

Barth, Andreas; Mansouri, Sasan; Wöbbeking, Fabian

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Information flow and market efficiency – unintended side effects of the Plain Writing Act

Andreas Barth, Sasan Mansouri and Fabian Woebbecking*

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ABSTRACT

This paper investigates the impact of precise language on market efficiency by examining the interplay between regulatory language simplification, as imposed by the Plain Writing Act of 2010, and information asymmetries in financial markets. To causally identify the effect of jargon on market efficiency, we analyze earnings conference call text data and employ the Plain Writing Act of 2010 in an instrumental variable setting. Our findings suggest that the Act's promotion of plain language usage results in a reduction of financial jargon. This reduction in jargon is associated with a decrease in market efficiency, implying that the Act may inadvertently hinder information flow and impair the market's price setting mechanism.

Keywords: market efficiency, information asymmetry, earnings conference calls, plain writing act, textual analysis

*Barth is with Goethe University Frankfurt, Saarland University and IWH – Leibniz Institute for Economic Research Halle. Mansouri is with University of Groningen and IWH – Leibniz Institute for Economic Research Halle. Woebbecking is with IWH – Leibniz Institute for Economic Research Halle and Martin Luther University Halle-Wittenberg.

✉: barth@finance.uni-frankfurt.de

✉: S.mansouri@rug.nl

✉: fabian.woebbecking@iwh-halle.de

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 and ultimately successful transfer of information is key in economics. The Plain Writing Act of 2010 particular highlights its relevance even for policymakers, as this law was designed to promote clear and understandable communication, making information more accessible and comprehensible to the general public. The SEC hereby identified “stilted jargon and complex constructions” in its ‘Plain English Handbook’ as the main issue that prevents an efficient flow of information. It is, however, not clear to date whether jargon hinders the flow of information by adding unnecessary complexity in all circumstances, or whether jargon allows in certain situations to access information at a much higher rate and precision and thus, reduces information asymmetries.

We answer this question by investigating whether financial jargon increases market efficiency. We focus on a very frequently-used firm disclosure environment, quarterly earnings conference calls, where financial analysts can directly approach firm managers in a question and answer setting. Importantly, all agents in these call usually have a finance background and speak finance language. Identifying the causal effect of jargon on the efficient transfer of information, however, is empirically challenging, as the usage of jargon might be not random. For example, a quarter with bad earnings might need more explanation by the management and thus, might come with more factual terminology. At the same time, low earnings might make the price discovery mechanism more challenging for investors. We overcome this challenge by employing an instrumental variable approach, where we use the signing of the Plain

English Act as instrument for financial jargon. We first show that the instrument is highly relevant: managers strongly reduce the usage of jargon in conference calls after the Plain Language Act. Moreover, the passage of the Plain Language Act is fairly exogenous to market efficiency, as it initially targeted policy communication and impacted firms only via SEC disclosure regulation. Using exogenous variation of financial jargon, we show that more jargon leads to a higher abnormal turnover, indicating a better information environment and less information asymmetries.¹ Thus, it turns out that regulation shut down financial jargon despite the fact that it improved the information environment in earnings conference calls. Interestingly, we do not observe a decrease in linguistic complexity as measured by the Gunning [1952] Fog index following the Plain Writing Act. We thus uncover an unintended consequence of the Plain Language Act regulation.

The concept of market efficiency, rooted in the Efficient Market Hypothesis (EMH), has been a foundational pillar in finance and economics literature. Formally proposed by Fama [1965, 1970], the EMH contends that security prices instantaneously incorporate and reflect all available information. The central tenet of the EMH can be succinctly represented as:

$$P_t = E [P_t | \Phi_{t-1} + \phi_t], \quad (1)$$

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]. This representation underscores the premise that asset prices in an efficient market are a function of the totality of information up to that point.

The dynamic of information assimilation in financial markets, especially how new information is integrated, has profound implications. Events such as corporate earnings announcements, policy changes, or macroeconomic data releases act as catalysts, contributing information ϕ_t to the market. The efficiency with which markets adjust to this novel infor-

¹Abnormal turnover has been frequently used in both theoretical and empirical papers as a measure of information asymmetries in the market, see Admati and Pfleiderer [1988], Foster and Viswanathan [1990], or Chae [2005]

mation has been the subject of extensive scientific scrutiny. We add to this literature by analyzing the information frictions that arise from the potential trade-off between precise yet complex language.

The trade-off between precision and complexity is a very common problem in linguistics. Jargon as a specialized language of a professional that is well understood in-group but meaningless out-group is a classical example. For instance, a patient might have a hard time understanding a doctor who uses a high degree of medical jargon. However, being versed in the contextual vocabulary allows the recipient to access information at a much higher rate and precision. In finance, too, financial jargon could retard the flow of information by adding complexity, conversely, the absence of financial jargon could indicate the unwillingness or inability to disclose precise information. We add to this literature focusing on the precise and efficient transfer of information, as well as the literature on linguistic complexity.

