 (for large filers) up to 90 days for Form 10-K. Including the aforementioned indicators in our models does not affect our inferences, as the coefficients of CW scores remain negative and statistically significant ($p < 0.05$). The same also applies to the home country enforcement measures, except for the C_LAW variable which becomes insignificant when we control for 20-F filings.

Second, we respond to the increased academic attention regarding reporting standards (Lang et al., 2006; Leuz, 2006) and to concerns over the quality of financial statements of foreign companies (Srinivasan et al., 2015). Thus, we also control for applied accounting standards (US GAAP or an accepted alternative set of accounting standards, i.e., IFRS or local accounting standards). We concentrate on the years after 2007 (as during this year the SEC began to accept IFRS for foreign companies without any reconciliation to US GAAP (SEC, 2007a)) and include in our model indicators signaling whether a firm's reports are in accordance with US GAAP or IFRS. We also repeat these tests and augment our model for filing types frequently associated with these two accounting standards (i.e., Form 10-K for US GAAP and Form 20-F for IFRS). None of these accounting variables attain a statistically-significant coefficient, though the 10-K indicator is negative and significant ($p < 0.10$) and the 20-F indicator is positive and significant ($p < 0.05$). Other inferences suggest that our results remain unchanged.

Third, the small size of our customized dictionary could imply that the CW comprises a subset of a larger domain-specific wordlist. Based on the extensive LM financial negative and positive wordlists, we implemented a random sampling technique and repeated the selection process 100 times. During the sampling process, every word within a random dictionary has the same probability of being selected. Similar to the CW negative and positive wordlists, each random dictionary contains 134 words, including 67 words with a negative connotation and 65 words with a positive connotation. The relative coefficients and Fama and MacBeth (1973) t-statistics suggest that our selected list of words (CW) is superior in explaining returns following CL releases when compared to randomly-selected financial wordlists of equal size.

Fourth, to test the impact of dictionary size we examined whether variations in the number of words within the CW negative and positive wordlists could affect our results. So, in addition to the initial 1% cutoff point (words which appear in at least 1% of the CL narratives), we examined word occurrences at several alternative levels (1.5%, 2%, 2.5%, and 3%). The inferences remain intact for the CW_NEG and CW_POS coefficients. Specifically, CW_NEG remains negative and statistically significant at 5%, while CW_POS is positive and but not significant for all alternative cutoff points. The CW_TONE coefficient is negative and significant at 5% for the 1.5% cutoff point, while it remains negative and significant at 10% for the 2%, 2.5%, and 3% cutoff points. Since the same level of cutoff point can be translated into different dictionary sizes for different types of examined filings, our results suggest the value of implementing a lower cutoff point for financial disclosures with limited length, i.e., CLs and enforcement releases. In this way, more consistent words could be examined and the negative and positive wordlists would be of sufficient size.

Fifth, we conduct additional tests to moderate concerns regarding the high representation of certain words in our customized wordlist. As Appendix C shows, the word "comment" consists of 99.71% of document frequency and 40.72% of Total CW negative word count. In this regard, we repeat our analyses using adjusted tone scores (that do not account for the words "comment"/"comments", namely the overall (CW_TONE_NOC), the positivity (CW_POS_NOC), and the negativity (CW_NEG_NOC) tone scores) and evidence that our inferences remain unchanged as both CW_TONE_NOC and CW_NEG_NOC attain negative and statistically significant coefficients at 5%. Therefore, we conclude that our inferences are not subject to the high frequency of the word "comment"/"comments" in our domain-specific wordlist. In addition to these tests and to accommodate concerns related to the net positivity tone scores of SEC CLs, we repeat our analyses and include only the negativity tone scores in our models. We observe that our results remain similar.

Sixth, in order to rule out the possibility of our results being driven by sample differences, we take into consideration the idiosyncrasy of our cross-country dataset. Hence, we rerun our analysis by limiting our sample to countries with at least five companies having received SEC comments within the sample period. The coefficients of CW language tone and negativity score are not affected and remain negative and statistically significant at 5%, while the positivity score remains positive and non-significant. Seventh, as utility companies and firms from the financial sector may face different enforcement and regulatory guidelines, we eliminate them from our additional analysis. The inferences for the CW_NEG and CW_POS are not affected, while the CW_TONE remains negative but significant at 10%.

Eighth, in an effort to disentangle whether SEC monitoring policy pertaining to CLs could impose equity-value reductions outside the US, we conducted a short-window event study in the home countries. As firms could experience delayed shareholder-wealth effects in their local markets (Chen & Khurana, 2015), we examined stock returns over alternative event windows (3-day to 11-day event windows). Our results suggest that there is no significant market reaction in the home countries upon CL releases, tentatively indicating that the US watchdog impacts market behavior solely within the US setting.

Finally, we re-estimate the regressions of CAR on the CW tone measure and negativity/positivity scores, including only time and cross-sectional fixed effects and employing the Russell 3000 market index. Our main results are unaffected. Thus, we confirm our prior findings that language tone and negativity are negatively related to investor reactions surrounding CL dissemination.

7 Conclusion

In this paper, we examine the tone content of US corporate filing reviews. We focus on SEC CLs relating to foreign firms listed on US stock exchanges as a salient mechanism of proactive enforcement. We find that capital markets do indeed pay attention to the tone of regulatory language. Specifically, we document that negative-tone language, in contrast to positive, elicits significant stock-price responses upon CL dissemination. We further evaluate different dictionaries employed in finance and accounting studies. We find that our wordlist, which was specifically designed for the US regulatory context, has a greater predictive ability in explaining market reactions to CL releases. We further demonstrate that foreign firms' strong home country enforcement is related to stronger market reactions upon the announcement of SEC CLs.

