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ORIGINAL ARTICLE

Does fair value accounting affect narrative disclosure obfuscation? Evidence from the United Kingdom consumer discretionary industry

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Abstract

Our understanding of the consequences of fair value representations in financial narratives is still limited. This study investigates the effect of fair value accounting on narrative disclosure obfuscation in the context of the United Kingdom (UK) consumer discretionary Industry. Narrative disclosure obfuscation is defined as the association between complex words disclosed in the company annual report and financial markets volatility. First the results show a positive association between the disclosure of complex words and market volatility, which confirms the existence of narrative obfuscation. Second, the effects of fair value accounting on obfuscation are identifiable in the post regulation period following the application of IFRS 13—Fair Value Measurement, and in the context of consumer discretionary firms in the UK. Our findings confirm the hypothesis that when fair value measurement is applied in practice to non-financial assets, for discretionary assets where fair value is unknowable, representations of fair value can be unstable leading to a contradiction and financial disclosure obfuscation.

Keywords IFRS 13—Fair value · Narrative disclosure · Obfuscation · Consumer discretionary · Market volatility

Introduction

This research aims to examine whether the complexity of financial reports increases market price volatility, a phenomenon we term "narrative disclosure obfuscation." Obfuscation, widely studied in accounting literature, is often viewed through the lens of managerial incentives, where it is seen as opportunistic and driven by agency costs (Beuselinck et al. 2018; Laksmana et al. 2012; Liao et al. 2023; Swanson and Theis 2019). These studies suggest that obfuscation arises from complex or less readable disclosures, particularly in cases of negative financial indicators like losses, non-going concern, tax aggressiveness, or non-family firms. However, Bloomfield(2008) challenges this by questioning whether the complexity linked to losses is intentional obfuscation or simply a necessity to explain difficult circumstances. Other studies (Burke and Gunny 2024; Bushee et al. 2018) attempt to isolate the obfuscation component of disclosures, focusing on managerial incentives. However, our approach differs by focusing on a market perspective, without presuming managerial intent behind the obfuscation. Our study contributes to the obfuscation literature by testing whether market uncertainty is a response to the complexity or reduced readability of disclosures, without assuming managerial motives. Building on Seavey et al. (2023) who link uncertainty to lower readability, we assess if complexity drives market volatility, offering a market-based view of obfuscation.

Specifically, the study investigates whether the use of complex words in company annual reports increases post annual report issuance share price volatility. It applies the use of predefined words consistent with the accounting literature on textual analysis applying keywords (Wang and Bright 2023). It also contributes to the market volatility literature adding to existing findings on readability and market (Loughran and McDonald 2014). The central hypothesis is that financial narrative complexity operationalised by complex words disclosure in company annual reports increases post annual report issuance share price volatility. This hypothesis is conceptualised and anchored to the literature on financial reporting complexity disclosure theory, and

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financial market volatility asymmetric information theory. Financial reporting complexity disclosure theory explores the relationship between complexity of textual financial reports and disclosure outcomes such as earnings (Dalwai et al. 2021; Li 2008). Financial market volatility asymmetric information theory explores the impact of the imbalance of information between principals and shareholders on market outcomes such as trading behaviour (Corwin and Coughenour 2008; Rahman and Oliver 2021).

We motivate our central hypothesis of narrative obfuscation (complexity and market volatility) in the context of the International Financial Reporting Standard (IFRS) 13 Fair value accounting standard and the United Kingdom consumer discretionary industry. Implicit in the application of IFRS 13 is the concept of the market participants—orderly transaction between market participants—*Fair value is measured using the assumptions that market participants would use when pricing the asset or liability, including assumptions about risk*.[1] We motivate our focus on the consumer discretionary fair value accounting disclosures using the findings in Barker and Schulte (2017), which finds a rejection of the generality of the market participants perspective presumed in IFRS 13. It argues that it is impossible to create a market where no market exists and in theory, seeking a valuation by a third party with no interest in buying the asset falsifies the assumptions of risk. Companies faced with the requirements of IFRS 13 for these discretionary asset values will usually outsource for multiple perspectives and select fair value arbitrarily. In addition, different practices emerge even in the valuation assumptions of similar assets leading to unstable representations (Barker and Schulte 2017). Firms in the consumer discretionary industry often deal with a wide range of assets, from inventory to intangible assets like brand value and must disclose the extent of judgment and estimation uncertainty involved in fair value measurements, which can increase the complexity of their financial reports. The reliance on unstable market assumptions and complex narrative explanations for these firms whose asset values may be closely tied to consumer behaviour and economic conditions can impact on market volatility compared to other industries.