It has been established that managers steer information in an opportunistic manner. For example, Mayew [2008], Cohen, Lou, and Malloy [2020] show that managers choose more favorable analysts to ask questions on the call. Likewise, managers obscure inconvenient information or a poor performance by using a more complex language in written disclosures [Li, 2008, Bloomfield, 2008, Loughran and McDonald, 2014, Bonsall, Leone, Miller, and Rennekamp, 2017] or by avoiding factual, quantitative statements [Zhou, 2018].²

The very extreme form of reducing the informativeness of a response is to openly refuse an answers [Hollander, Pronk, and Roelofsen, 2010, Gow, Larcker, and Zakolyukina, 2021, Barth, Mansouri, and Woebbeking, 2023]. Hollander et al. [2010], for example, manually classify answers where managers withhold information, and show that markets interpret this silence negatively. We add to this literature by exploring the effect of financial jargon on financial markets. While jargon is in its nature complex, it remains an open question if its use is perceived as *obfuscation* or *information* by finance professionals. Moreover, we present

²There is an ongoing discussion on the measure of linguistic complexity: while Li [2008] and Bloomfield [2008] use the popular Gunning [1952] Fog Index, this measure has been challenged by Loughran and McDonald [2014] as being “poorly specified in financial applications.”

a novel identification strategy that allows for a causal interpretation for the effect of financial jargon on information asymmetries on financial markets.

2 Identification and empirical setup

Establishing the causal relationship between the use of financial jargon in earnings conference calls and information asymmetries on financial markets poses an empirical challenge, primarily because plausible exogenous variation in the usage of financial jargon is rare. 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. However, the use of financial jargon by managers in conference calls is unlikely to be 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]. Thus, although listeners to conference calls usually have a finance background and should therefore certainly understand financial language, a simple OLS regression might indicate that financial jargon in conference calls has detrimental effects on the information flow.

We solve this issue by employing an instrumental variable (IV) approach, where we instrument the usage of jargon with the Plain Writing Act of 2010. The Plain Writing Act aimed to promote clear and concise communication, making information more understandable and accessible to the public. While the Plain Writing Act targeted essentially government documents, listed companies interacting with the Security and Exchange Commission (SEC) were also affected as they had to adapt to the SEC's plain language requirements.³ While the SEC has been advocating for plain English in financial disclosures for quite some time and issued a "Plain English Handbook" in 1998, the guidelines legally enacted only from

³Moreover, while the Act was referring to written statements, we observe that the law spilled over to verbal communication - an observation that is crucial for our identification.

2010 on. The SEC hereby particularly identified “stilted jargon and complex constructions” in its ‘Plain English Handbook’ as the main issue that prevents an efficient information flow. Hence, if regulation was successful, one might expect that managers avoid the usage of jargon – also in verbal statements once they are trained towards a plain language culture – after the Plain Writing Act was signed in October 2010. Thus, in the first stage regression, we will expect to find a decreased usage of jargon in conference calls after October 2010, which we summarize in the following hypothesis:

Hypothesis 1. *The use of financial jargon decreased after the enactment of the Plain Writing Act in 2010.*

Importantly for the identification of the effect of jargon on market efficiency, the Plain Writing Act is not related to firms’ performance in 2010 and thereafter, which ensures the exogeneity of the instrument.

2.1 Trading volume and information asymmetry

Trading volume⁴ plays an important role in financial markets. 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. Trading volume can be broadly categorized into two types: informed trading and liquidity (or uninformed) trading and has been extensively studied in the literature.⁵

Theoretical models proposed by Admati and Pfleiderer [1988] and Foster and Viswanathan [1990] suggest that if liquidity traders can choose their trading timings, 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

⁴In this paper, trading volume refers to the number of shares traded in a given stock during one trading day.

⁵See e.g. Easley and O’Hara [1992], Easley, Engle, O’Hara, and Wu [2008] and references therein.

rectified. As a consequence, trading volume may see a decline before announcements and a subsequent rise afterward.

Chae [2005] provide empirical evidence that corresponds to the aforementioned theory. In their paper, they show that “cumulative trading volume decreases inversely to information asymmetry prior to scheduled announcements [such as earnings conference calls], while the opposite relation holds for volume after the announcement.”

In order to empirically test the link between jargon and market efficiency, we build on the research and variables devised in Chae [2005]. This is, we calculate the turnover of share i at time t as

$$\text{Turnover}_{i,t} = \tau_{i,t} = \frac{\text{Trading Volume}_{i,t}}{\text{Shares Outstanding}_{i,t}}, \quad (2)$$

which is a measure for trading volume relative to the free floating shares of a company. We then define

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

where

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

The cumulative Abnormal Turnover $_{i,t}$ from $t - 15$ days before to $t + 15$ after the call is displayed in Figure 1. In line with the empirical finding is 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. We therefore postulate the following hypothesis.

