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Andreas Barth, Sasan Mansouri, Fabian Wöbbeking

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Authors

Andreas Barth
University of Würzburg and Halle Institute for Economic Research (IWH) – Member of the Leibniz Association
andreas.barth@uni-wuerzburg.de

Sasan Mansouri
University of Groningen and Halle Institute for Economic Research (IWH) – Member of the Leibniz Association
s.mansouri@rug.nl

Fabian Wöbbeking
Halle Institute for Economic Research (IWH) – Member of the Leibniz Association, Department of Financial Markets, and Martin-Luther-University Halle-Wittenberg
E-mail: fabian.woebbeking@iwh-halle.de
Tel +49 345 7753 851

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Halle Institute for Economic Research (IWH) – Member of the Leibniz Association

Address: Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany
Postal Address: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

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Information Flow and Market Efficiency – The Economic Impact of Precise Language*

Abstract

This paper examines the impact of complex yet precise language, particularly financial jargon, on information dissemination and ultimately market efficiency. As a natural laboratory, we analyze the information exchanged during earnings conference calls, where we instrument jargon with the Plain Writing Act of 2010. Our findings suggest that the Act's promotion of plain language usage results in a reduction in complex financial jargon for US firms. However, in contrast to the presumed benefits of accessible language, this reduction in jargon is associated with a decrease in market efficiency, implying that the Act may inadvertently hinder information flow. This finding is particularly important at the juncture where human-generated information is received by machines, which are known to be vunerable to ambiguous inputs.

Keywords: earnings conference calls, information asymmetry, jargon, market efficiency, Plain Writing Act, precise language

JEL classification: G00, G14, M40, M41

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1 Introduction

> *"[...] The language of money is a powerful tool, and it is also a tool of power. Incomprehension is a form of consent. If we allow ourselves not to understand this language, we are signing off on the way the world works today [...]"*
>
> — The New Yorker, *"Money Talks – Learning the language of finance", published in the print edition of the August 4, 2014, issue.*

The efficient transfer of information between companies and investors – or lack thereof – constitutes a key friction in economics. The importance of language usage in facilitating this transfer is evident even at the regulatory level. For instance, the Plain Writing Act of 2010 emphasizes that "stilted jargon and complex constructions" hinder effective communication. While plain language widens the audience for corporate disclosures, it remains unclear whether it outperforms concise technical jargon in promoting market efficiency when specialists communicate with one another in a time-constrained environment.

We investigate this question using earnings conference calls, a central venue for information exchange between firm managers, investors, and financial analysts. Crucially, both sides in these calls have a strong finance background, making industry-specific terminology not just common, but arguably efficient for conveying important details. As a main result, we establish that precise language is beneficial in exchanging information between experts. We measure financial jargon based on the Finance Glossary developed by Harvey (2016) for all conference calls held by US firms between 2005 and 2019 and find that higher levels of financial jargon correlate with increased abnormal turnover and narrower bid-ask spreads around the conference call, suggesting lower information asymmetry and smoother price discovery (Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990; Chae, 2005; Glosten and Milgrom, 1985; Stoll, 1989, 2000).

In our baseline regression, we absorb time-constant, firm-specific effects, as for example the general disclosure style of a management team, as well as shocks to all US firms at a given point in time, as for example macroeconomic or political changes, by saturating our model with firm and time fixed effects. As our sample period includes the 2008/09 financial crisis, our market-efficiency metrics may partly capture the liquidity shocks of that period. If the firms hit hardest by those liquidity shortages also happened to use less financial jargon, the coefficient could simply be picking up this shared movement rather than a causal effect. To rule out this possibility, we exclude in robustness tests the years spanning the crisis and show that our results remain unaffected by the financial crisis period.

Extending the argument above, one might still worry that the choice of language in earnings conference calls is potentially endogenous, posing an empirical challenge to causally identify the effect of jargon using within-firm variation. For instance, quarters with poor earnings may require more detailed explanations, leading to increased factual terminology. At the same time, (surprisingly) low earnings may complicate the price discovery process for investors.

To address this challenge, we employ an instrumental variable approach as a further robustness test, utilizing the enactment of the Plain Writing Act of 2010, a fairly exogenous event to market efficiency, as an instrument for financial jargon. In a first-stage regression, we establish the relevance of our instrument and show that this regulation of written disclosures spills over even into verbal communications. That is, managers significantly reduce jargon in conference calls following the Plain Writing Act.Leveraging this exogenous variation in financial jargon, we confirm the findings from our panel regressions that increased jargon improves the information environment and reduces information asymmetries.

Hence, our analysis unveils an unintended side effect of the Plain Writing Act, namely, a reduction of market efficiency. The concept of market efficiency, formally proposed by Fama (1965, 1970), contends that security prices instantaneously incorporate and reflect all available information. The central tenet of the EMH can be represented as:

$$P_t = E\left[P_t \mid \Phi_{t-1} + \phi_t\right], \tag{1}$$

where Φ_t designates the cumulative information set at time t. This set is the aggregation of the prior information set, Φ_{t-1}, with the novel information ϕ_t obtained at that juncture (Grossman and Stiglitz, 1980). In our setting, information ϕ_t, revealed at time t, is subject to the market's ability to understand and absorb said addition.

Naturally, market's assimilation of new information affects trading volume (Easley and O'hara, 1992; Easley et al., 2008). Theoretical models (Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990) as well as empirical findings (e.g. Chae, 2005) suggest a link between trading volume and information asymmetries. This link is based on market participants – especially uninformed traders – ability to defer their trades around information events until information asymmetries are resolved. We add to this literature by presenting a channel that links trading volume to the market's ability to understand and absorb arriving information.

In addition, we consider bid-ask spreads as an alternative proxy for information asymmetries. Informed traders exploit private information by buying at the ask if they know the true price should be higher, or by selling at the bid if they know the true price should be lower. When their private information eventually becomes public, these traders realize gains at the expense of liquidity providers. In equilibrium, market makers (or other liquidity suppliers) widen the spread to recoup these potential losses (Glosten and Milgrom, 1985; Stoll, 1989, 2000). This mechanism, too, we empirically link to information frictions arising from the usage of complex yet precise language or a lag thereof.

The trade-off between precision and complexity is a very common problem in linguistics. Take, for example, jargon as a specialized language of professionals that is well understood in-group but meaningless out-group. For instance, a patient might have a hard time understanding a physician who uses a high degree of medical jargon (Castro et al., 2007). However, being versed in the contextual vocabulary allows in-group communication – in this example between health professionals – at a much higher speed and precision.

In finance, too, the usage of factual finance language might impede the flow of information, which has already been established in the context of written disclosures (Li, 2008;

Bloomfield, 2008; Loughran and McDonald, 2014; Bonsall et al., 2017). Conversely, the absence of financial jargon could suggest an unwillingness or inability to disclose precise information. Related literature has already shown that managers avoid unfavorable factual quantitative information (Campbell et al.), up to the extreme of refusing to provide any information (Hollander et al., 2010; Gow et al., 2021; Barth et al., 2023). In either case, both the inclusion and exclusion of jargon in financial communication potentially open up an additional information friction between firms and investors. Our study provides empirical evidence of this trade-off by showing how managers' strategic use (or avoidance) of financial jargon shapes the information environment that investors face.