We begin by examining the relationship between the complexity of financial reports and market volatility, finding evidence of a positive and significant association within a sample of FTSE 100 firms from 2011 to 2021. The cross-sectional analysis indicates that the use of more complex language in financial reports. Specifically, words containing three or more syllables, increases the difficulty for investors to interpret the financial information. This is reflected in post-issuance volatility, even after controlling for other relevant factors. This confirms narrative disclosure obfuscation phenomenon, where the complexity of financial reports increases market price volatility. Next, we focus on the adoption of IFRS 13 to assess whether the observed relationship between financial report complexity and market volatility is amplified by the application of fair value accounting. This is further analysed within the context of the consumer discretionary industry, compared to industries less impacted by the IFRS 13 standard, using a Difference-in-Difference framework. The findings support the notion that the IFRS standard exacerbates the complexity-volatility relationship.

In additional analysis, we explore the magnitude of the effect of complex language on market volatility. We find that a 1 percent increase in the use of complex words leads to an increase of 2 basis points in post-issuance volatility. Furthermore, applying the Global Industry Classification Standard (GICS) for industry complexity yields results consistent with the Industry Classification Benchmark (ICB), reaffirming the pronounced effect in the consumer discretionary sector.

This study makes two primary contributions. First, we build on the literature examining the market effect of textual characteristics of disclosure. While prior research explores the impact of readability characteristics on market outcomes (Loughran and McDonald 2014), we extend this work by isolating the effect of complex words and find that contrary to the existing findings showing that complexity is irrelevant for market outcomes, in the case of the UK and fair value accounting, complexity has a significant impact on market volatility. We term this phenomenon obfuscation. Our results also complement Barker and Schulte (2017), which documents that fair value accounting does not objectively reflect institutional reality even for core operating assets. Second, we add to the information asymmetry literature examining the impact of narrative complexity on market participants behaviour (Lehavy et al. 2011; Miller 2010) by documenting increased market volatility with complex words disclosure, and enhanced obfuscation associated with fair value disclosures and the consumer discretionary industry.

Hypotheses development

Prior accounting literature has studied the concept of obfuscation in various forms. It has been shown that the complexity in the disclosures can reduce investors' ability to process costs because managers can use complex language to obfuscate disclosures (Li 2008). Given the role of financial disclosures to provide useful information for investors, regulators have also noted concerns about the complexity of disclosures (Nadeem 2021). We define disclosure obfuscation as

[1] https://www.ifrs.org/issued-standards/list-of-standards/ifrs-13-fair-value-measurement.html/content/dam/ifrs/publications/html-standards/english/2024/issued/ifrs13/.

the relationship between the post-issuance market volatility and financial report complexity. Extant literature sets the premise that the more effective managers convey valuation relevant information, the lower the market volatility in the period following the financial report filing (Loughran and McDonald 2014). Thus, we expect that disclosure obfuscation is reduced where firms' financial report complexity as measured using readability measures is positively associated with post-issuance market volatility.

The extensive literature on market volatility as a market-based measure for the impact of information on equity valuation traces its origins to the Efficient Market Hypothesis (EMH). The EMH posits that in an efficient market, asset prices should fully reflect all available information, resulting in return volatility that is inherently unpredictable. However, Grossman and Stiglitz (1980) challenge this notion by arguing that arbitrage is not always costless. They propose a theoretical model of an inefficient market characterized by the presence of both informed and uninformed traders, where market inefficiency creates conditions for predictable volatility. Building on this, Foster and Viswanathan (1990) examine the "Monday effect" in return volatility, demonstrating that specific factors, such as liquidity shocks, can lead to market inefficiency. Their findings indicate that volatility is more pronounced among firms with better financial reporting, thereby linking the information content of financial reports to market volatility. Additionally, Daniel et al. (1998) propose a theoretical mechanism whereby irrational trading behaviours and investor over- and under-reactions contribute to market inefficiency and increased volatility. Empirical studies within these theoretical frameworks provide evidence that various sources of information serve as indicators of market inefficiency. For instance, Loughran and McDonald (2014) find that the low readability of financial reports significantly influences volatility, while Boudoukh et al. (2018) provide evidence that firm-specific news explains variations in volatility, particularly overnight. Furthermore, Vyshnevskyi et al. (2024) extend this analysis to the foreign exchange market, highlighting the broader applicability of these findings.