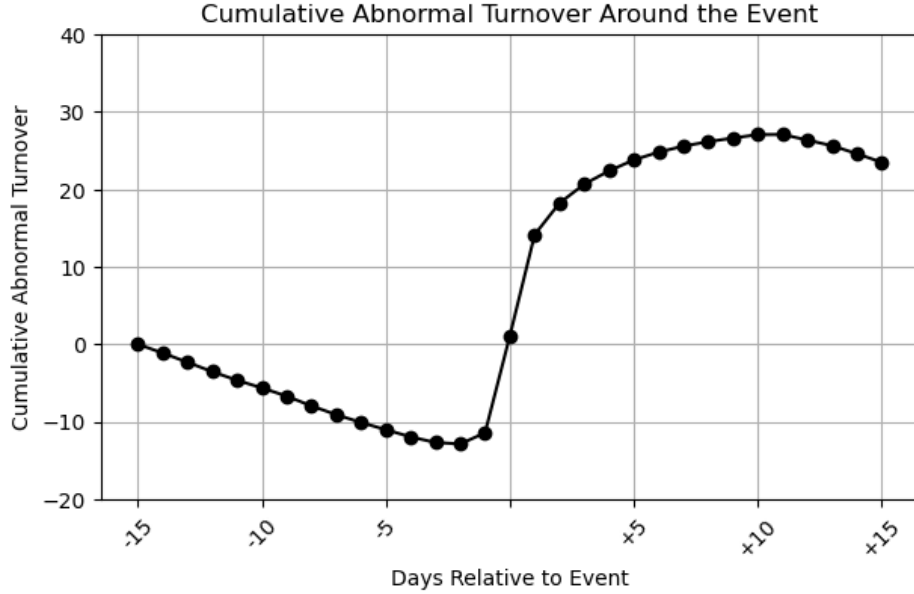


Figure 1: Cumulative abnormal turnover from $t - 15$ to $t + 15$ days after the earnings conference call.

Hypothesis 2. *An increase in the use of financial jargon is associated with a rise in abnormal turnover after the call.*

In order to test Hypothesis 2, we first examine the cumulative Abnormal Turnover $_{i,t}$ during and immediately after the earnings conference call. Secondly, we consider the difference in Abnormal Turnover $_{i,t}$ before and after the call. This latter approach is grounded in the notion that Abnormal Turnover $_{i,t}$ diminishes prior to the call due to increasing information asymmetry. We argue that the use of jargon plays a pivotal role in alleviating these information asymmetries, which should consequently lead to a more pronounced "rebound" effect post-call.

2.2 Data

Our sample comprises of all quarterly earnings conference call transcripts available on Thomson Reuters' 'StreetEvents' held between 2005 and 2019 by US firms, which amounts to 137,144 calls by 5,084 firms.

Earnings conference calls are voluntary disclosures that aim to reduce information asym-

metries among investors [Brown, Hillegeist, and Lo, 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, Hendry, Roberts, and Sanderson, 2012], and by financial analysts, who base their earnings forecasts – in part – on information extracted from the call, thereby decreasing the dispersion among their forecasts [Bushee, Matsumoto, and Miller, 2004]. Earnings conference calls usually consist of two parts: they start with a short (prepared) presentation by the management, followed by a Q&A session. We zoom in into the relatively more informative question and answer section within the calls [Matsumoto, Pronk, and Roelofsen, 2011] and aim to measure to what extent the language used in management answers to analysts’ questions can help to remove information asymmetries. Our main focus is on one particular linguistic characteristic within management responses, which is the usage of financial jargon. While the Plain Writing Act aims to reduce jargon, the example above of an information interchange between two doctors (medical experts) clearly suggests that jargon is the most efficient way of transferring information between experts.

2.2.1 Financial jargon

To identify finance jargon, we use the Hypertextual Finance Glossary by Campbell R. Harvey [2016] with more than 8,500 entries,⁶ but remove common English stop-words that could bias our metric.⁷ We then quantify presence of jargon for all management responses in the earnings call by company i in quarter t as the amount of jargon in responses as a fraction of total words used:

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

⁶The glossary is available at <http://people.duke.edu/~charvey/>

⁷For 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 B for a list of all 45 English stop-words in Harvey’s finance glossary.

We differentiate whether the answer provided was given to a question with or without finance terminology and calculate a Jargon for responses to finance-related questions ($Jargon_{Fin}$) and a Jargon for all responses in the conference call ($Jargon_{All}$).