In contrast to written disclosures with their long preparation periods, managers have to react more spontaneously during earnings conference calls. This, however, does not prevent them from opportunistically managing the flow of information, for example, by selecting more favorable analysts to ask questions (Mayew, 2008; Cohen et al., 2020). We contribute along this line of research by testing whether markets perceive jargon as beneficial information or an attempt to obfuscate. This question is particularly relevant at critical junctures in human–machine information exchange. For instance, corporate leaders are legally required to release information in person, especially during earnings conference calls. This human-produced information, already shown to be highly relevant to financial markets,[1] is increasingly analyzed by machines such as large language models. Although these models possess extensive contextual windows and sophisticated linguistic capabilities, they remain vulnerable to ambiguity and imprecision (Bender and Koller, 2020; Kamath et al., 2024).

The remainder of the paper is structured as follows. Section 2 presents the data used in the analysis. Section 3 lays out the empirical method and identification strategy together with the main findings, followed by additional robustness checks. Section 4 concludes.

[1]See, e.g., Matsumoto et al. (2011a), who show that the human-centered Q&A section in earnings conference calls is particularly informative for financial markets.

2 Data

Our sample consists of all quarterly earnings conference call transcripts from US firms held between 2005 and 2019 that we procure from Thomson Reuters' 'StreetEvents' platform, amounting to 137,144 calls from 5,084 firms.

Earnings conference calls are voluntary disclosures that aim to reduce information asymmetries among investors (Brown et al., 2004). The calls are typically attended by financial experts, i.e., institutional investors who hold a large stake in the company and therefore wish to improve their understanding of the company (Barker et al., 2012), as well as by financial analysts, who base their earnings forecasts, at least in part, on information extracted from the call (Bushee et al., 2004). They usually consist of two parts: a short (prepared) presentation by the management, followed by a question-and-answer (Q&A) session. We focus on the relatively more informative Q&A section of the calls (Matsumoto et al., 2011b) and aim to measure the extent to which the language used in management's answers to analysts' questions can help reduce information asymmetries.

2.1 Measuring information asymmetry

Trading volume. A market's readiness to buy and sell an asset facilitates the price discovery process and is therefore directly related to our notion of market efficiency. Thus, trading volume plays an important role in financial markets, and can be broadly categorized into trading by informed agents and trading by liquidity (or uninformed) traders.[2] Theoretical models proposed by Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) suggest that if liquidity traders can choose the timing of their trades, trading volume may diminish in the face of information asymmetry. Specifically, discretionary liquidity traders (DLTs) who encounter exogenous trade demands preceding announcements might defer trading. They would typically wait until post-announcement when information disparities are

[2]Trading volume on financial markets has been extensively studied in the literature, see e.g. Easley and O'hara (1992); Easley et al. (2008) and references therein.

rectified. As a consequence, trading volume should show a decline before announcements and a subsequent rise thereafter. Chae (2005) provide empirical evidence that corresponds to the aforementioned theory. It is shown that trading volume decreases inversely to information asymmetry prior to scheduled announcements or corporate disclosures such as earnings conference calls, while the opposite relation holds for trading volume after the announcement. We build on Chae (2005) and measure the turnover $\tau_{i,t}$ as the trading volume of share i at time t relative to the free floating shares of a company,

$$\tau_{i,t} = \frac{\text{Trading Volume}_{i,t}}{\text{Shares Outstanding}_{i,t}}. \tag{2}$$

We then define

$$\text{Abnormal Turnover}_{i,t} = \tau_{i,t} - \hat{\tau}_{i,t}, \tag{3}$$

where

$$\hat{\tau}_{i,t} = \frac{1}{30} \sum_{t=-40}^{t=-11} \tau_{i,t}. \tag{4}$$

We calculate the *Abnormal Turnover*$_{i,t}$ for the first trading day after the information of the conference call arrived at the market. That is, we use the trading volume on the conference call day in case the call takes place during market hours, and utilize volume data from the subsequent trading day for conference calls taking place after regular trading hours.[3]

In order to account for some delayed trading on new information, we aggregate the *Abnormal Turnover*$_{i,t}$ over the day of the conference call and one trading day after the earnings conference call following immediately after the call, which we denote cumulative abnormal turnover $CAT_{i,t,t+1}$.

[3] Roughly 35% of earnings conference calls take place after regular trading hours.

$$\text{CAT}_{i,t_1,t_2} = \sum_{k=t_1}^{t_2} \text{Abnormal Turnover}_{i,k} \tag{5}$$

The average cumulative abnormal turnover across all firms from $t-15$ days before to $t+15$ after the call is displayed in Figure 1. In line with the empirical findings in Chae (2005), Abnormal Turnover$_{i,t}$ decreases in the days leading up to the call and experiences a strong increase at and shortly after the call. Given the established link between Abnormal Turnover$_{i,t}$ and information asymmetry, we aim to test whether the use of precise language (jargon) has an effect on information flow, which, in turn, relieves the market of information asymmetries.

[**Figure 1 about here**]

In addition to the *Abnormal Turnover*$_{i,t}$ as a measure of the trading volume on the day of and the day following the earnings conference call, we further calculate the difference in *Abnormal Turnover*$_{i,t}$ immediately before and after the call,

$$\Delta\text{Abnormal Turnover}_{i,t} = \text{Abnormal Turnover}_{i,t} - \text{Abnormal Turnover}_{i,t-1}, \tag{6}$$

This approach is grounded in the notion that information asymmetries lead to trade timing and, hence, a diminishing *Abnormal Turnover*$_{i,t}$ prior to the call. If the use of jargon plays a pivotal role in alleviating these information asymmetries, one should consequently observe a more pronounced 'rebound' effect post-call.

Bid-ask spread. A frequently used proxy for information asymmetry in financial markets is the bid-ask spread, reflecting adverse selection risk faced by liquidity providers. Informed traders capitalize on private information by trading against market makers: buying at the ask when expecting prices to rise and selling at the bid when anticipating declines. When the private information is eventually incorporated into market prices, informed traders profit at the liquidity providers' expense. Market makers thus respond by widening the spread to offset these potential adverse selection costs (Glosten and Milgrom, 1985; Stoll, 1989, 2000). Consequently, a broader spread signals increased information asymmetry, whereas a narrower spread indicates more symmetric information.

In an ideal setting, intraday bid-ask spreads would be observed precisely at the moments information is revealed. However, such granular microstructure data is typically unavailable, necessitating the use of proxies derived from daily aggregated data. To approximate the unobservable intraday bid-ask spreads, we utilize the efficient discrete generalized bid-ask spread estimator (EDGE) proposed by Ardia et al. (2024). EDGE fully leverages daily open, high, low, and close (OHLC) prices, addressing limitations inherent in previous estimators such as those proposed by Roll (1984), Corwin and Schultz (2012), and Abdi and Ranaldo (2017), which either omit relevant intraday price information or implicitly assume continuous trading.

The EDGE methodology is built upon two complementary spread estimators that exploit distinct subsets of the OHLC price points. The intuition is that the daily high-low range reflects intraday volatility and captures trades executed at extreme bid or ask prices, while open and close prices provide additional insights into price adjustments relative to the day's equilibrium midpoint. The final estimate is then built using Hansen's (1982) generalized method of moments (GMM) procedure, yielding an unbiased and minimum-variance estimator across different liquidity and volatility regimes.