Drawing on insights from asymmetric information theory, we explore the relationship between financial report complexity and financial market volatility. Asymmetric information theory posits that management holds an informational advantage over shareholders, and this gap may widen when financial reporting is complex (Ashraf et al. 2024). We hypothesize that increased information asymmetry, driven by the use of complex language in financial reports, heightens market uncertainty, resulting in greater price volatility. Specifically, when firms produce complex financial reports, the timely dissemination of firm-specific information is impeded, contributing to heightened volatility in market reactions and pricing. Complex information is seen as an information barrier and usually viewed as poor information content in disclosure (Lehavy et al. 2011). Bendriouch et al. (2023) find that the more complex the language in an annual report the more difficult it is to make strategic financial decisions using the reported information. Using the case of assessing post earnings announcement drift, it has been shown that this is heightened with firms with more organisational complexity (Barinov et al. 2024).

Notwithstanding these asymmetric information theory and evidence, regarding complex words, and more broadly readability, shareholders with information advantage have been noted to be unaffected by this information asymmetry effect. Yu and Zhao (2023) show that analysts selectively use their private information advantage depending on the level of textual complexity. Umar (2022) finds that when information complexity increases it reduces the use of that information by less sophisticated investors. However, they also find that these can affect overall market outcomes including market volatility.

In this study, we adopt the premise advanced by Loughran and McDonald (2014) that the complexity of financial reports affects post-issuance market volatility. Specifically, we hypothesize that higher complexity in financial reports leads to increased market volatility due to reader confusion and disagreement in firm valuation. To measure market volatility, we employ the Residual Mean Square Error (RMSE) of the Capital Asset Pricing Model (CAPM). This metric captures the deviations of actual returns from those predicted by the CAPM, with higher RMSE values indicating greater volatility. This process of complex reporting leading to market outcomes of increased information uncertainty and asymmetry is theoretically termed narrative obfuscation, widely studied in the literature through the lens of management incentives (de Souza et al. 2019). By analysing the relationship between financial report complexity and market volatility, unlike prior studies focused on management incentive lens, this study aims to contribute to the understanding of how fair-value information dissemination impacts market dynamics and valuation. We hypothesise as follows:

Hypotheses 1 (H1): *Financial report complexity operationalised by complex words disclosure in company annual reports increases post report issuance share price volatility.*

"Fair value is a market-based measurement, not an entity-specific measurement. For some assets and liabilities, observable market transactions or market information might be available. For other assets and liabilities, observable market transactions and market information might not be available…. Because fair value is a market-based measurement, it is measured using the assumptions that market participants would use when pricing the asset or liability, including assumptions about risk" (IFRS 13).

The consumer discretionary industry includes companies that produce goods that are discretionary but not essential to consumers. The goods are usually desirable by consumers and can be significantly affected by fair value accounting. In addition, the market assumptions for the goods can be perceptive and thus prices by market participants can be volatile or difficult to value leading to extensive complexity. Regarding disclosure transparency, the link between reporting complexity and market volatility is amplified when firms use fair value accounting for their fair value measurements.

We expect that the application of fair value accounting will increase agency costs because the accounting literature shows that while valuation at fair value can enhance information for equity investors, it will reduce the contracting usefulness of financial liabilities (Ball et al. 2015). In addition, the use of fair value is efficient in cases of reliable fair value estimates at a lower costs (Christensen and Nikolaev 2013). Where consumer discretionary goods are limited in the obtainability of fair values at a lower costs these increases agency costs and, in this case, we expect it will contribute to the positive relationship between complexity in financial reports and post report market volatility.

These agency costs are expected to increase in the form of market volatility because fair value accounting tends to increase volatility in the income statements while historical costs accounting reduces financial statements volatility. Magnan et al. (2015) note that analysts perceive that managers convey useful information through level 2 fair value figures but act opportunistically in measuring level 3 fair value figures. Level 3 fair value inputs are based on unobservable inputs where market information on relevant fair values is not available this allows for situations in which there is little, if any, market activity for the asset or liability at the measurement date. The use of these inputs then leads to less reliable measurement where assets are not traded in an active market. This tends to increase in the complexity in financial reports. These agency costs are further enhanced through increase in the costs of preparing and maintaining fair value accounting information. For example, IAS 16 would usually require that the fair value be current at balance sheet date. Where there are significant costs in obtaining fair value information, this can lead to an increase in the costs of financial reports.