2.2.2 Additional controls

To isolate the effect of the 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, *Negativity*, as the ratio of uncertain words to total words.⁸

We collect additional information for firm i at time t , as for example analyst data from IBES 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, Wagner, and Zeckhauser [2016], 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.

2.2.3 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

⁸For both the *Negativity* and *Uncertainty* measures, we employ the word list by Loughran and McDonald [2011].

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: Descriptive statistics

This table shows descriptive statistics for our firm-quarter level observations. $Jargon_{Fin}$ ($Jargon_{All}$) is the amount of financial jargon in replies to the financial (all) questions in a call. $Negativity$ 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]. $EarnSurp$ 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. BTM is articulated as the ratio of total Common/Ordinary Equity to the market equity value. $ln(Assets)$ refers to the natural logarithm of total assets, and Q symbolizes Tobin’s Q. FOG is the Gunning FOG index. Abnormal Turnover $_{i,t}$, Δ Abnormal Turnover $_{i,t}$, and $CAT_{t,t+1}$ are our key dependent variable and detailed in Subsection 2.1. All the Turnover variables are winsorized at the 1/99% percentiles.

Variable	Obs.	Mean	Std. Dev.	Min	P10	P50	P90	Max
$Jargon_{Fin}$	137,144	.06	.013	0	.045	.06	.077	.19
$Jargon_{All}$	137,144	.059	.012	0	.045	.058	.075	.19
$Negativity$	137,144	.027	.0079	0	.018	.027	.037	.13
$EarnSurp$	137,144	.3	1.8	-5	-1	0	3	5
$Uncertainty$	137,144	.016	.0067	0	.0086	.015	.025	.095
$Ln(Assets)$	137,144	7	2	-.17	4.5	7	9.7	15
BTM	137,144	.51	.83	-115	.098	.43	1	41
Q	137,144	2.1	1.8	.2	.99	1.6	3.9	106
FOG	137,144	17	1.6	10	16	17	19	33
$CAT_{0:1}$	132,579	12	19	-8.2	-.48	6	32	113
Δ Abnormal Turnover	132,568	16	26	-11	-.47	6.9	42	155
Abnormal Turnover	132,590	19	30	-7.1	-.29	8.7	49	179

2.3 Empirical methodology

To examine whether financial jargon eases the flow of information in earnings conference calls and thus helps to efficiently resolve information asymmetries, we estimate the following regression:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \times Jargon_{i,t} + \gamma' \mathbf{X}_{i,t} + \epsilon_{i,t}. \quad (5)$$

$Y_{i,t}$ is the Abnormal Turnover $_{i,t}$ as measures for information asymmetry after the conference call of firm i at time t . Jargon $_{i,t}$ measures the usage of financial jargon in the managements' responses to analysts questions in the Q&A of the corresponding conference call. We saturate the model with firm and time fixed effects and account for autocorrelation in the errors by clustering at the firm level. Our main interest is in the coefficient of the Jargon $_{i,t}$ measure. According to Hypothesis 2, we would expect β to be positive.

We instrument for Jargon $_{i,t}$ with a dummy variable that equals 1 after the Plain Writing Act was signed in October 2010 and zero otherwise. Thus, we run the following first stage regression:

$$\text{Jargon}_{i,t} = \alpha_i + \alpha_t + \beta \times \text{Post Plain Writing Act}_t + \gamma' \mathbf{X}_{i,t} + \epsilon_{i,t}. \quad (6)$$

According to Hypothesis 1, we would expect that the Plain Writing Act was 'successful' in reducing managers' use of financial jargon after the Act.

3 Results

3.1 Financial jargon (first stage regression)

We plot in Figure 2 finance jargon over time and observe that there was a strong decrease in the usage of jargon following the Plain Writing Act. The results of the first stage regression in Table 2 conform this observation. In columns (1) and (2), we instrument the amount of jargon in response to finance-related questions, while we use the jargon measure based on all responses in columns (3) and (4). We find that the instrument is quite strong, with an F-statistic varying between 23.45 in column (4) and 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