Formally, the EDGE estimator $\hat{s}_i$ for stock i is calculated from OHLC prices over a given interval. To analyze the impact of earnings calls on bid-ask spreads, we estimate the EDGE-based bid-ask spread for the k-day window immediately following the earnings call date t, comparing it to the baseline spread calculated from a 30-day reference window (from $t - 40$ to $t - 11$). Owing to the differing window lengths, we standardize both spread estimates robustly by subtracting the median and scaling by the inter-quartile range. This approach provides a reliable approximation of changes in bid-ask spreads attributable to shifts in information asymmetry around earnings announcements. We then compare the baseline to the post-call bid-ask spread by calculating the change in bid-ask spreads as

$$\text{BA-Spread}_{i,t,k} = \hat{s}_i(t, t+k) - \hat{s}_i(t-40, t-11). \tag{7}$$

2.2 Financial jargon

Our main focus is on one particular linguistic characteristic within management responses, which is the usage of financial jargon. To identify finance jargon, we use the Hypertextual Finance Glossary by Campbell R. Harvey (2016) with more than 8,500 entries,[4] but remove common English stop-words that could bias our metric.[5] We then quantify the presence of jargon for all management responses to questions that contain financial jargon[see my comment below, could also add a footnote to explain this decision further] in the earnings call by company i in quarter t as

$$\text{Jargon}_{i,t} = \frac{\text{Finance glossary words}_{i,t}}{\text{Total words}_{i,t}} \times 100, \tag{8}$$

2.3 Additional controls

To isolate the effect of jargon, we control for several factors capturing additional linguistic characteristics of the conference call and firm-specific characteristics, respectively. In particular, for the conference call held by firm i at time t, we measure the tone sentiment, *Negativity*, as the ratio of negative words to total words and the uncertainty of management statements, *Uncertainty*, as the ratio of uncertain words to total words.[6] To control for the complexity of the written disclosures, we rely on Bonsall et al. (2017) and collect the BOG

[4] The glossary is available at `http://people.duke.edu/~charvey/`

[5] For example, the words 'MY' or 'ARE' are defined in Harvey's finance glossary as "the two-character ISO 3166 country code for Malaysia" or "the three-character ISO 3166 country code for United Arab Emirates", respectively. See Appendix A for a list of all 45 English stop-words in Harvey's finance glossary.

[6] For both the *Negativity* and *Uncertainty* measures, we employ the word list by Loughran and McDonald (2011).

index of the 10-K reports for the firms in our sample. We collect additional information for firm i at time t, as for example analyst data from I/B/E/S to measure quarterly earnings surprises. Earnings surprises are calculated as the difference between the actual and consensus forecast earnings, divided by the share price five trading days prior to the announcement. Thus, any positive (negative) number indicates a better (worse) performance than expected. As in Dzielinski et al. (2021), we rank all firms' earnings surprises into deciles and categorize earnings surprises from 1 (most negative) to 5 (least negative) and from 6 (least positive) to 10 (most positive).

We further collect quarterly balance sheet statistics (total assets, book equity, and return on equity) as well as banks' market capitalizations from Compustat to calculate the book-to-market ratio, the natural logarithm of total assets, and Tobin's Q as additional firm characteristics.

2.4 Descriptive statistics

Descriptive statistics are presented in Table 1. We note that about 6 percent of the words in management responses are identified as finance jargon. A notable instance of jargon usage is seen in the conference call by 'Synagro Technologies Inc.' on 2005-08-03, while a total absence of financial terminology is observed in the responses by the management of 'QAD Inc.' on 2013-03-07. The distribution of the other linguistic characteristics is quite comparable to the literature, with an average share of negative words of 2.7%, and an average share of uncertain words of 1.6%.

[Table 1 about here]

3 Empirical analysis

In our empirical setting, we aim to identify the effect of jargon on market efficiency. We thus model information asymmetry after the conference call of firm i at time t, as indicated by the following equation:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \times \text{Jargon}_{i,t} + \gamma' \mathbf{X_{i,t}} + \epsilon_{i,t}. \tag{9}$$

$Y_{i,t}$ is the *Abnormal Turnover*$_{i,t}$ and the *Bid-Ask-Spread*$_{i,t}$ as described in Subsection 2.1. *Jargon*$_{i,t}$ measures the usage of financial jargon in the management's responses to analysts' questions in the Q&A of the corresponding conference call. $\mathbf{X_{i,t}}$ captures a vector of control variables, as presented in Subsection 2.3. In order to absorb the general style of managers in responses and economic-wide shocks, we saturate the model with firm fixed effects α_i and time fixed effects α_t, and further account for autocorrelation in the errors by clustering at the firm level.

[**Table 2 about here**]

[**Table 3 about here**]

The results for the abnormal turnover measures are shown in Table 2. Starting with the *Abnormal Turnover*$_{i,t}$ in column (1), we find that the usage of jargon leads to a higher abnormal trading volume, indicating that jargon helps to resolve information asymmetries. abaWe now only use $Jargon_{wfq}$, right? So this sentence can be commented!?!?Note that this result holds true for the amount of jargon following questions with and without financial context. In column (2), we use Δ*Abnormal Turnover*$_{i,t}$ and capture the 'rebound' effect in trading volume post-call, where results are very similar to the abnormal turnover. Finally, when focusing on the cumulative abnormal turnover in column (3), we again find a positive and highly significant effect.

The results for our second measure of market efficiency, the Bid-Ask Spread, are shown in Table 3. We find that bid-ask spreads are in the short term significantly lower following conference calls with a large amount of jargon. In the longer run, however, the effect disappears, which is not surprising given that the lack of jargon neither withholds information nor provides incorrect information but merely slows down the flow of information. All these results support the hypothesis that jargon is perceived as precise information, and a lack of factual language vis-à-vis the presence of imprecise language hinders the flow of information, thereby retarding the reduction of information asymmetries following an earnings conference call.

A potential concern regarding the general applicability of our findings might be the variability in jargon during market distress periods. One could expect, for instance, that significant events like the global financial crisis would have temporarily influenced communication patterns between investors and managers. At the same time, crisis times usually come with wider bid-ask spreads and lower turnover due to market liquidity risk, and our effect might have picked up this comovement. To address the concern that our results might be driven by these 'abnormal' information periods, we revisit the analysis, deliberately masking the periods of heightened market stress from our sample. Specifically, we exclude the years 2008 and 2009, pertaining to the global financial crisis. The corresponding results of the second-stage regression in Table 8 align closely with our main findings, suggesting that the results are not driven by these crisis events.

[**Table 8 about here**]

Instrumental variable estimation A more general potential concern might be that the usage of financial jargon is endogenous to liquidity and trading pattern of investors. In an ideal setting, we aim to measure how quickly new information is incorporated into stock prices following a conference call that extensively uses financial jargon, and to compare this with the hypothetical outcome if the management had avoided using jargon in the very same call. However, the use of financial jargon by managers in conference calls is potentially not random. For example, unexpectedly (low) earnings might need more explanation, leading to a higher usage of jargon, but at the same time, they also affect trading volume, a commonly used measure for information asymmetry (Chae, 2005), as the price discovery mechanism becomes more challenging for investors after unexpectedly (low) earnings.