The empirical findings of our study could be useful to enforcement agencies, companies, lenders (i.e., banks or private firms), and investors. The SEC and foreign firms should be aware that the tone of important CLs causes a significant negative market reaction. Companies should be aware that any market reactions upon the release of SEC letters are conditioned to the tone of the language employed, which should be an important factor to consider in their overall strategy for managing the impacts and responses of comment releases. Lenders, which in some instances use firms' equity as collateral against lending, should pay close attention to this – perhaps not so well recognized – interaction between the firm and the regulator. They should source additional information to evaluate the risk they are undertaking, since our analysis suggests the impact can be significant. Finally, considering the increased interest from the US and international investors in foreign firms listed on US markets, our findings suggest that portfolio decisions should consider home country enforcement quality, at least for those firms more likely to engage in questionable accounting practices. This suggestion is obviously relevant for the broad investor base and even more so for investors engaging in arbitrage strategies between multiple listings of the same entity.

Our study shares limitations inherent to the “bag-of-words” methodology. Considering that language can be contextual (Pennebaker, Mehl, & Niederhoffer, 2003), this methodology does not account for context. In addition, the low explanatory power of our models, although similar or higher than other relevant studies, might indicate limitations related to the model specification. Future research could extend the current study in several ways. First, the determinants of regulatory tone on enforcement actions could be further explored. Second, it would be important to examine other reactions to regulatory wording apart from the equity market reactions. For example, an essential area for future research would include whether borrowing and audit decisions are influenced by SEC language tone. Third, future research could shed light on the relationship between the applied accounting standards of foreign firms and market reactions. Fourth, the interplay effects between home country enforcement regimes, SEC tone, and other formal (regulation, governance) and informal institutions (trust, culture, social norms) is a valuable avenue for future research. Finally, the similarity of CLs across SEC registrants in terms of, *inter alia*, tone, size, subject of issues raised, and severity of issues addressed requires systematic investigation. Any dissimilarity across specific corporate characteristics, such as size, locality, age, industry, growth, reputation, and political orientation, might run contrary to the SEC’s fundamental objectives to have “propriety, fairness, and objectivity in investigations” (SEC, 2017, p. 30).

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Table 1. Sample selection

	Number of firms	Number of SEC-initiated comment letters (uploads)
Initial sample cross-listed SEC registrants with stock data	400	3,896
Less: Firms trading Over-the-Counter (OTC)	-51	-309
Less: Firms with no trading securities in the US markets	-14	-95
Less: Firms without any comment letter conversation identified by Audit Analytics	-5	0
Less: One comment letter conversation corresponding to year 2005	-1	1
Final sample	**329**	**3,491**

Note: This table presents the impact of data filters on the initial firm and CL sample size.

Table 2. Sample distribution of firms and comment letter filings by country, industry, and year

Panel A: Distribution of cross-listed firms and comment letter filings by country of incorporation							
Country	**Firm frequency**	**Firm percentage**	**Country representation in SEC (percentage)**	**Number of comment letter conversations**	**Comment letter conversations/firm**	**Number of comment letters (uploads)**	**Comment letters (uploads)/firm**
Argentina	9	2.74	1.40	28	3.11	68	7.56
Australia	6	1.82	1.59	24	4.00	69	11.50
Belgium	1	0.30	0.19	4	4.00	9	9.00
Brazil	22	6.69	3.05	105	4.77	289	13.14
Canada	107	32.52	38.21	342	3.19	893	8.35
Chile	11	3.34	1.48	40	3.64	110	10.00
China	11	3.34	1.10	54	4.91	153	13.91
Colombia	1	0.30	0.21	3	3.00	7	7.00
Denmark	2	0.61	0.26	11	5.50	30	15.00
Finland	1	0.30	0.18	6	6.00	15	15.00
France	6	1.82	1.45	30	5.00	86	14.33
Germany	3	0.91	1.07	19	6.33	60	20.00
Greece	1	0.30	0.28	5	5.00	19	19.00
Hong Kong	4	1.22	0.77	21	5.25	51	12.75
India	7	2.13	1.14	36	5.14	97	13.86
Indonesia	2	0.61	0.19	8	4.00	16	8.00
Ireland	7	2.13	0.90	30	4.29	74	10.57
Israel	32	9.73	7.77	85	2.66	199	6.22
Italy	3	0.91	0.63	21	7.00	51	17.00
Japan	14	4.26	2.47	69	4.93	178	12.71
Korea	7	2.13	1.16	29	4.14	74	10.57
Mexico	13	3.95	2.39	47	3.62	120	9.23
Netherlands	7	2.13	2.21	36	5.14	100	14.29
New Zealand	1	0.30	0.16	3	3.00	7	7.00
Norway	1	0.30	0.31	5	5.00	15	15.00
Peru	1	0.30	0.17	4	4.00	7	7.00
Philippines	1	0.30	0.16	3	3.00	5	5.00
Portugal	1	0.30	0.12	6	6.00	18	18.00
Russia	2	0.61	0.37	10	5.00	23	11.50
South Africa	5	1.52	0.71	25	5.00	67	13.40
Spain	3	0.91	0.58	18	6.00	56	18.67
Sweden	1	0.30	0.51	6	6.00	15	15.00
Switzerland	5	1.52	0.86	33	6.60	94	18.80

Table 2. (continued)

Country	Firm frequency	Firm percentage	Country representation in SEC (percentage)	Number of comment letter conversations	Comment letter conversations/firm	Number of comment letters (uploads)	Comment letters (uploads)/firm
Taiwan	6	1.82	0.61	18	3.00	43	7.17
Turkey	1	0.30	0.10	6	6.00	14	14.00
United Kingdom	24	7.29	4.71	134	5.58	359	14.96
Total	**329**	**100**	**79.45**	**1,323**	**-**	**3,491**	**-**
Average	**-**	**-**	**-**	**-**	**4.68**	**-**	**12.34**