While fair value accounting provides users with a better understanding of the valuation of complex assets. The disclosures associated with fair value tend to be complex. Fair value disclosures have been noted to be a significant source of disclosure complexity (Filip et al. 2017; KPMG 2017). Markets still find it difficult to price assets given the complex nature of fair values, thus we expect that disclosure complexity will increase with fair value, and this contributes to its relationship with market volatility. We hypothesise as follows:

Hypothesis 2 (H2): *Financial report complexity operationalised by complex words disclosure in company annual reports increases post report issuance share price volatility, which is more pronounced with the application of IFRS 13*

Research design

Sample selection

To examine the impact of fair value accounting on narrative disclosure obfuscation, we choose as our setting the United Kingdom (UK) reporting for consumer discretionary products—that is non-essential goods and services purchased from disposable income. These includes, automobiles, media, specialty retailers, travel and leisure. The consumer discretionary industry represents those industries that tend to be the most sensitive to economic cycles and represents a major part of the economy (Maksy 2017). Specifically, we examine the market response to consumer discretionary firm disclosure events after the application of IFRS 13 fair value reporting for these discretionary goods and services.

Thus, our primary sample to assess the impact of fair value reporting on narrative disclosures is the UK consumer discretionary industry, chosen for the following reasons. First, this is a setting in which products are more sensitive to attributes of recession and social trends thus making fair value hierarchy measurements susceptible to management discretionary reporting. Second, this setting allows examination of market volatility of fair value reporting where firms face hurdles in measuring assets and liabilities at fair value. UK consumer discretionary companies adapt to fair value reporting by voluntarily disclosing brand values on balance sheets in the absence of clear regulations, with recent tighter regulations focusing on intangible assets like brands. Thirdly, the consumer discretionary industry is a broad range of firms/goods and service, which provides significant evidence for IFRS 13 application. Finally, there is very limited evidence of the impact of IFRS 13 on these firms unlike firms such as the real estate, and it is not subject to significant regulation like banks (Conaway et al. 2023), but has evident subjectivity in valuation. The evidence on the impact of implementation of IFRS 13 suggest that management has a significant impact on reporting quality and decision usefulness (Filip et al. 2017).

Our initial sample is derived from FTSE100 constituents. For each firm-year observation, we download the corresponding annual report. We retrieve annual reports from various databases, including Mergent Archives, Bloomberg, and AnnualReports.com. If reports are not found in these databases, we check additional sources such as Annual Report Service, Northcote Database, and the company's website. We download a total of 1501 annual reports in PDF format. We convert the PDF versions of the annual reports to text files using the Xpdf software. This procedure successfully converts a total of 1450 annual reports excluding reports with poor conversion. To assess market volatility, relevant variables such as the market index, stock price, market capitalization, and price-to-book ratio for each firm-year observation are obtained from Bloomberg. After eliminating firm-year entries with missing data, the final sample consists of 784 observations.

Econometrics models

To test the first hypothesis, the same regression, which is used in Loughran and McDonald (2014), is applied to assess the impact of complexity measures to the stock market volatility in the UK market.

$$RMSE_{it} = \alpha_0 + \beta_0 Complexity_{it} + \gamma_j Controls_{it} + \varepsilon_{it} \quad (1)$$

The main independent variable in the regression is the $Complexity_{it}$. The complexity measures include the Fog index, percentage of complex words, word complexity, and number of complex words per sentence. The number of complex words per sentence and the percentage of complex words are the two components of the fog index. To capture this, we use the Lingua::EN::Fathom Perl module to compute complexity statistics, following the methodologies of Lang and Stice-Lawrence (2015) and Li (2008). The Fathom package generates the following textual statistics, which we use to validate data by comparing them to manual counts and to assess various attributes of the disclosed texts: number of characters, number of words, percentage of complex words, number of sentences, number of text lines, number of paragraphs, syllables per word, and words per sentence. The package also provides complexity statistics, which are crucial for our analysis. We compute the complex words per sentence as the words with two or more syllables. This is the word complexity component of the fog index. The word complexity is an alternative measure of the percentage of complex words, which provides the magnitude of the word complexity measure. Sentence complexity is the second component of the fog index which measures number of words per sentence. ComplexityWordsPercent is the percentage of complex words using the complexity words identified in (Loughran and McDonald 2023).