We solve this endogeneity issue and establish a causal relationship between the use of financial jargon in earnings conference calls and information asymmetries on financial markets by employing an instrumental variable (IV) approach, where we instrument the usage of jargon with the Plain Writing Act of 2010, which is unrelated to firms' performance from 2010 onward, thus providing a plausible source of exogenous variation in the use of financial jargon. The Plain Writing Act aimed to promote clear and concise communication, making information more understandable and accessible to the public. The SEC singled out "stilted jargon and complex constructions" in its "Plain English Handbook" as principal barriers to effective information flow. Although the Plain Writing Act's prime intent was to target government communications, it also affects listed companies that interact with the Securities and Exchange Commission (SEC), as they are forced to comply with the SEC's plain language requirements.[7] The Act initially applied to written statements, which might put in question the relevance of the instrument. However, since written communication reflects a firm's corporate culture (Guiso et al., 2015; Barth and Mansouri, 2021) as well as the documents that managers are briefed on, there is likely a spill-over effect into verbal communication. We provide a detailed analysis on this prediction in the first-stage regression below. If the regulation indeed proved successful, managers, once adapted to a plain-language culture, would be expected to avoid such jargon, even in verbal statements, after the Plain Writing Act was signed in October 2010.

In the first stage regression, we extract plausibly exogenous variation in $\text{Jargon}_{i,t}$ using the Plain Writing Act as an instrument. More precisely, we instrument for $\text{Jargon}_{i,t}$ with a dummy variable that equals 1 after the Plain Writing Act was signed in October 2010 and zero otherwise, and run the following first stage regression:

$$\text{Jargon}_{i,t} = \alpha_i + \beta \times \text{Post Plain Writing Act}_t + \gamma' \mathbf{X_{i,t}} + \epsilon_{i,t}, \tag{10}$$

[7]While the SEC has advocated for plain English in financial disclosures for many years, including through its 1998 "Plain English Handbook," legally binding guidelines were only enacted once in 2010.

with firm fixed effects α_i and $\mathbf{X_{i,t}}$ containing control variables as presented in Section 2. If the Plain Writing Act was 'successful' in reducing managers' use of financial jargon after the Act, we would expect a negative coefficient for β in this first-stage regression.

In the second stage, we use the exogenous variation in jargon to investigate the variation in information asymmetry post conference calls, and estimate the following regression:

$$Y_{i,t} = \alpha_i + \beta \times \text{Jargon}_{i,t} + \gamma' \mathbf{X_{i,t}} + \epsilon_{i,t}. \tag{11}$$

$Y_{i,t}$ is the *Abnormal Turnover*$_{i,t}$ and the *Bid-Ask-Spread*$_{i,t}$ as described in Subsection 2.1. *Jargon*$_{i,t}$ measures the usage of financial jargon in the management's responses to analysts' questions in the Q&A of the corresponding conference call. We again add the full vector controls $\mathbf{X_{i,t}}$, saturate the model with firm fixed effects α_i, and account for autocorrelation in the errors by clustering at the firm level.

[**Table 4 about here**]

[**Table 5 about here**]

Results of the second-stage regression are shown in Table 4 for the different abnormal turnover measures and in Table 5 for the Bid-Ask Spread measure. In line with the panel regressions, we find a positive and highly significant effect of the instrumented jargon, suggesting that jargon is perceived as precise information. In Table 5, we present results for the Bid-Ask Spread measure over a 3, 5, 10, and 30 days window following the earnings call and find, just as in the panel results, significantly smaller bid-ask spreads following calls with high jargon in the short term, but no effect in the long run. Thus, the lack of factual language hinders the flow of information, resulting in a smaller reduction in information asymmetries following an earnings conference call. As expected, since the lack of precise language neither withholds information nor provides incorrect information but merely slows down the flow of information, it has no long-term effect.

First stage regression While the primary goal of this paper is to investigate the causal effect of jargon on market efficiency using the IV approach, a closer look at the first-stage regression not only helps validate the relevance of our instrument but also provides interesting insights into how the Language Act influenced communication practices.

We show results of the first stage regression in Table 6. In columns (1) and (2), we instrument the amount of jargon in response to finance-related questions, and find that the instrument is quite strong, with an F-statistic of 44.35 in column (1). The results, however, do not only show the relevance of the instrument, but also the direction of the point estimate provides interesting insights. In particular, we find that managers significantly avoid using jargon after the Plain Writing Act became a federal law.While the goal of the Plain Writing Act was mainly to reduce the complexity of firm disclosures, the reduction in jargon was just one aspect among many. More precisely, the target of the Act was the orderly and clear presentation of complex information. While jargon might be understood as factual complexity, information transmission might also suffer from linguistic complexity. A commonly used measure of linguistic complexity is the Gunning (1952) Fog index, which indicates how easy or difficult a text is to understand in a linguistic sense.[8] We repeat our first stage regression for the Fog index measured for the management responses in the conference call of firm i at time t in columns (3) and (4) of Table 6. Interestingly, we do not observe a reduction in linguistic complexity following the Plain Writing Act. Thus, while the Plain Writing Act reduced jargon as a means of factual complexity, it did not improve the clarity of presentation in the linguistic sense.

[Table 6 about here]

We investigate the first stage results further and plot in Figure 2 the finance jargon over time for our sample of US firms, as well as for a control sample of firms that are not included

[8] The Fog index is a function of the number of words per sentence (length of a sentence) and the share of complex words (words with more than two syllables) relative to total words, $Fog = 0.4 \times \left(\frac{\text{Total words}}{\text{Total sentences}} + \frac{\text{Complex words}}{\text{Total words}}\right)$, and has been commonly used to proxy for the linguistic complexity of a text.

in Compustat.[9] Interestingly, we observe a jump in the usage of jargon following the Plain Writing Act for both sets of firms. However, the trends of these two sets of firms diverge a lot thereafter. Non-US firms are not so heavily affected by the regulation and thus, remain at a high level of jargon, while US firms strongly decrease the amount of jargon in conference calls.

To formally test this pattern, we estimate a difference-in-differences regression comparing the use of jargon in US versus non-US firms before and after the enactment of the Plain Writing Act. The results, presented in Table 7, confirm the visual evidence and indicate a statistically significant reduction in jargon usage among US firms following the Act's implementation, relative to their non-US counterparts.

[**Figure 2 about here**]

[**Table 7 about here**]

Jargon, as measured in this paper, is a ratio that relates finance terminology to total words. Naturally, one might be interested in whether the observed change in the ratio is driven by the actual use of financial terminology (numerator) or the overall length of answers (denominator). We plot, in Figure 3, the yearly average number of words in management responses. We observe that the total length of answers (red dots) did not change significantly. The opposite is true for the total number of words used in responses to questions that contain financial jargon (blue dots), i.e., those questions that are most likely to provoke an answer that requires precise financial terminology. In these responses, the number of words is increasing after the plain language act. Thus, managers pad precise financial terminology with plain language explanations. Our results suggest that these lengthier explanations leave room for interpretation and ambiguity, thereby retarding the market's ability to effectively consume information.

[**Figure 3 about here**]

[9]While we do observe conference calls for these firms, we do not have any information on the control sample other than firm name and textual measures.

4 Conclusion

Using a large sample of earnings conference call textual data, this study seeks to shed light on the efficient transfer of information using factual language. Earnings calls are an ideal setting for this research, as they allow us to directly study the exchange of information between the demand side (analysts) and the supply side (management) of information.