Panel B: Distribution of cross-listed firms and comment letter filings by Fama-French industry groupings

Industry	Firm frequency	Firm percentage	Industry representation in SEC (percentage)	Number of comment letter conversations	Number of comment letters (uploads)
Automobiles	4	1.21	0.91	20	49
Banks, Insurance Companies and Other Financials	54	16.36	10.19	260	712
Chemicals	7	2.12	1.44	34	78
Construction and Construction Materials	5	1.52	1.71	23	68
Consumer Durables	3	0.91	1.11	19	44
Drugs, Soap, Perfumes and Tobacco	20	6.06	3.18	98	261
Fabricated Products	0	0	0.01	0	0
Food	12	3.64	2.46	45	120
Machinery and Business Equipment	28	8.48	9.33	94	226
Mining and Minerals	51	15.45	15.99	188	504
Oil and Petroleum Products	25	7.58	7.52	101	283
Other	79	23.94	33.84	279	730
Retail Stores	3	0.91	1.25	13	35
Steel Works Etc.	7	2.12	1.65	37	102
Textiles, Apparel and Footwear	1	0.3	0.63	3	5
Transportation	16	4.85	6.39	52	141
Utilities	14	4.24	2.38	57	133
Total	**329**	**100**	**100**	**1,323**	**3,491**

Panel C: Distribution of comment letter filings per year

Year	Number of comment letter conversations released	Number of comment letters released (uploads)
2006	141	314
2007	172	460

Table 2. (continued)

Year	Number of comment letter conversations released	Number of comment letters released (uploads)
2008	135	365
2009	146	390
2010	170	448
2011	153	430
2012	196	525
2013	163	455
2014	47	104
Total	**1,323**	**3,491**

Notes: This table illustrates the sample distribution of firms and comment letter filings by the following: country of incorporation/organization provided by SEC; industry; and year of comment letter dissemination. CL conversations are an interconnected series of SEC-initiated comment letters (form type: upload) and the relative firm response letters (form type: correspondence) identified by a unique numeric key (Conversation ID by Audit Analytics). For the sample distribution by industry, we follow Fama-French's 17-industry group classification. Country representation in SEC indicates the average percentage of SEC foreign issuers per country of incorporation, as reported by the SEC's Division of Corporation Finance for the whole sample period. The remainder of the country representation in SEC (20.55%) includes the following countries: Antigua, Austria, Bahamas, Belgium, Belize, British West Indies, Curacao, Cyprus, Czech Republic, Dominican Republic, Guernsey, Hungary, Isle of Man, Jersey, Liberia, Mauritius, Netherlands Antilles, Panama, Papua New Guinea, Poland, Singapore and Venezuela. Industry representation in SEC indicates the average percentage of SEC foreign issuers per industry as reported by the SEC's Division of Corporation Finance during our sample period. The "Other" Fama-French industry group is defined in footnote 7. SEC staff began publicly filing uploads for disclosures made after August 1, 2004. Releases of comment letter conversations are possible after the final resolution of comments. Prior to January 1, 2012, SEC review filings were publicly available no earlier than 45 calendar days later; while from this date onward, comment letter correspondence is released no earlier than 20 business days. The SEC started publicly releasing comment letter conversations in 2005.

Table 3. Negative and positive words in our customized comment letter wordlist in alphabetical order

Negative wordlist		Positive wordlist	
absence	limitations	ability	growth
adverse	litigation	accuracy	helpful
against	loss	achieved	important
amend	losses	adequacy	improved
amended	negative	adequate	improvements
amending	omitted	Agree	informed
amendment	preclude	agreed	meaningful
amendments	proceeding	approval	positive
avoid	proceedings	approved	profitability
charge	raise	assist	progress
comment	remove	available	properly
comments	restatement	benefit	protection
concern	restrictions	benefits	reasonable
concerns	revise	best	reasonably
decline	revised	better	reconciliation
default	revising	certain	reconciliations
delete	revision	clear	reliable
disagree	revisions	compliance	reliably
discontinued	risk	complied	rewards
disposal	risks	conform	robust
divestment	sanctions	consent	secured
eliminate	sponsor	correct	sufficient
enforcement	sponsoring	defense	sufficiently
error	sponsors	development	support
exposure	terrorism	effectiveness	supporting
exposures	terrorist	enhance	supports
foreclose	unable	enhanced	timely
impaired	uncertainties	exact	transparency
inapplicable	uncertainty	expedite	useful
inappropriate	unclear	facilitate	welcome
inconsistent	unnecessary	gain	true
lack	volatility	gains	
limit	write*	greater	
limitation		greatly	

Note: **Write* in the comment letter context is a collocation with *off*, so as to declare write-offs.