Before processing the text files through the Perl module, we clean the data by removing full stops between numbers to prevent the fog index from misidentifying decimals as sentence boundaries, following Bushee et al. (2018). We avoid using the Lingua::EN::Sentence routine, which relies on line breaks to detect sentences and risks inflating sentence counts due to text wrap issues. Addressing decimal parsing helps prevent this overestimation. To minimise errors from poor PDF-to-text conversion, we exclude reports with fewer than 3000 words or 100 lines of text, consistent with Li (2008) to ensure full annual filings are analysed rather than incomplete or heading-only documents. Recognising that conversion errors may still persist, we further drop reports with fog scores below 12 or above 30, or with fewer than 50 sentences, as per Lang and Stice-Lawrence (2015).

The regression follows the same design proposed by Loughran and McDonald (2014) to assess the impact of complexity measures to the stock market volatility. The stock market volatility is measured by RMSE of a market model regression in the period shortly after the release of the financial reports. Since the price and return of a stock reflects the financial information revealed in the financial report, the complexity of the financial report obstructs the investors in the process of equity valuation. The volatility in the valuation reflects the degree of agreement in interpreting the information, and hence better readability should improve the post-filing asset return volatility. The financial statement should be easy to read to improve the market efficiency, i.e., reducing volatility caused by release of information, to allocate capital. As the dependent variable, it is assumed that the post-filing RMSE is affected by the complexity of the financial reports and other factors in the $Controls_{it}$. Specifically, the post-announcement RMSE window is defined as a three-week period beginning one week after the announcement. This delay accounts for the time required for the market to process and respond to the financial report. The three-week duration represents the minimum length necessary to obtain a sufficient number of daily observations for a reliable volatility estimate. We have set a threshold of at least 10 observations for the RMSE calculation. This approach is consistent with the methodology used in Loughran and McDonald (2014). The full detailed definitions of variables in the regression can be viewed in Appendix A. By running the regression multiple times with the proposed alternative complexity measures, the most appropriate measure can be revealed in the UK context.

For comparison, the regression is run four times with a different complexity measure each time. The model uses industry and year dummies, and the reported standard errors are clustered by year and industry. To test the second hypothesis, a difference-in-difference design is applied to identify the effect of the implementation of the IFRS Fair Value standard in the UK. The specification can be described as follows:

$$\begin{aligned} RMSEit = & \alpha 0 + \beta 0 Complexityit \\ & + \beta 1 Dpost2013 \times Complexityit \\ & + \beta 2 DIndustry \times \text{ Complexity}it \\ & + \beta 3 Dpost2013 \times DIndustry \\ & \times \text{ Complexity}it + \gamma_j Controls_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

The difference-in-difference model can identify the effect of a treatment by comparing the difference between the treatment and the control groups and across the time before and after the treatment. The first difference can be considered to be between treatment and control groups before the treatment is applied, and the second difference is afterwards. The difference between two differences can thus identify the effect of the treatment from other factors causing the variations between the two groups. By the second hypothesis, the treatment is the application of IFRS 13 in the UK in the year 2013. It is theorised that the sector "consumer discretionary" is subject to heavy influence of the Fair Value standard. Therefore, we define the treatment group as the samples in the "consumer discretionary" industry and the samples in other industries as the control group. In terms of the dummies in the regression specification, the treatment dummy, denoted as $D_{Industry}$, is defined to take the value 1 when the company is within the sector of "consumer discretionary", and 0 otherwise, whereas the trend dummy, denoted as $D_{post2013}$, takes the value 1 if the year is after 2013, and 0 otherwise. The categorisation of the samples by the dummy variables helps to realise the comparisons needed in the difference-in-difference setting. The model still includes the year and industry dummies for the intercepts and the standard errors are clustered for robustness. The categorisation of the "consumer discretionary" is according to ICB. In the sensitivity analysis we apply the GICS.