We start with panel regressions and further exploit plausibly exogenous variation in jargon, using the Plain Writing Act in an instrumental variable approach. Our analysis reveals a positive association between jargon and abnormal turnover around earnings conference calls, and a negative association between jargon and bid-ask spreads. Thus, our results suggest that the use of financial jargon facilitates information flow, thereby leading to the efficient resolution of information asymmetries.

All results are robust to a number of fixed effects as well as language and firm control variables. We also confirm that the results are not driven by distress periods such as the global financial crisis or COVID-19, which could impact the choice of language used during earnings conference calls.

From a policy perspective, these findings underscore concerns about mandated speech legislation. While the goal of such regulations is to enhance transparency and accessibility for the general public, the unintended consequences might prove counterproductive, especially in time-constrained environments where a specialized language is paramount for information dissemination.

Furthermore, the policy stance that (financial) information can be made more accessible through language simplification should be revisited, especially in the context of time-constrained settings or human–machine information exchange. In the setting analyzed by this paper, corporate leaders are legally required to release information in person in a short period of time. This human-produced information is increasingly analyzed by large language models that are equipped with a very large context and linguistic capabilities, yet are vulnerable to ambiguity and imprecision. Taken together, our findings caution that wellintentioned plain-language mandates can erode, rather than enhance, the precision and speed of information transmission that sophisticated participants, and now increasingly machines, require to keep markets efficient.

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Figures and Tables

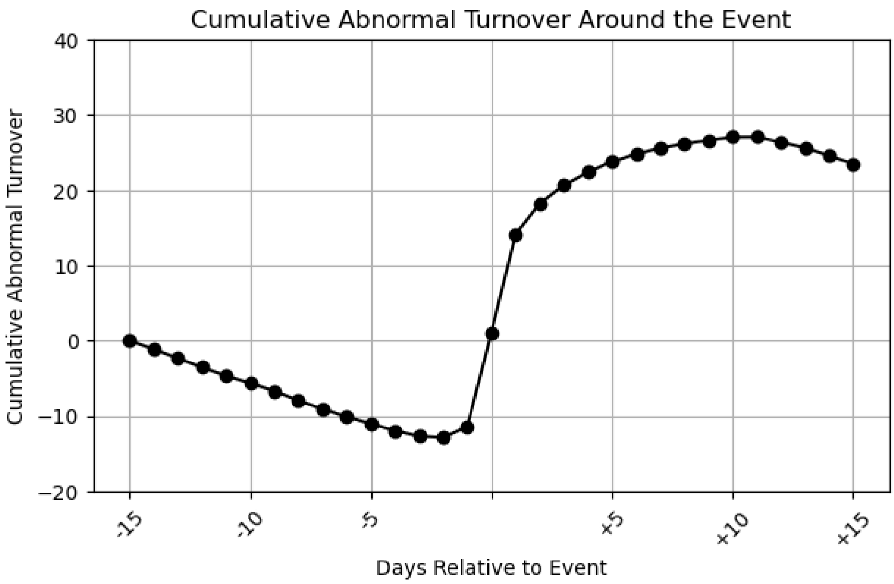

Figure 1: Cumulative abnormal turnover from $t - 15$ to $t + 15$ days after the earnings conference call.

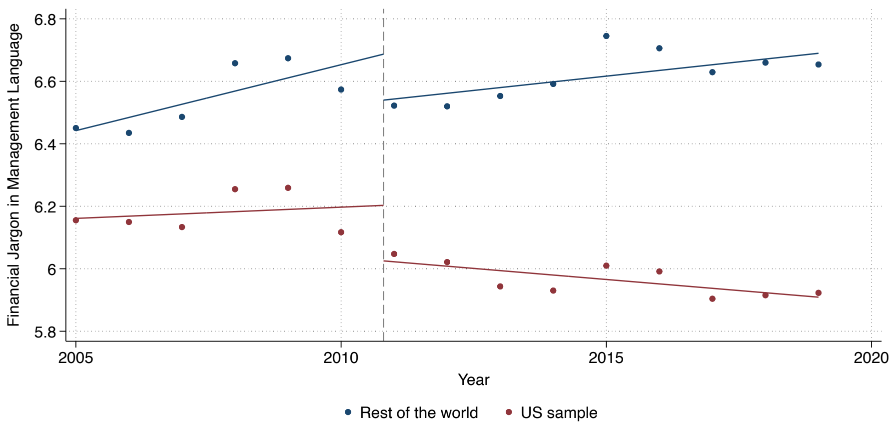

Figure 2: Finance jargon over time. Top: Binned scatter plot showing the presence of financial jargon over time, with trend lines highlighting the pre and post language-act periods. Bottom: Comparing the presence of jargon in non-treated earnings calls (blue) with the treated calls of US firms (red).

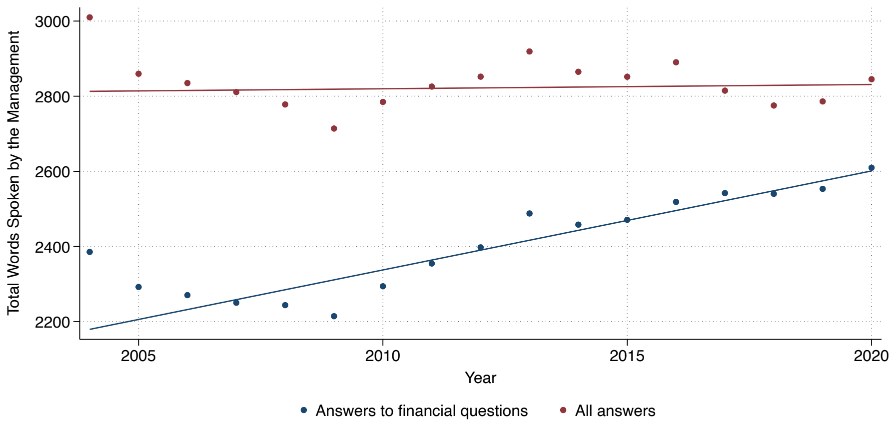

Figure 3: Total words in management responses over time. The blue binned scatter plots the number of words spoken by the management in response to finance-context questions, while the red binned scatter shows the number of words spoken by the management in response to question outside the contextual domain of finance.

Table 1: Descriptive statistics

This table shows descriptive statistics for our firm-quarter level observations. *Jargon* is the amount of financial jargon in replies to the financial questions in a call. *EarnSurp* denotes the decile classification of firms based on earnings surprises, defined as the discrepancy between actual and consensus forecast earnings relative to the share price 5 trading days prior to the disclosure. *Negativity* and *Uncertainty* represent the proportion of negative and uncertain terms relative to the total word count, with the respective lexicons sourced from Loughran and McDonald (2011). *FOG* is the Gunning FOG index of the management answers. $ln(Assets)$ refers to the natural logarithm of total assets. *BTM* is articulated as the ratio of total Common/Ordinary Equity to the market equity value, and Q symbolizes Tobin's Q. $BOG(10-K)$ is a measure of the complexity of annual reports, as developed by Bonsall et al. (2017). Abnormal Turnover$_{i,t}$, ΔAbnormal Turnover$_{i,t}$, CAT$_{i,t,t+1}$, and BA-Spread$_{k\in[3,5,10,30]}$ are our key dependent variable and detailed in Subsection 2.1. All of the dependent variables are winsorized at the 1/99% percentiles.