Table 4. Variable definitions

Variable	Definition and source
Dependent variable	
CAR (%)	Cumulative abnormal returns from day 0 to day +2 following the comment letter conversation announcement date (Bloomberg).
Language measures	
CW_TONE	Percentage of negative words minus the percentage of positive words found in a comment letter conversation, based on the negative and positive words on our customized wordlists.
CW_NEG (%)	Frequency count of negative words on our customized wordlist scaled by the total number of words in a comment letter conversation.
CW_POS (%)	Frequency count of positive words on our customized wordlist scaled by the total number of words in a comment letter conversation.
LM_TONE	Percentage of negative words minus the percentage of positive words found in a comment letter conversation based on the negative and positive words on the Loughran and McDonald (2011) wordlists.
LM_NEG (%)	Frequency count of negative words on the Loughran and McDonald (2011) wordlist scaled by the total number of words in a comment letter conversation.
LM_POS (%)	Frequency count of positive words on the Loughran and McDonald (2011) wordlist scaled by the total number of words in a comment letter conversation.
HL_NEG (%)	Frequency count of negative words on the Henry (2008) wordlist scaled by the total number of words in a comment letter conversation.
HL_POS (%)	Frequency count of positive words on the Henry (2008) wordlist scaled by the total number of words in a comment letter conversation.
HL_TONE	Percentage of negative words minus the percentage of positive words found in a comment letter conversation based on the negative and positive words on the Henry (2008) wordlists.
Comment letter characteristics	
ISSUES	Number of accounting-related issues raised by SEC staff (Audit Analytics).
CL_SIZE	Comment letter complete submission text file-size in kilobytes (SEC EDGAR).
MULT_CONV	Indicator variable set equal to 1 whenever there is more than one released comment letter conversation for a company within a given year, 0 otherwise (Audit Analytics).
Firm characteristics	
SIZE	Natural logarithm of total assets (Compustat).
LARGE_FILER	Indicator variable set equal to 1 if firm is an accelerated or a large accelerated filer, 0 otherwise (Audit Analytics).
ROA	Return on assets (Compustat).
LEVERAGE	Leverage is the ratio of total liabilities over total assets (Compustat).
PRICE_BOOK	Price to book ratio (Compustat).
DISTRESS	Indicator variable set equal to 1 for financially-distressed firms, 0 otherwise. We follow Altman's Z-score (the components of Altman's Z-score are downloaded from Compustat).
UEPS	Earnings per-share minus earnings per-share reported in the previous year, scaled by beginning of period share price (Compustat).
EVENT	Indicator variable set equal to 1 whenever the event window taken into consideration contains a firm-confounding event, 0 otherwise. The variable takes into consideration earnings releases, dividend announcements, stock splits, M&A and equity offerings (Bloomberg).
NASDAQ	Indicator variable set equal to 1 if firms are listed on the NASDAQ stock exchange at the time of comment letter conversation release, 0 otherwise (Bloomberg).
Country characteristics	
RoL	Home country rule of law index (Worldwide Governance Indicators created by the World Bank (Kaufmann & Kraay, 2017), as used in La Porta, Lopez-De-Silanes, and Shleifer (2006)).
ENFORCE_INDEX	Home country enforcement strength (La Porta et al., 1998).

Table 4. (continued)

Variable	Definition and source
AUDIT_ENF	Firm's home country audit and enforcement index as measured in 2008 (Brown et al., 2014).
C_LAW	Indicator variable set to equal 1 if the firm's home country legal environment is English common law and 0 if it follows either German, Scandinavian or French civil law (La Porta et al., 1998).
CORRUPTION	Firm's home country corruption index. To facilitate interpretation, we multiply the original corruption index with -1, in order for higher values of the index to denote greater corruption. (Transparency International, 2013).
DISTANCE	Geographical proximity measured as the natural logarithm of the bilateral great circle distance between the capital city of the firm's home country and Washington DC, in kilometers. We obtain the latitudes and longitudes of each country's capital city and apply the formula of Erel et al. (2012). (http://www.mapsofworld.com/utilities/world-latitude-longitude.htm).

Note: All financial and language continuous variables are winsorized at the 1st and 99th percentiles.

Table 5. Descriptive statistics

	N	Mean	Std Dev	Minimum	25^{th}	Median	75th	Maximum
CAR	1,156	-0.072	4.981	-29.399	-2.27	-0.111	2.181	29.553
CW_TONE	1,156	1.255	0.715	-1.273	0.764	1.244	1.695	4.966
LM_TONE	1,156	0.813	0.531	-0.439	0.456	0.726	1.05	3.247
HL_TONE	1,156	-0.059	0.336	-1.242	-0.25	-0.047	0.125	1.688
CW_POS	1,156	1.871	0.58	0	1.453	1.862	2.283	3.738
CW_NEG	1,156	3.129	0.783	0.835	2.568	3.103	3.645	5.892
LM_POS	1,156	0.37	0.194	0	0.227	0.347	0.477	1.414
LM_NEG	1,156	1.185	0.52	0.338	0.803	1.097	1.444	3.656
HL_POS	1,156	0.559	0.247	0.105	0.379	0.523	0.679	1.896
HL_NEG	1,156	0.499	0.257	0	0.325	0.449	0.619	1.954
ISSUES	1,156	4.458	5.134	0	1	3	6	40
CL_SIZE	1,156	162.15	124.37	6.021	90.55	130.018	198.67	1138.072
MULT_CONV	1,156	0.215	0.411	0	0	0	0	1
SIZE	1,156	9.453	2.686	1.662	7.909	9.628	11.29	15.143
LARGE_FILER	1,156	0.756	0.43	0	1	1	1	1
ROA	1,156	1.558	16.665	-222.535	0.192	2.98	7.267	45.733
LEVERAGE	1,156	0.575	0.264	0.001	0.392	0.553	0.793	1.867
PRICE_BOOK	1,156	2.498	4.336	-87.643	0.949	1.721	3.023	40.187
DISTRESS	1,156	0.659	0.474	0	0	1	1	1
UEPS	1,156	0.023	0.759	-8.437	-0.03	0.004	0.027	12.973
EVENT	1,156	0.046	0.21	0	0	0	0	1
NASDAQ	1,156	0.175	0.38	0	0	0	0	1
RoL	1,156	1.069	0.859	-0.784	0.357	1.543	1.74	1.968
ENFORCE_INDEX	1,094	8.268	1.69	2.877	6.523	9.167	9.75	10
AUDIT_ENF	1,156	40.93	14.017	9	28	46	54	54
C_LAW	1,156	0.528	0.499	0	0	1	1	1
CORRUPTION	1,156	-65.754	17.883	-91	-81	-74	-43	-28
DISTANCE	1,156	8.266	1.185	6.328	6.328	8.712	9.148	9.692

Note: Variables are defined in Table 4.