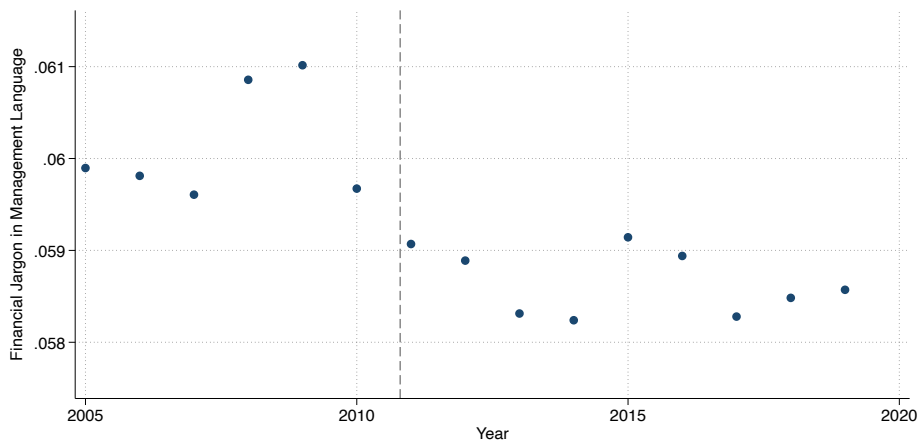


Figure 2: Finance jargon over time

jargon after the Plain Writing Act became a federal law.⁹ Thus, in line with Hypothesis 1, the Plain Writing Act was ‘successful’ in reducing the use of financial jargon.

While the goal of the Plain Writing Act was mainly to increase readability and reduce 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, readability 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.¹⁰ 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 (5) and (6) of Table 2. Interestingly, we do not observe a reduction in linguistic complexity following the Plain Writing Act. Thus, while the Plain Writing Act reduced jargon as means of factual complexity, it did not improve the clarity of presentation. We next investigate whether or

⁹The Plain Writing Act, as its name suggests, does not mandate a specific choice of words in verbal communication. However, our results indicate a pronounced spill-over effect. We posit that the preparation of earnings conference calls, which also encompass a written component, and the corresponding management briefings, result in the observed change of language.

¹⁰The 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.

Table 2: First-stage IV regression

This table shows the first stage regression specified in Equation 6. Columns (1) and (2) feature the amount of jargon in replies to financial inquiries as the dependent variable, while columns (3) and (4) employ the jargon metric derived from all responses. In columns (5) and (6), the Gunning Fog Index serves as the dependent variable. *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]. *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. *BTM* is articulated as the ratio of total Common/Ordinary Equity to the market equity value. $\ln(Assets)$ refers to the natural logarithm of total assets, and Q symbolizes Tobin's Q. t -statistics are enclosed in parentheses, with standard errors being clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	<i>Jargon_{Fin}</i>		<i>Jargon_{All}</i>		<i>FOG</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>LanguageACT</i>	-0.001*** (-6.83)	-0.001*** (-6.32)	-0.001*** (-5.18)	-0.001*** (-4.68)	-0.019 (-0.57)	0.001 (0.03)
<i>Negativity</i>	0.185*** (17.34)	0.094*** (10.30)	0.172*** (16.56)	0.087*** (9.83)	-0.246 (-0.22)	-0.285 (-0.35)
<i>EarnSurp</i>	-0.000*** (-3.30)	-0.000 (-0.73)	-0.000*** (-3.67)	-0.000 (-1.22)	0.001 (0.36)	-0.007** (-2.48)
<i>Uncertainty</i>	-0.091*** (-9.35)	-0.043*** (-6.31)	-0.099*** (-10.15)	-0.047*** (-7.07)	-3.445** (-2.51)	3.927*** (4.31)
$\ln(Assets)$	0.000*** (3.18)	-0.001*** (-7.07)	0.000*** (5.23)	-0.001*** (-4.84)	0.033*** (3.69)	-0.098*** (-3.92)
<i>BTM</i>	0.000*** (3.52)	0.000** (2.43)	0.000*** (3.49)	0.000** (2.38)	0.002 (0.19)	0.018** (2.14)
Q	-0.000*** (-6.44)	-0.000*** (-5.09)	-0.000*** (-6.01)	-0.000*** (-4.88)	0.022*** (3.72)	-0.021*** (-4.02)
Observations	136245	137144	136245	137144	136245	137144
R^2	0.029	0.012	0.030	0.010	0.002	0.002
FE	Industry	Firm	Industry	Firm	Industry	Firm

not a reduction in jargon – the most precise language among experts – is good or bad in an environment where financial experts discuss financial topics.

3.2 Abnormal turnover

In this section we test Hypothesis 2, namely, whether an increase in the use of financial jargon is associated with a rise in abnormal turnover after the call. Please refer to Subsection 2.1 for the theoretical justification and hypothesis development.

In order to test Hypothesis 2, we first examine the cumulative Abnormal Turnover $_{i,t}$ both during and immediately after the earnings conference call. The results are presented in Table 3. Specifications (1) and (2) use Abnormal Turnover $_{i,t}$ as the dependent variable. In this context, t represents the trading day of the earnings conference call.¹¹ The regression coefficient for the instrumental variable Jargon is both statistically significant and positive. This finding is evident for the use of financial jargon in response to all types of questions; however, it is more pronounced when replying to questions that already contain financial jargon. This indicates that questions with high jargon invite (or request) a more precise answer, further substantiating the claim that jargon serves as an important information transmission vehicle.