Variable	Obs.	Mean	Std. Dev.	Min	P10	P50	P90	Max
$Jargon$	126,067	6	1.3	0	4.5	6	7.7	19
$EarnSurp$	126,067	.3	1.8	-5	-1	0	3	5
$Negativity$	126,067	.027	.0078	0	.018	.027	.037	.13
$Uncertainty$	126,067	.016	.0067	0	.0086	.016	.025	.089
FOG	126,067	17	1.6	10	16	17	19	33
$Ln(Assets)$	126,067	7	2	-.17	4.5	7	9.6	15
BTM	126,067	.51	.83	-115	.099	.42	1	41
Q	126,067	2.1	1.8	.2	.99	1.6	3.9	81
$BOG(10-k)$	126,067	88	7.3	54	79	87	97	163
$CAT_{0:1}$	126,067	13	19	-8.3	-.44	6.1	33	115
$\Delta Abnormal\,Turnover$	126,046	14	24	-11	-.59	6.1	38	145
$Abnormal\,Turnover$	126,067	17	28	-8.4	-.56	7.7	45	167
$BA-Spread_3$	125,749	-.15	1.3	-5.8	-1.4	-.043	1.1	3.6
$BA-Spread_5$	125,973	-.16	1.2	-5.5	-1.4	-.06	.98	3.3
$BA-Spread_{10}$	126,044	-.14	1.1	-5.1	-1.3	-.059	.95	3.3
$BA-Spread_{30}$	126,060	-.078	1.1	-4.4	-1.1	-.042	.94	3.6

Table 2: Financial jargon and abnormal turnover - Panel Regression

This table shows results of an OLS regression using firm and time fixed effects. Column (1) uses Abnormal Turnover$_{i,t}$ as the dependent variable, while column (2) uses ΔAbnormal Turnover$_{i,t}$. In column (3), CAT$_{i,t,t+1}$ serves as the dependent variable. *Jargon* is the amount of financial jargon in replies to the financial questions in a call. *EarnSurp* denotes the decile classification of firms based on earnings surprises, defined as the discrepancy between actual and consensus forecast earnings relative to the share price 5 trading days prior to the disclosure. *Negativity* and *Uncertainty* represent the proportion of negative and uncertain terms relative to the total word count, with the respective lexicons sourced from Loughran and McDonald (2011). *FOG* is the Gunning FOG index of the management answers. $ln(Assets)$ refers to the natural logarithm of total assets. *BTM* is articulated as the ratio of total Common/Ordinary Equity to the market equity value, and Q symbolizes Tobin's Q. $BOG(10-K)$ is a measure of the complexity of annual reports, as developed by Bonsall et al. (2017). t-statistics are enclosed in parentheses, with standard errors being double clustered at the firm and quarter-year level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	$Abnormal\,Turnover$	$\Delta Abnormal\,Turnover$	$CAT_{0:1}$
	(1)	(2)	(3)
$Jargon$	0.175*	0.151*	0.130**
	(1.93)	(1.90)	(2.12)
$EarnSurp$	-0.257***	-0.286***	-0.187***
	(-4.66)	(-5.81)	(-4.44)
$Negativity$	133.143***	126.141***	92.455***
	(9.48)	(10.10)	(9.57)
$Uncertainty$	21.569	15.311	12.414
	(1.61)	(1.34)	(1.28)
FOG	-0.057	-0.071	-0.058
	(-0.89)	(-1.33)	(-1.33)
$Ln(Assets)$	2.905***	2.464***	2.281***
	(5.64)	(5.64)	(6.26)
BTM	-0.501**	-0.385**	-0.376**
	(-2.22)	(-2.22)	(-2.31)
Q	1.156***	0.952***	0.814***
	(5.82)	(5.92)	(6.02)
$BOG(10-k)$	0.025	0.016	0.013
	(0.69)	(0.54)	(0.50)
Observations	126067	126046	126067
R^2	0.363	0.302	0.365
FE	Firm,Quarter	Firm,Quarter	Firm,Quarter

Table 3: Financial jargon and Bid-Ask-Spreads - Panel Regression
This table shows results of an OLS regression using firm and time fixed effects. The dependent variable is the change in the bid-ask spread over 3, 5, 10, and 30 days following the earnings call of firm i on day t. $Jargon$ is the amount of financial jargon in replies to the financial questions in a call. $EarnSurp$ denotes the decile classification of firms based on earnings surprises, defined as the discrepancy between actual and consensus forecast earnings relative to the share price 5 trading days prior to the disclosure. $Negativity$ and $Uncertainty$ represent the proportion of negative and uncertain terms relative to the total word count, with the respective lexicons sourced from Loughran and McDonald (2011). FOG is the Gunning FOG index of the management answers. $ln(Assets)$ refers to the natural logarithm of total assets. BTM is articulated as the ratio of total Common/Ordinary Equity to the market equity value, and Q symbolizes Tobin's Q. $BOG(10-K)$ is a measure of the complexity of annual reports, as developed by Bonsall et al. (2017). t-statistics are enclosed in parentheses, with standard errors being double clustered at the firm and quarter-year level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	$BA-Spread_3$	$BA-Spread_5$	$BA-Spread_{10}$	$BA-Spread_{30}$
	(1)	(2)	(3)	(4)
$Jargon$	-0.008**	-0.011***	-0.008*	-0.002
	(-2.10)	(-3.39)	(-1.97)	(-0.48)
$EarnSurp$	0.001	-0.003	-0.004*	-0.006***
	(0.32)	(-1.26)	(-1.70)	(-3.06)
$Negativity$	-2.787***	-1.713***	-1.478***	-1.171**
	(-5.17)	(-3.17)	(-2.86)	(-2.45)
$Uncertainty$	0.796	0.927	0.978	0.881
	(1.01)	(1.58)	(1.35)	(1.25)
FOG	-0.002	-0.002	-0.003	0.000
	(-0.91)	(-0.86)	(-1.21)	(0.04)
$Ln(Assets)$	0.236***	0.199***	0.152***	0.069***
	(12.36)	(10.79)	(9.85)	(5.94)
BTM	-0.038*	-0.034*	-0.026	-0.033**
	(-1.77)	(-1.76)	(-1.56)	(-2.03)
Q	0.033***	0.027***	0.017***	-0.002
	(4.61)	(3.75)	(3.22)	(-0.42)
$BOG(10-k)$	-0.007***	-0.005***	-0.004***	-0.001
	(-4.55)	(-3.10)	(-2.79)	(-0.78)
Observations	126142	126369	126441	126458
R^2	0.230	0.198	0.154	0.089
FE	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter

Table 4: Financial jargon and abnormal turnover: IV estimation

This table shows the second stage regression specified in Equation 11. Column (1) uses Abnormal Turnover$_{i,t}$ as the dependent variable, while column (2) uses ΔAbnormal Turnover$_{i,t}$. In column (3), CAT$_{i,t,t+1}$ serves as the dependent variable. Jargon represents the estimates from the first-stage regression in column (2) of Table 6. *EarnSurp* denotes the decile classification of firms based on earnings surprises, defined as the discrepancy between actual and consensus forecast earnings relative to the share price 5 trading days prior to the disclosure. $Negativity$ and $Uncertainty$ represent the proportion of negative and uncertain terms relative to the total word count, with the respective lexicons sourced from Loughran and McDonald (2011). FOG is the Gunning FOG index of the management answers. $ln(Assets)$ refers to the natural logarithm of total assets. BTM is articulated as the ratio of total Common/Ordinary Equity to the market equity value, and Q symbolizes Tobin's Q. $BOG(10-K)$ is a measure of the complexity of annual reports, as developed by Bonsall et al. (2017). t-statistics are enclosed in parentheses, with standard errors being double clustered at the firm and quarter-year level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	$Abnormal\,Turnover$	$\Delta Abnormal\,Turnover$	$CAT_{0:1}$
	(1)	(2)	(3)
$Jargon$	8.607*	9.011**	5.906*
	(1.94)	(2.62)	(1.85)
$EarnSurp$	-0.256***	-0.284***	-0.187***
	(-4.45)	(-5.35)	(-4.27)
$Negativity$	52.204	41.305	33.479
	(1.22)	(1.23)	(1.09)
$Uncertainty$	62.108**	58.054***	38.214*
	(2.26)	(2.71)	(1.93)
FOG	-0.602**	-0.646***	-0.440**
	(-2.12)	(-2.93)	(-2.20)
$Ln(Assets)$	3.578***	2.998***	2.872***
	(5.65)	(5.83)	(6.33)
BTM	-0.816***	-0.695***	-0.615***
	(-2.70)	(-2.86)	(-2.71)
Q	1.430***	1.216***	1.028***
	(5.52)	(5.84)	(5.71)
$BOG(10-k)$	-0.028	-0.039	-0.009
	(-0.76)	(-1.33)	(-0.38)
Observations	126067	126046	126067
FE	Firm	Firm	Firm

Table 5: Financial jargon and Bid-Ask Spreads: IV estimation

This table shows the second stage regression specified in Equation 11. The dependent variable is the change in the bid-ask spread over 3, 5, 10, and 30 days following the earnings call of firm i on day t. Jargon represents the estimates from the first-stage regression in column (2) of Table 6. $EarnSurp$ denotes the decile classification of firms based on earnings surprises, defined as the discrepancy between actual and consensus forecast earnings relative to the share price 5 trading days prior to the disclosure. $Negativity$ and $Uncertainty$ represent the proportion of negative and uncertain terms relative to the total word count, with the respective lexicons sourced from Loughran and McDonald (2011). FOG is the Gunning FOG index of the management answers. $ln(Assets)$ refers to the natural logarithm of total assets. BTM is articulated as the ratio of total Common/Ordinary Equity to the market equity value, and Q symbolizes Tobin's Q. $BOG(10-K)$ is a measure of the complexity of annual reports, as developed by Bonsall et al. (2017). t-statistics are enclosed in parentheses, with standard errors being double clustered at the firm and quarter-year level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	$BA-Spread_3$	$BA-Spread_5$	$BA-Spread_{10}$	$BA-Spread_{30}$
	(1)	(2)	(3)	(4)
$Jargon$	-0.815**	-0.707*	-0.636	-0.286
	(-2.08)	(-1.89)	(-1.58)	(-0.82)
$EarnSurp$	0.002	-0.003	-0.004	-0.006***
	(0.48)	(-1.04)	(-1.44)	(-3.07)
$Negativity$	2.195	2.715	2.774	0.515
	(0.63)	(0.78)	(0.73)	(0.15)
$Uncertainty$	-4.025*	-3.077	-2.535	-0.943
	(-1.97)	(-1.65)	(-1.29)	(-0.52)
FOG	0.044*	0.038	0.034	0.016
	(1.72)	(1.54)	(1.30)	(0.71)
$Ln(Assets)$	0.197***	0.168***	0.122***	0.080**
	(4.73)	(4.10)	(2.69)	(2.25)
BTM	-0.048*	-0.041*	-0.031	-0.044**
	(-1.80)	(-1.72)	(-1.41)	(-2.12)
Q	0.037***	0.029**	0.018*	0.005
	(3.46)	(2.66)	(1.72)	(0.54)
$BOG(10-k)$	-0.004	-0.002	-0.002	0.001
	(-1.32)	(-0.72)	(-0.60)	(0.63)
Observations	126142	126369	126441	126458
FE	Firm	Firm	Firm	Firm

Table 6: First-stage IV regression

This table shows the first stage regression specified in Equation 10. The dependent variable is *Jargon*, that is the amount of financial jargon in replies to the financial questions in a call. *LanguageACT* is a dummy variable set to one post the enactment of the Plain Writing Act in October 2010. *EarnSurp* denotes the decile classification of firms based on earnings surprises, defined as the discrepancy between actual and consensus forecast earnings relative to the share price 5 trading days prior to the disclosure. *Negativity* and *Uncertainty* represent the proportion of negative and uncertain terms relative to the total word count, with the respective lexicons sourced from Loughran and McDonald (2011). *FOG* is the Gunning FOG index of the management answers. *ln*(*Assets*) refers to the natural logarithm of total assets. *BTM* is articulated as the ratio of total Common/Ordinary Equity to the market equity value, and *Q* symbolizes Tobin's Q. $BOG(10-K)$ is a measure of the complexity of annual reports, as developed by Bonsall et al. (2017). t-statistics are enclosed in parentheses, with standard errors being double clustered at the firm and quarter-year level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	Jargon	
	(1)	(2)
LanguageACT	-0.204***	-0.163***
	(-9.81)	(-6.81)
EarnSurp	-0.009***	-0.001
	(-3.34)	(-0.37)
Negativity	17.619***	9.153***
	(16.80)	(9.89)
Uncertainty	-9.424***	-4.881***
	(-9.58)	(-6.96)
FOG	0.094***	0.064***
	(18.79)	(17.87)
Ln(*Assets*)	0.023***	-0.067***
	(3.76)	(-4.48)
BTM	0.039***	0.024**
	(3.47)	(2.33)
Q	-0.040***	-0.019***
	(-6.26)	(-4.23)
$BOG(10-k)$	-0.002	0.002
	(-1.15)	(1.41)
Observations	129630	130466
R^2	0.049	0.021
FE	Industry	Firm

Table 7: Financial jargon US vs. Non-US Sample
This table shows results of an OLS regression using firm and time fixed effects for an international sample. The dependent variable is *Jargon*, that is the amount of financial jargon in replies to the financial questions in a call. *Treated* observations are earnings calls belonging to the sample of US Compustat. *LanguageACT* is a dummy variable set to one post the enactment of the Plain Writing Act in October 2010. *Negativity* and *Uncertainty* represent the proportion of negative and uncertain terms relative to the total word count, with the respective lexicons sourced from Loughran and McDonald (2011). *FOG* is the Gunning FOG index of the management answers. t-statistics are enclosed in parentheses, with standard errors being double clustered at the firm and quarter-year level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	Jargon			
	(1)	(2)	(3)	(4)
$Treated \times LanguageACT$	-0.092***	-0.087***	-0.092***	-0.087***
	(-4.55)	(-4.34)	(-4.55)	(-4.33)
LanguageACT	-0.109***	-0.104***	-0.090	-0.090
	(-4.06)	(-4.05)	(-1.17)	(-1.20)
Treated	0.098***	0.117***	0.098***	0.115***
	(3.53)	(4.28)	(3.55)	(4.23)
Negativity		6.510***		5.944***
		(9.92)		(10.28)
Uncertainty		-3.459***		-3.617***
		(-7.75)		(-8.30)
FOG		0.070***		0.070***
		(21.41)		(21.17)
Observations	248494	248494	248494	248494
R^2	0.523	0.529	0.525	0.531
FE	Firm	Firm	Firm,Quarter	Firm,Quarter