Table 6. Pearson correlation matrix

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. CAR	1.00													
2. CW_TONE	-0.03***	1.00												
3. LM_TONE	-0.02	0.32***	1.00											
4. HL_TONE	0.01	0.15***	0.12***	1.00										
5. CW_POS	-0.01***	-0.28***	-0.36***	-0.03	1.00									
6. CW_NEG	-0.03***	0.70***	0.02	0.12***	0.47***	1.00								
7. LM_POS	0.04	-0.11***	-0.24***	-0.09***	0.21***	0.05*	1.00							
8. LM_NEG	-0.01	0.29***	0.93***	0.09***	-0.29***	0.05*	0.13***	1.00						
9. HL_POS	0.03	-0.12***	0.08***	-0.64***	-0.06**	-0.16***	0.14***	0.13***	1.00					
10. HL_NEG	0.04	0.07***	0.23***	0.68***	-0.09***	-0.01	0.02	0.24***	0.12***	1.00				
11. ISSUES	-0.04	-0.02	0.24***	0.05*	-0.51***	-0.40***	0.08***	0.27***	0.09***	0.16***	1.00			
12. CL_SIZE	-0.04	0.04	0.17***	-0.08***	-0.42***	-0.27***	-0.15***	0.12***	0.19***	0.08***	0.39***	1.00		
13. MULT_CONV	0.04	0.09***	0.00	0.01	-0.05*	0.05*	-0.05*	-0.02	-0.05*	-0.04	0.00	-0.05*	1.00	
14. SIZE	-0.03	0.14***	0.23***	0.04	-0.23***	-0.03	-0.08***	0.20***	0.09***	0.13***	0.16***	0.14***	0.22***	1.00
15. LARGE_FILER	-0.02	0.00	0.06**	-0.01	-0.11***	-0.07***	-0.09***	0.03	0.01	0.01	0.10***	0.04	0.11***	0.29***
16. ROA	-0.03	-0.01	-0.04	-0.06**	0.00	0.00	-0.05*	-0.06**	0.03	-0.05*	0.00	-0.01	0.01	0.30***
17. LEVERAGE	-0.01	0.13***	0.24***	0.08***	-0.23***	-0.04	0.01	0.26***	0.07**	0.16***	0.17***	0.07***	0.15***	0.55***
18. PRICE_BOOK	-0.03	-0.01	-0.02	0.02	0.07**	0.04	0.06**	0.00	-0.01	0.01	0.01	-0.05*	-0.06**	-0.17***
19. DISTRESS	-0.02	0.05	0.14***	0.04	-0.17***	-0.08***	-0.02	0.14***	0.02	0.07**	0.14***	0.13***	0.11***	0.31***
20. UEPS	-0.10***	-0.03	0.01	0.00	0.05*	0.00	0.00	0.00	0.00	0.00	0.00	0.05*	-0.08***	-0.11***
21. EVENT	-0.02	-0.02	0.03	0.02	-0.03	-0.04	-0.01	0.03	0.02	0.05*	0.01	0.06**	-0.03	0.05*
22. NASDAQ	0.00	-0.11***	-0.09***	-0.04	0.09***	-0.04	0.04	-0.08***	0.03	-0.02	-0.04	-0.08***	-0.12***	-0.48***
23. RoL	-0.03	-0.01	0.02	0.04	0.06**	0.04	0.10***	0.06**	0.00	0.04	-0.01	-0.03	-0.02	0.01
24. ENFORCE_INDEX	-0.02	-0.02	-0.01	0.02	0.09***	0.05*	0.11***	0.03	-0.01	0.01	-0.05*	-0.02	-0.02	0.00
25. AUDIT_ENF	-0.01	-0.03	-0.03	0.00	0.08***	0.04	0.10***	0.01	-0.01	-0.02	-0.05	-0.04	-0.02	-0.08***
26. C_LAW	0.00	-0.06**	-0.09***	-0.03	0.09***	0.01	0.10***	-0.05*	0.01	-0.04	-0.07**	-0.07**	-0.10***	-0.32***
27. CORRUPTION	0.03	0.02	-0.01	-0.04	-0.08***	-0.04	-0.10***	-0.05	0.01	-0.04	0.03	0.03	0.03	0.01
28. DISTANCE	0.00	0.01	0.03	0.00	-0.11***	-0.07**	-0.09***	0.00	0.02	0.02	0.07***	0.02	0.12***	0.26***

Variable	15	16	17	18	19	20	21	22	23	24	25	26	27	28
15. LARGE_FILER	1.00													
16. ROA	0.22***	1.00												
17. LEVERAGE	0.12***	-0.14***	1.00											
18. PRICE_BOOK	-0.06*	-0.06**	-0.10***	1.00										
19. DISTRESS	0.16***	-0.21***	0.51***	-0.15***	1.00									
20. UEPS	-0.10***	0.05*	-0.06**	0.01	-0.03	1.00								
21. EVENT	0.01	0.03	0.03	-0.02	0.05*	-0.01	1.00							
22. NASDAQ	-0.10***	-0.14***	-0.23***	0.04	-0.08***	0.04	-0.06**	1.00						
23. RoL	-0.32***	-0.11***	-0.01	0.11***	-0.19***	-0.01	0.01	0.12***	1.00					
24. ENFORCE_INDEX	-0.35***	-0.13***	-0.01	0.08***	-0.21***	0.00	-0.03	0.10***	0.92***	1.00				
25. AUDIT_ENF	-0.41***	-0.16***	-0.03	0.09***	-0.20***	0.00	-0.03	0.19***	0.73***	0.84***	1.00			

Table 6. (continued)

Variable	15	16	17	18	19	20	21	22	23	24	25	26	27	28
26. C_LAW	-0.46***	-0.17***	-0.13***	0.12***	-0.18***	0.01	-0.04	0.29***	0.50***	0.47***	0.68***	1.00		
27. CORRUPTION	0.34***	0.12***	0.03	-0.11***	0.21***	0.00	0.00	-0.11***	-0.98***	-0.94***	-0.73***	-0.45***	1.00	
28. DISTANCE	0.64***	0.17***	0.11***	-0.10***	0.27***	-0.03	0.00	-0.01	-0.46***	-0.53***	-0.55***	-0.50***	0.50***	1.00

Notes: ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, two-tailed. Variables are defined in Table 4.