The impact of the IFRS 13 is identified by the setting of the dummy variables. The coefficient of complexity without any dummy, i.e., β_0, measures the impact of the control group before the treatment year 2013. The coefficient of trend dummy, i.e., β_1, reflects the difference before and after the year 2013 in the control group. β_2, of treatment dummy, shows the impact difference between the control and treatment groups before the treatment. The last coefficient, β_3, of the interaction dummies of trend and treatment, demonstrates the difference between the treatment and control in the difference after the year 2013. This difference-in-difference term, β_3, if significant, is designed to indicate the effect of the IFRS 13.

Results analysis

The descriptive statistics in Table 1 present the means and standard deviations of relevant variables across two periods, divided by the year 2013. This year marks the adoption of the Fair Value standard in the UK. The Pre-2013 period, which includes 2011, 2012, and 2013, contains 210 firm-year observations, while the Post-2013 period, spanning from 2014 to 2021, comprises 574 observations. For instance, the FOG index has an average value of 16.9335 in the Pre-2013 period and 17.2051 in the Post-2013 period. The standard deviation of the FOG index is 0.8829 for the Pre-2013 period and 0.7486 for the Post-2013 period.

Table 1 illustrates the comparison between these two periods. Regarding the complexity measures of financial reports, the mean values remain relatively stable, though a slight increase is observable in the Post-2013 period. Specifically, the mean FOG index rises from 16.9335 to 17.2051, driven by increases in both its components: "WORDCOMPLEXITY" increases from 10.3743 to 10.5724, and "SENTENCECOMPLEXITY" rises from 6.5592 to 6.6327. Additionally, post-issuance market volatility, as measured by "RMSE", increases slightly in the Post-2013 period, from 0.01057 to 0.01572. The variation in complexity measures

Table 1 Descriptive statistics

Variables	Pre-2013 Period		Post-2013 period	
	Mean	Standard deviation	Mean	Standard deviation
FOG	16.93351679	0.882947533	17.2051074	0.748616331
WORDCOMPLEXITY	10.37428745	0.553238776	10.57240902	0.480976379
SENTENCECOMPLEXITY	6.559229339	0.814754626	6.632698378	0.618759729
PERCENTCOMPLEXWORDS	25.93571862	1.383096939	26.43102255	1.202440947
COMPLEXITYWORDSPERCENT	0.466151319	0.165238994	0.426411297	0.144453495
RSME	0.010568211	0.006296842	0.015719282	0.015054272
RSMEPre	0.013642263	0.005096662	0.015242002	0.007581528
AlphaPre	0.000200374	0.000985873	1.6418E-05	0.001125378
LogSize	8.645196473	1.30410074	8.916658331	1.170396931
AbsAbR	0.015220339	0.015349964	0.018163936	0.017069408
LogB2M	-0.984106775	0.943467214	-1.148056138	1.049473265
No. of Observations	210		574	

The Pre-2013 period includes years 2011, 2012 and 2013. The Post-2013 period includes years from 2014 to 2021. Year 2013 marks the adoption of the Fair Value standard in the UK. The description of the variables can be seen in Appendix A decreases, as reflected by smaller standard deviations, while the variation in post-filing market volatility rises. This analysis suggests that as financial reports grow more complex, market volatility correspondingly increases.

IFRS 13's introduction mandated explicit Level 3 disclosures. Examining 2014 annual reports of consumer-discretionary firms illustrates this shift. After IFRS 13, Burberry Group's 2014 accounts include a clear hierarchy disclosure. The report provides a narrative that the fair value is derived using a present value model with both observable and unobservable inputs (2014, p. 127). This additional narrative and grouping of £51 m under "Level 3" underscore the greater disclosure complexity post-IFRS13. Entain Plc reported €7.6 m of deferred consideration as a Level 3 item based on cash-flow projections (2014, p. 57). ITV Plc identified contingent consideration as its sole Level 3 instrument, valuing it using post-acquisition performance expectations and a discount rate reflective of the business (2014, pp. 154–155). Flutter Entertainment introduced comprehensive Level 3 reconciliation tables for its contingent deferred consideration and sports-betting revenue, completing the hierarchy disclosure (2014, p. 115).

Importance of complex words in the UK

To test hypothesis one Table 2 reports the results of the regressions between the market volatility and the complexity measures. The fog index and its components serve as crucial indicators of complexity. Table 2 illustrates the regressions utilising these metrics as factors influencing post-filing stock market volatility in the UK. Decomposing the fog index sheds light on the distinct textual reporting features across countries and standards.