In columns (3) and (4), we consider the difference

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

before and after the call. These specifications are grounded in the notion that the abnormal turnover diminishes prior to the call due to information asymmetry. We argue that the use of jargon plays a pivotal role in alleviating these information asymmetries, which should consequently lead to a more pronounced ‘rebound’ effect post-call.¹² As with the previous

¹¹Roughly 35% of earnings conference calls take place after regular trading hours. In such cases, we utilize volume data from the subsequent trading day, hence, the first regular trading day after the arrival of new information.

¹²Please refer to Subsection 2.1 for the theoretical justification.

Table 3: Financial jargon and abnormal turnover

This table shows the second stage regression specified in Equation 5. Columns (1) and (2) use the amount Abnormal Turnover $_{i,t}$ as the dependent variable, while columns (3) and (4) Δ Abnormal Turnover $_{i,t}$. In columns (5) and (6), CAT $_{t,t+1}$ serves as the dependent variable. Jargon $_{Fin}$ and Jargon $_{All}$ are the estimates of the first stage regression in the columns (2) and (4) of the Table 2, respectively. *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]. *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. *BTM* is articulated as the ratio of total Common/Ordinary Equity to the market equity value. $\ln(Assets)$ refers to the natural logarithm of total assets, and Q symbolizes Tobin's Q. t -statistics are enclosed in parentheses, with standard errors being clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	<i>Abnormal Turnover</i>		Δ <i>Abnormal Turnover</i>		<i>CAT</i> $_{0:1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Jargon</i> $_{Fin}$	924.886*** (3.24)		1015.856*** (4.16)		627.344*** (3.40)	
<i>Jargon</i> $_{All}$		1224.320*** (3.17)		1344.182*** (4.00)		830.408*** (3.32)
<i>Negativity</i>	52.098* (1.70)	32.800 (0.89)	35.005 (1.32)	13.879 (0.43)	27.038 (1.36)	13.951 (0.58)
<i>EarnSurp</i>	-0.296*** (-4.96)	-0.279*** (-4.58)	-0.320*** (-5.88)	-0.302*** (-5.39)	-0.164*** (-4.40)	-0.153*** (-3.98)
$\ln(Assets)$	4.307*** (7.54)	4.219*** (7.53)	3.616*** (7.39)	3.518*** (7.25)	2.844*** (7.84)	2.784*** (7.80)
<i>Uncertainty</i>	66.278*** (3.27)	82.530*** (3.36)	64.528*** (3.68)	82.324*** (3.83)	41.749*** (3.18)	52.756*** (3.32)
<i>BTM</i>	-0.978*** (-3.16)	-1.048*** (-3.09)	-0.865*** (-3.25)	-0.941*** (-3.15)	-0.592*** (-2.96)	-0.639*** (-2.91)
Q	1.641*** (8.00)	1.690*** (7.81)	1.358*** (7.85)	1.412*** (7.66)	1.026*** (7.85)	1.059*** (7.66)
Observations	132545	132545	132523	132523	132534	132534
FE	Firm	Firm	Firm	Firm	Firm	Firm

specifications, the results indicate a significant positive association, supporting Hypothesis 2.

Specifications (5) and (6) introduce a minor modification to (1) and (2), wherein we examine the cumulative abnormal turnover $CAT_{t,t+1}$ on the day of as well as one day after the earnings conference call.¹³ This observation is consistent with our prior findings. Further derivatives of the analysis are presented in the robustness Appendix A, including a logged version of abnormal turnover, which produces identical results.

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. To address the concern that our results might be driven by these ‘abnormal’ market periods, we revisit the analysis from Section 3.2, deliberately omitting the periods of heightened market stress. Specifically, we exclude the years 2008–2009 (pertaining to the global financial crisis) and 2019 onward (related to the Covid-19 pandemic). The corresponding results in Table 3 align closely with our main findings, suggesting that the results are not driven by such landmark events.

Considering the empirical evidence presented in this section, we accept the hypothesis (Hypothesis 2) that financial jargon is positively associated with abnormal turnover.

While the instrumental variable approach exploits exogenous variation in jargon introduced by the Plain Writing Act, one potential concern with the approach might be that our instrument picks up a simple trend in finance jargon that goes hand in hand with a trend in market efficiency. While graphical evidence in Figure 2 suggests that there is no time trend in jargon but rather a jump around the time of the Plain Writing Act, we aim to account for a potential time trend in our regression setting. However, as our instrument varies only over time but not in the cross-section, we cannot include time fixed effects in the first stage regression. A common approach to absorb a time trend in a difference in difference setting would be to add in our regression a country-specific trend to the regressors. The results of

¹³The strongest increase in cumulative abnormal turnover is observed near the call date, as shown in Figure 1. Extending the range by a few days does not have a strong effect on the results.