Table 7. Comparison of the predictive ability of language tone, negativity and positivity scores of various wordlists on cumulative abnormal returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Language-tone score measures				Negativity and positivity score measures			
CW_TONE	-0.539**			-0.614**				
	(-2.18)			(-2.40)				
LM_TONE		0.029		0.268				
		(0.08)		(0.75)				
HL_TONE			0.089	0.237				
			(0.19)	(0.50)				
CW_NEG					-0.636**			-0.671**
					(-2.36)			(-2.43)
CW_POS					0.115			0.090
					(0.35)			(0.26)
LM_NEG						0.100		0.215
						(0.28)		(0.56)
LM_POS						0.719		0.507
						(0.71)		(0.47)
HL_NEG							0.581	0.685
							(0.81)	(0.94)
HL_POS							0.522	0.212
							(0.95)	(0.37)
ISSUES	-0.117***	-0.105***	-0.105***	-0.124***	-0.141***	-0.107***	-0.113***	-0.157***
	(-3.13)	(-2.83)	(-2.87)	(-3.25)	(-3.64)	(-2.85)	(-2.96)	(-3.79)
CL_SIZE	0.005**	0.004**	0.004**	0.005**	0.004**	0.004**	0.004**	0.004**
	(2.39)	(2.15)	(2.16)	(2.43)	(2.12)	(2.04)	(2.17)	(2.01)
MULT_CONV	0.659	0.616	0.615	0.683	0.635	0.636	0.640	0.685
	(1.35)	(1.26)	(1.26)	(1.39)	(1.30)	(1.30)	(1.32)	(1.41)
SIZE	0.981*	1.052*	1.052*	0.982*	0.986*	1.061*	1.005*	0.960
	(1.67)	(1.76)	(1.77)	(1.68)	(1.67)	(1.79)	(1.69)	(1.64)
LARGE_FILER	0.087	0.069	0.077	0.109	0.172	0.051	0.042	0.162
	(0.07)	(0.06)	(0.07)	(0.09)	(0.15)	(0.04)	(0.04)	(0.14)
ROA	-0.015	-0.016	-0.016	-0.014	-0.015	-0.016	-0.014	-0.013
	(-0.89)	(-0.93)	(-0.92)	(-0.84)	(-0.88)	(-0.92)	(-0.82)	(-0.76)
LEVERAGE	-0.302	-0.112	-0.096	-0.269	-0.207	-0.200	-0.067	-0.202
	(-0.11)	(-0.04)	(-0.03)	(-0.10)	(-0.08)	(-0.07)	(-0.02)	(-0.07)
PRICE_BOOK	-0.053	-0.053	-0.053	-0.053	-0.049	-0.054	-0.056	-0.052
	(-0.94)	(-0.93)	(-0.93)	(-0.94)	(-0.88)	(-0.95)	(-0.96)	(-0.91)
DISTRESS	-0.198	-0.184	-0.184	-0.178	-0.188	-0.176	-0.138	-0.127
	(-0.36)	(-0.34)	(-0.34)	(-0.33)	(-0.34)	(-0.32)	(-0.25)	(-0.23)
UEPS	-1.176*	-1.160*	-1.159*	-1.185*	-1.150*	-1.165*	-1.163*	-1.157*
	(-1.93)	(-1.88)	(-1.88)	(-1.96)	(-1.88)	(-1.90)	(-1.88)	(-1.90)
EVENT	0.352	0.385	0.380	0.313	0.325	0.357	0.339	0.232
	(0.31)	(0.34)	(0.33)	(0.28)	(0.29)	(0.31)	(0.29)	(0.20)
NASDAQ	1.178	1.102	1.093	1.139	1.225	1.052	1.042	1.102
	(0.58)	(0.57)	(0.56)	(0.55)	(0.62)	(0.55)	(0.53)	(0.56)
Constant	-7.522	-8.979*	-8.973*	-7.649	-6.362	-9.428*	-9.067*	-6.859
	(-1.42)	(-1.68)	(-1.70)	(-1.44)	(-1.20)	(-1.78)	(-1.72)	(-1.28)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. (continued)

N	1,156	1,156	1,156	1,156	1,156	1,156	1,156	1,156
adj. R^2	4.10%	3.50%	3.50%	4.10%	4.20%	3.50%	3.60%	4.20%
R^2	5.90%	5.30%	5.30%	6.00%	6.10%	5.40%	5.40%	6.30%
VIF	1.34	1.35	1.34	1.33	1.41	1.34	1.33	1.41

Notes: ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, two-tailed. The dependent variable is CAR. Regressions use robust standard errors. Variables are defined in Table 4.