Table 8: Financial jargon and abnormal turnover excluding times of market distress - Panel
table reports OLS regression results with firm and time fixed effects, excluding observations from the 2008–2009 financial crisis. Column (1) uses Abnormal Turnover$_{i,t}$ as the dependent variable, while Columns (2) and (3) use ΔAbnormal Turnover$_{i,t}$ and CAT$_{i,t,t+1}$, respectively, as the dependent variables. The dependent variable in Column (4) is the change in the bid–ask spread over the five days following firm i's earnings call on day t. $Jargon$ is the amount of financial jargon in replies to the financial questions in a call. $EarnSurp$ denotes the decile classification of firms based on earnings surprises, defined as the discrepancy between actual and consensus forecast earnings relative to the share price 5 trading days prior to the disclosure. $Negativity$ and $Uncertainty$ represent the proportion of negative and uncertain terms relative to the total word count, with the respective lexicons sourced from Loughran and McDonald (2011). FOG is the Gunning FOG index of the management answers. $ln(Assets)$ refers to the natural logarithm of total assets. BTM is articulated as the ratio of total Common/Ordinary Equity to the market equity value, and Q symbolizes Tobin's Q. $BOG(10-K)$ is a measure of the complexity of annual reports, as developed by Bonsall et al. (2017). t-statistics are enclosed in parentheses, with standard errors being double clustered at the firm and quarter-year level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	$Abnormal\,Turnover$	$\Delta Abnormal\,Turnover$	$CAT_{0:1}$	$BA-Spread_5$
	(1)	(2)	(3)	(4)
$Jargon$	0.191*	0.169*	0.152**	-0.008**
	(1.87)	(1.88)	(2.21)	(-2.36)
$EarnSurp$	-0.297***	-0.323***	-0.218***	-0.005**
	(-5.54)	(-6.73)	(-5.32)	(-2.01)
$Negativity$	137.536***	131.395***	95.067***	-1.475***
	(9.01)	(10.08)	(9.17)	(-2.79)
$Uncertainty$	12.235	8.980	7.141	-0.061
	(0.85)	(0.74)	(0.67)	(-0.10)
FOG	-0.078	-0.086	-0.071	-0.003
	(-1.10)	(-1.45)	(-1.47)	(-0.96)
$Ln(Assets)$	2.615***	2.192***	2.090***	0.181***
	(4.87)	(4.80)	(5.45)	(11.24)
BTM	-0.684**	-0.462*	-0.546**	-0.023
	(-2.13)	(-1.72)	(-2.36)	(-1.31)
Q	1.028***	0.835***	0.715***	0.021***
	(5.16)	(5.27)	(5.28)	(3.18)
$BOG(10-k)$	0.041	0.031	0.027	-0.004***
	(1.14)	(1.02)	(1.04)	(-2.72)
Observations	107890	107870	107890	108213
FE	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter

Appendix

A Stop words in the Harvey finance glossary

Table 1: List of stop-words in the Harvey finance glossary

a	Fifth letter of a Nasdaq stock symbol specifying Class A shares.
ago	The three-character ISO 3166 country code for ANGOLA.
all	The ISO 4217 currency code for Albanian Lek.
am	The two-character ISO 3166 country code for ARMENIA.
an	The two-character ISO 3166 country code for NETHERLANDS ANTILLES.
and	The three-character ISO 3166 country code for ANDORRA.
are	The three-character ISO 3166 country code for UNITED ARAB EMIRATES.
as	The two-character ISO 3166 country code for AMERICAN SAMOA.
at	The two-character ISO 3166 country code for AUSTRIA.
be	The two-character ISO 3166 country code for BELGIUM.
by	The two-character ISO 3166 country code for BELARUS.
can	The three-character ISO 3166 country code for CANADA.
clear	To settle a trade by the seller delivering securities and the buyer delivering funds in the proper form.
close	The close is the period at the end of the trading session. Sometimes used to refer to closing price.
d	Fifth letter of a NASDAQ stock symbol specifying that it is a new issue, such as the result of a reverse split.
do	The two-character ISO 3166 country code for DOMINICAN REPUBLIC.

i	Fifth letter of a Nasdaq stock symbol specifying that it is the third preferred bond of the company.
in	The two-character ISO 3166 country code for INDIA.
is	The two-character ISO 3166 country code for ICELAND.
it	The two-character ISO 3166 country code for ITALY.
its	Intermarket Trading System (ITS)
m	Fifth letter of a NASDAQ stock symbol specifying that the issue is the company's fourth class of preferred shares.
ma	The two-character ISO 3166 country code for MOROCCO.
me	The two-character ISO 3166 country code for MONTENEGRO.
mean	The expected value of a random variable. Arithmetic average of a sample.
my	The two-character ISO 3166 country code for MALAYSIA.
no	The two-character ISO 3166 country code for NORWAY.
nor	The three-character ISO 3166 country code for NORWAY.
now	Negotiable Order of Withdrawal
o	Fifth letter of a Nasdaq stock symbol specifying that it is the company's second class of preferred shares.
on	Used in the context of general equities. Conjunction that denotes trade execution /indication, usually during a pre-opening look. "Looks 6 on 6000 shares at opening."
or	Operations research: A method of decision-making that uses analytical tactics such as mathematical models and statistical data to reduce risk and assist in answering complex business problems.
out	Used in the context of general equities. (1) No longer obligated to an order, as it has already been canceled: (2) advertised on Autex.
re	The two-character ISO 3166 country code for REUNION.

right	Privilege granted shareholders of a corporation to subscribe to shares of a new issue of common stock before it is offered to the public. Such a right, which normally has a life of two to four weeks, is freely transferable and entitles the holder to buy the new common stock below the public offering price.
run	A run consists of a series of bid and offer quotes for different securities or maturities. Dealers give and ask for runs from each other.
s	Fifth letter of a Nasdaq stock symbol specifying a beneficial interest.
so	The two-character ISO 3166 country code for SOMALIA.
t	Fifth letter of a Nasdaq stock symbol indicating that the stock has warrants or rights.
take	(1) To agree to buy. A dealer or customer who agrees to buy at another dealer's offered price is said to take the offer. (2) Euro bankers speak of taking deposits rather than buying money.
top	The ISO 4217 currency code for the Tonga Pa'anga.
us	The two-character ISO 3166 country code for UNITED STATES.
up	Market indication; willingness to go both ways (buy or sell) at the mentioned volume and market. Print; up on the ticker tape, confirming that the trade has been executed.
ve	The two-character ISO 3166 country code for VENEZUELA.
y	Fifth letter of a Nasdaq stock symbol specifying that it is an ADR

Halle Institute for Economic Research –
Member of the Leibniz Association

Kleine Maerkerstrasse 8

D-06108 Halle (Saale), Germany

Postal Adress: P.O. Box 11 03 61

D-06017 Halle (Saale), Germany

Tel +49 345 7753 60

Fax +49 345 7753 820

www.iwh-halle.de

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