Table 4: Financial jargon and abnormal turnover excluding times of market distress

This table shows the second stage regression specified in Equation 5, excluding the observations during the financial crisis of 2008-2009. Columns (1) and (2) use the amount $\text{Abnormal Turnover}_{i,t}$ as the dependent variable, while columns (3) and (4) $\Delta\text{Abnormal Turnover}_{i,t}$. In columns (5) and (6), $\text{CAT}_{t,t+1}$ serves as the dependent variable. $\text{Jargon}_{\text{Fin}}$ and $\text{Jargon}_{\text{All}}$ are the estimates of the first stage regression in the columns (2) and (4) of the Table 2, respectively. *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]. *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. *BTM* is articulated as the ratio of total Common/Ordinary Equity to the market equity value. $\ln(\text{Assets})$ refers to the natural logarithm of total assets, and Q symbolizes Tobin's Q . t -statistics are enclosed in parentheses, with standard errors being clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	<i>Abnormal Turnover</i>		$\Delta\text{Abnormal Turnover}$		$\text{CAT}_{0:1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Jargon_{Fin}</i>	1728.914*** (3.55)		1763.580*** (4.16)		1135.513*** (3.40)	
<i>Jargon_{All}</i>		2580.288*** (3.11)		2630.279*** (3.36)		1694.733*** (3.06)
<i>Negativity</i>	6.029 (0.13)	-43.758 (-0.65)	-5.747 (-0.14)	-56.319 (-0.89)	-1.943 (-0.06)	-34.646 (-0.78)
<i>EarnSurp</i>	-0.368*** (-4.62)	-0.332*** (-3.67)	-0.384*** (-5.17)	-0.348*** (-4.01)	-0.207*** (-4.09)	-0.183*** (-3.17)
$\ln(\text{Assets})$	4.697*** (6.43)	4.693*** (5.91)	3.932*** (6.27)	3.925*** (5.40)	3.086*** (6.39)	3.083*** (5.95)
<i>Uncertainty</i>	114.207*** (3.38)	165.815*** (3.17)	112.001*** (3.92)	164.486*** (3.42)	71.827*** (3.14)	105.676*** (3.05)
<i>BTM</i>	-0.903** (-2.19)	-1.025** (-2.02)	-0.730** (-2.17)	-0.854* (-1.97)	-0.596** (-2.08)	-0.676* (-1.94)
Q	1.602*** (5.91)	1.742*** (5.68)	1.312*** (6.13)	1.455*** (5.72)	0.994*** (5.50)	1.086*** (5.30)
Observations	113740	113740	113719	113719	113729	113729
FE	Firm	Firm	Firm	Firm	Firm	Firm

this analysis using an annual trend are shown in Table 5 and are qualitatively very similar to our main results.

Table 5: Financial jargon and abnormal turnover controlling for time trend

This table shows the second stage regression specified in Equation 5. Columns (1) and (2) use the amount Abnormal Turnover $_{i,t}$ as the dependent variable, while columns (3) and (4) Δ Abnormal Turnover $_{i,t}$. In columns (5) and (6), CAT $_{t,t+1}$ serves as the dependent variable. Jargon $_{Fin}$ and Jargon $_{All}$ are the estimates of the first stage regression in the columns (2) and (4) of the Table 2, respectively. *Year* indicates the year of the conference call and thus absorbs the common time trend. *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]. *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. *BTM* is articulated as the ratio of total Common/Ordinary Equity to the market equity value. $\ln(Assets)$ refers to the natural logarithm of total assets, and Q symbolizes Tobin's Q. *t*-statistics are enclosed in parentheses, with standard errors being clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	<i>Abnormal Turnover</i>		Δ <i>Abnormal Turnover</i>		<i>CAT</i> $_{0:1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Jargon</i> $_{Fin}$	989.270** (2.37)		869.300** (2.39)		857.544*** (3.05)	
<i>Jargon</i> $_{All}$		993.170** (2.40)		872.498** (2.42)		860.745*** (3.10)
<i>Year</i>	0.019 (0.23)	-0.050 (-0.80)	-0.042 (-0.60)	-0.102* (-1.91)	0.066 (1.21)	0.007 (0.16)
<i>Negativity</i>	46.715 (1.15)	51.043 (1.33)	47.253 (1.35)	51.084 (1.54)	7.790 (0.28)	11.557 (0.45)
<i>EarnSurp</i>	-0.295*** (-4.92)	-0.285*** (-4.73)	-0.322*** (-5.98)	-0.312*** (-5.79)	-0.162*** (-4.18)	-0.153*** (-3.94)
$\ln(Assets)$	4.313*** (7.51)	4.220*** (7.62)	3.603*** (7.41)	3.521*** (7.53)	2.865*** (7.68)	2.784*** (7.77)
<i>Uncertainty</i>	69.628*** (2.86)	70.377*** (2.90)	56.920*** (2.69)	57.574*** (2.73)	53.702*** (3.25)	54.348*** (3.32)
<i>BTM</i>	-0.992*** (-3.11)	-0.998*** (-3.10)	-0.834*** (-3.17)	-0.840*** (-3.16)	-0.640*** (-2.92)	-0.645*** (-2.91)
Q	1.654*** (7.83)	1.643*** (7.94)	1.326*** (7.54)	1.316*** (7.64)	1.075*** (7.73)	1.065*** (7.85)
Observations	132545	132545	132523	132523	132534	132534
FE	Firm	Firm	Firm	Firm	Firm	Firm