Table 8. The impact of home country characteristics and language tone, negativity and positivity scores of our customized wordlist on cumulative abnormal returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Language-tone score measures				Negativity and positivity score measures			
CW_TONE	-0.539**	-0.520**	-0.539**	-0.539**				
	(-2.12)	(-2.01)	(-2.12)	(-2.12)				
CW_NEG					-0.636**	-0.606**	-0.636**	-0.636**
					(-2.28)	(-2.13)	(-2.28)	(-2.28)
CW_POS					0.115	0.132	0.115	0.115
					(0.31)	(0.35)	(0.31)	(0.31)
RoL	-7.011***				-6.967***			
	(-3.54)				(-3.63)			
ENFORCE_INDEX		-1.362***				-1.348***		
		(-3.08)				(-3.05)		
AUDIT_ENF			-0.667***				-0.652***	
			(-3.46)				(-3.44)	
C_LAW				19.422***				19.725***
				(2.75)				(2.78)
CORRUPTION				0.357**				0.364**
				(2.21)				(2.25)
DISTANCE	4.452**	-1.935*	0.322	4.262***	4.585**	-1.871*	0.653	4.479***
	(2.13)	(-1.82)	(0.11)	(3.22)	(2.25)	(-1.77)	(0.23)	(3.39)
ISSUES	-0.117***	-0.115***	-0.117***	-0.117***	-0.141***	-0.137***	-0.141***	-0.141***
	(-3.02)	(-2.92)	(-3.02)	(-3.02)	(-3.30)	(-3.13)	(-3.30)	(-3.30)
CL_SIZE	0.005**	0.004*	0.005**	0.005**	0.004*	0.004*	0.004*	0.004*
	(2.20)	(1.90)	(2.20)	(2.20)	(1.95)	(1.67)	(1.95)	(1.95)
MULT_CONV	0.659	0.635	0.659	0.659	0.635	0.610	0.635	0.635
	(1.39)	(1.31)	(1.39)	(1.39)	(1.34)	(1.26)	(1.34)	(1.34)
SIZE	0.981	0.953	0.981	0.981	0.986*	0.958	0.986*	0.986*
	(1.64)	(1.55)	(1.64)	(1.64)	(1.65)	(1.56)	(1.65)	(1.65)
LARGE_FILER	0.087	0.128	0.087	0.087	0.172	0.206	0.172	0.172
	(0.07)	(0.10)	(0.07)	(0.07)	(0.14)	(0.16)	(0.14)	(0.14)
ROA	-0.015	-0.015	-0.015	-0.015	-0.015	-0.014	-0.015	-0.015
	(-0.92)	(-0.89)	(-0.92)	(-0.92)	(-0.91)	(-0.88)	(-0.91)	(-0.91)
LEVERAGE	-0.302	0.650	-0.302	-0.302	-0.207	0.750	-0.207	-0.207
	(-0.11)	(0.23)	(-0.11)	(-0.11)	(-0.08)	(0.27)	(-0.08)	(-0.08)
PRICE_BOOK	-0.053	-0.054	-0.053	-0.053	-0.049	-0.051	-0.049	-0.049
	(-1.02)	(-1.04)	(-1.02)	(-1.02)	(-0.96)	(-0.98)	(-0.96)	(-0.96)
DISTRESS	-0.198	-0.220	-0.198	-0.198	-0.188	-0.219	-0.188	-0.188
	(-0.36)	(-0.39)	(-0.36)	(-0.36)	(-0.34)	(-0.38)	(-0.34)	(-0.34)
UEPS	-1.176*	-1.159*	-1.176*	-1.176*	-1.150*	-1.135*	-1.150*	-1.150*
	(-1.79)	(-1.73)	(-1.79)	(-1.79)	(-1.74)	(-1.68)	(-1.74)	(-1.74)
EVENT	0.352	0.345	0.352	0.352	0.325	0.322	0.325	0.325
	(0.33)	(0.32)	(0.33)	(0.33)	(0.30)	(0.30)	(0.30)	(0.30)
NASDAQ	1.178	1.114	1.178	1.178	1.225	1.158	1.225	1.225
	(0.61)	(0.58)	(0.61)	(0.61)	(0.64)	(0.61)	(0.64)	(0.64)
Constant	-22.319	19.139**	27.630	-23.778**	-21.962	19.742**	25.993	-23.618**
	(-1.30)	(2.24)	(0.97)	(-2.19)	(-1.31)	(2.27)	(0.93)	(-2.17)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. (continued)

N	1,156	1,094	1,156	1,156	1,156	1,094	1,156	1,156
adj. R^2	8.60%	9.00%	8.60%	8.60%	8.70%	9.00%	8.70%	8.70%
R^2	33.80%	34.40%	33.80%	33.80%	33.90%	34.50%	33.90%	33.90%
VIF	1.47	1.50	1.49	1.52	1.53	1.56	1.55	1.57

Notes: ***, ** and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively, two-tailed. The dependent variable is CAR. Regressions use robust standard errors. Variables are defined in Table 4.

Appendix A

Analysis of comment letters

Our typical sample firm has approximately 5 CL conversations or 12 uploads (see Table 2, Panel A). The sample resolution time, from the first CL filed until the announcement of the CL conversation, has a mean (median) of 185 (117) days. In line with Cassell et al. (2013), the mean (median) number of rounds until the completion of the review is approximately 3 (2), with a range of 1 to 10 rounds. The majority of the issues are resolved after 2 or 3 CLs, in contrast to Ernst & Young (2015) findings which conclude that the resolution of the filing review requires 1 or 2 rounds. In addition, since the main topics of comments are of paramount importance to firms and investors, we find that the number of comment issues per CL conversation varies considerably, with a mean (median) of 16 (10) and a range from 1 to 221 issues.

Although trends may vary across time and industries, there are some key areas to which SEC reviewers consistently pay attention. Specifically, following Audit Analytics coding, we classify our comment topics into 32 group types for every upload within our sample. Accounting rule and disclosure type are ranked highest, including issues related to revenue recognition, segment reporting, fair value measurement, and intangible assets. Other disclosure matters are ranked second, including issues related to non-GAAP measures and terrorist-sponsor reporting. International Accounting Standards matters are ranked third, while management discussion and analysis issues related to contingencies come in at fourth place. Overall, our sample's most frequent comment topics seem to follow similar trends to those reported by large audit firms (Deloitte, 2012; Ernst & Young, 2015; PricewaterhouseCoopers, 2014); although some minor differences exist, especially in the order of comment-topic frequency.

Appendix B

Composition of negative and positive wordlists

Using the methodology employed by Loughran and McDonald (2011), we identify the 20 most common negative- and positive-tone words with the highest document frequency within the CL filings. Panel A of Appendix C reports the most frequently-occurring words appearing in the LM negative and positive wordlists, and Panel B lists the most frequently-occurring words in the CW dictionary. The analysis of the CW composition is based on the LM dictionary, as it is the most extensive and finance-specific dictionary of all the other highly-cited wordlists. In Panel A, the negative word that occurs in the largest number of documents is the word *questions*, accounting for 20.45% of the total negative LM word count. In the 10-K reports, the word *questions* has a negative connotation. However, within the CL context, *questions* is used as a closing note (e.g., "if you have any questions please contact…"), indicating the absence of a negative connotation. In addition to the word *questions*, other LM words not appearing in the CW dictionary (such as *disclose*, *disclosed*, *impairment,* and *closing*) are not perceived as negative in the CL domain. *Disclose* and *disclosed* are used by the SEC staff mainly to encourage companies to provide more information in future filings (e.g., "please disclose the trends…"). Similarly, *impairment* describes the respective accounting principle and *closing* is used to refer to SEC closing remarks. As the aforementioned words account for approximately 50% of the total negative word count in CL narratives, there appears to be a significant misclassification of negative words based on the LM dictionary. On the other hand, the positive LM words seem to be more-accurately classified in the CL domain, as 16 of the 20 most frequent words are also found in the CW dictionary. However, a few exceptions do exist, with the notable example of the word *effective,* which in the CL filings mainly refers to "effective date" and, thus, does not indicate a positive connotation.

In Panel B of Appendix C, only 6 out of the 20 CW negative words appear in the LM dictionary. The most common CW negative word not included in the LM dictionary is *comments*, which refers to certain doubts or issues raised by the SEC reviewers concerning firms' non-compliance with the applicable disclosure requirements. Since the mere existence of comments indicates poor financial reporting quality, the word by itself should have a negative meaning within our regulatory context. Similarly, the word *proceeding*, the second most common word appearing in the CW negative list, is used in the context of criminal proceedings, thus expressing a negative connotation. In the positive CW tone wordlist, the most frequent word appearing in CLs, but not in the LM dictionary, is the word *certain*. Since *certain* is used as a synonym for the word assured, it denotes a positive connotation. Overall, in the domain of regulatory disclosures, our analysis highlights the problem of word misclassification if generic-finance wordlists are employed. This phenomenon becomes more pronounced with the employment of negative-tone lists. Thereby, in the CL context, wordlists generated for corporate disclosure might principally disregard words with a negative connotation or include words with meanings not relevant to the regulatory context. We further test our customized wordlist against 134 randomly-selected LM words (see Sensitivity Analysis Section).

Appendix C Tone words with the highest document frequency

Panel A: 20 most common words included in the Loughran and McDonald (2011) wordlist

Negative words				Positive words			
Word in CW wordlist	Negative word	% Document frequency	% of Total LM negative word count	Word in CW wordlist	Positive word	% Document frequency	% of Total LM positive word count
	questions	66.78	20.45	√	better	57.16	31.42
√	foreclose	53.95	8.06	√	enhance	27.95	14.65
	disclose	30.50	16.50	√	greatly	25.17	12.74
√	disagree	19.10	2.89		effective	7.93	9.22
√	unnecessary	18.30	2.74	√	greater	6.41	4.77
√	loss	15.89	6.90		able	4.64	3.11
	disclosed	14.38	3.82	√	gain	4.61	3.54
	impairment	12.63	6.43	√	benefit	4.55	4.01
	closing	12.54	1.92	√	gains	3.95	3.83
√	losses	11.63	5.98	√	best	2.72	1.87
	critical	7.65	1.74	√	transparency	2.12	1.39
√	absence	7.16	1.17		advances	1.92	1.69
√	divestment	5.30	1.07	√	positive	1.66	1.21
√	unable	4.95	0.99		enable	1.52	0.88
	disclosing	4.61	0.96	√	enhanced	1.43	0.93
√	impaired	4.52	2.33	√	improvements	1.20	0.69
√	preclude	4.24	0.64	√	improved	1.20	0.72
√	against	4.01	0.84	√	profitability	1.17	0.81
	question	3.72	0.72	√	rewards	1.06	0.69
	claims	3.58	1.27	√	progress	1.06	0.67

Panel B: 20 most common words included in our customized comment letter wordlist

Negative words				Positive words			
Word in LM wordlist	Negative word	% Document frequency	% of Total CW negative word count	Word in LM wordlist	Positive word	% Document frequency	% of Total CW positive word count
	comments	99.71	40.72		certain	59.45	8.96
	proceeding	54.01	3.14	√	better	57.16	6.46
√	foreclose	53.95	3.13		accuracy	56.53	14.68
	comment	49.77	8.67		adequacy	56.50	14.64
	revise	36.37	6.87		defense	54.01	5.63
	raise	32.85	1.92		compliance	30.47	3.56
	amendment	26.03	3.50		welcome	28.09	2.92
	enforcement	23.77	1.38	√	enhance	27.95	3.01
	revision	19.39	1.30		assist	26.63	2.83
√	disagree	19.10	1.12		facilitate	25.80	2.74
√	unnecessary	18.30	1.06	√	greatly	25.17	2.62
	inapplicable	18.10	1.05		informed	23.02	2.40
	risk	17.73	3.49		reconciliation	12.46	2.37
	amend	17.01	1.14		reasonable	11.34	1.59
√	loss	15.89	2.68		available	10.14	1.60
	amending	14.29	0.83		development	9.91	2.47
	revised	12.03	1.10		expedite	9.19	0.95
√	losses	11.63	2.32		support	9.14	1.32
	unclear	8.05	0.69		reasonably	8.19	1.47
√	absence	7.16	0.45		true	6.56	0.87