4 Conclusion

Using a large sample of earnings conference call textual data, this study aims to shed light on the efficiency of financial markets. We define efficiency as the market’s capacity to assimilate novel information. These earnings calls allow us to directly study the exchange of information between the demand side (analysts) and the supply side (management) of information.

Within an instrumental variable (IV) regression framework, we treat the US Plain Language Act as an exogenous shock to the usage of jargon in financial market communications. We contend that financial jargon represents a form of specialized, and consequently precise, language that plays a pivotal role in the efficient exchange of information.

In a first-stage, our empirical findings show a significant decline in jargon usage after the Plain Language Act’s implementation (Hypothesis 1). Second, our analysis reveals a positive association between jargon and abnormal turnover (Hypothesis 2). As supported by both theoretical and empirical literature, abnormal turnover around earnings conference calls relates to information asymmetries in the market. Thus, our results suggest that the use of financial jargon facilitates improved information flow, leading to the efficient resolution of information asymmetries.

Interestingly, while the Plain Language Act ‘succeeded’ in decreasing financial jargon, it did not influence the general linguistic complexity of financial communications, as gauged by the FOG index. This indicates that the reduction in jargon might have inadvertently led to a decrease in market efficiency without necessarily rendering the information more accessible or understandable to a broader audience.

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,

the unintended consequences might prove counterproductive, especially in sectors like finance where a specialized language is paramount for information dissemination.

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Appendix

A Abnormal turnover

Table 6: Financial jargon and log abnormal turnover

This table shows the second stage regression specified in Equation 5. The dependent variables are constructed from the logarithmic measure of Abnormal Turnover. Columns (1) and (2) use the amount $Abnormal\ Turnover_{i,t}$ as the dependent variable, while columns (3) and (4) $\Delta Abnormal\ Turnover_{i,t}$. In columns (5) and (6), $CAT_{t,t+1}$ serves as the dependent variable. $Jargon_{Fin}$ and $Jargon_{All}$ are the estimates of the first stage regression in the columns (2) and (4) of the Table 2, respectively. *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]. *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. *BTM* is articulated as the ratio of total Common/Ordinary Equity to the market equity value. $ln(Assets)$ refers to the natural logarithm of total assets, and Q symbolizes Tobin's Q. t -statistics are enclosed in parentheses, with standard errors being clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively.

	<i>Abnormal Turnover</i>		$\Delta Abnormal\ Turnover$		$CAT_{0:1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Jargon_{Fin}</i>	0.023*** (3.25)		0.025*** (4.16)		0.016*** (3.41)	
<i>Jargon_{All}</i>		0.031*** (3.17)		0.034*** (4.00)		0.021*** (3.32)
<i>Negativity</i>	0.001* (1.70)	0.001 (0.89)	0.001 (1.32)	0.000 (0.42)	0.001 (1.35)	0.000 (0.58)
<i>EarnSurp</i>	-0.000*** (-4.96)	-0.000*** (-4.57)	-0.000*** (-5.88)	-0.000*** (-5.39)	-0.000*** (-4.39)	-0.000*** (-3.98)
$ln(Assets)$	0.000*** (7.55)	0.000*** (7.53)	0.000*** (7.40)	0.000*** (7.26)	0.000*** (7.85)	0.000*** (7.81)
<i>Uncertainty</i>	0.002*** (3.28)	0.002*** (3.36)	0.002*** (3.69)	0.002*** (3.84)	0.001*** (3.18)	0.001*** (3.32)
<i>BTM</i>	-0.000*** (-3.16)	-0.000*** (-3.09)	-0.000*** (-3.25)	-0.000*** (-3.15)	-0.000*** (-2.96)	-0.000*** (-2.91)
Q	0.000*** (8.00)	0.000*** (7.81)	0.000*** (7.85)	0.000*** (7.66)	0.000*** (7.85)	0.000*** (7.67)
Observations	132545	132545	132523	132523	132534	132534
FE	Firm	Firm	Firm	Firm	Firm	Firm

B 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