Notably, not all controls exhibit significance. However, as identified factors affecting post-filing volatility in the US market (Loughran and McDonald 2014), they are all retained for the sake of comparability. Among the significant controls are "Pre-filing RMSE," representing pre-filing volatility, company size, and abnormal returns. Consistent with their counterparts in the US market, these coefficients demonstrate that "Pre-filing RMSE" and abnormal returns ("AbsAbr") positively impact "Post-filing RMSE," while company size ("LogSize") exerts a negative influence. Larger companies tend to experience lower volatility following earnings announcements, with "Pre-filing RMSE" reflecting a company's typical volatility level and abnormal returns serving as a predictor.

Table 2 Regressions of the impact on market volatility by the components of fog index as readability measures

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.0180	0.0168	0.0281**	0.0295***
	(0.0142)	(0.0135)	(0.0117)	(0.0113)
FOG	0.0007			
	(0.0005)			
WORDCOMPLEXITY		0.0013**		
		(0.0006)		
SENTENCECOMPLEXITY			0.0003	
			(0.0006)	
COMPLEXITYWORDSPERCENT				−0.0053
				(0.0056)
RSMEPre	0.3517**	0.3560**	0.3548**	0.3647**
	(0.1469)	(0.1454)	(0.1460)	(0.1451)
AlphaPre	−0.1684	−0.1952	−0.1808	−0.1926
	(0.4881)	(0.4842)	(0.4875)	(0.4809)
LogSize	−0.0022***	−0.0022***	−0.0022***	−0.0019***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
AbsAbR	0.0942**	0.0915**	0.0944**	0.0915**
	(0.0395)	(0.0395)	(0.0391)	(0.0398)
LogB2M	0.0003	0.0002	0.0002	0.0004
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
R2	0.5124	0.5126	0.5115	0.5127
Adj. R2	0.4705	0.4707	0.4694	0.4708
Num. obs.	784	784	784	784

***$p<0.01$; **$p<0.05$; *$p<0.1$

The dependent variable of the models is RMSE, the residual mean square error from CAPM representing the market volatility after the release of the financial reports. Each of the four included models uses a different measure to represent the complexity of financial reports, i.e., "FOG", "WORDCOMPLEXITY", "SENTENCECOMPLEXITY", and

"COMPLEXITYWORDSPERCENT". The definitions of the variables are included in the Appendix A

The influence of complexity measures is evident through a notable contrast across models in Table 2. While the Fog index itself may not be significant, one of its components, particularly complex words, exhibit significance in Models 2. Model 3 shows that the other component, i.e., sentence complexity, exerts no significant impact. The findings regarding the Fog index and its components in the UK diverge from empirical evidence in the US, where overall Fog index significance contrasts with the insignificance of complex word usage Loughran and McDonald (2014). This suggests that the choice of complexity measures for financial reports depends on the environmental and institutional characteristics of the financial market. The absence of significance in complex word usage may be a unique feature of the US market, potentially attributable to differences in financial reporting standards.

The significance of the fair value

To test hypothesis two, the sample period can be divided into Pre-2013 and Post-2013. The influence of the complexity may vary depending on environmental factors such as country and period. Notably, the usage of complex words emerges as a distinctive feature between the US and the UK, prompting an investigation into the temporal dimension within the UK context. To bolster the robustness of our findings, we introduce an additional measure—"WORDCOMPLEXITY"—and segment the sample into sub-periods corresponding to financial years. The WORDCOMPLEXITY is an alternative measure of the percentage of complex words, which provides the magnitude of the word complexity measure. Our analysis reveals a notable shift in the significance of complex words, particularly in the year 2013. Coinciding with the introduction of the IFRS 13, this year marks a pivotal moment in the textual characteristics of financial statements. The section first demonstrates the distinction between the two periods before and after the introduction of the standard, and then further identifies the effect of the Fair Value standard by using a Difference-in-Difference setting.

The difference before and after 2013

To present our findings, we delineate the Pre- and Post2013 sub-samples in Tables 3 and 4, employing the same regression framework as in Table 2.

The signs of the control variables in the sub-samples exhibit consistent directionality with the total sample, featuring positive coefficients for "RMSEPre" and "AbsAbR," and negative coefficients for "LogSize." However, in the pre2013 sample (as displayed in Table 3), fewer controls reach statistical significance. Regarding the overall model fit, we observe a similar level of adjusted-R^2 between the post-2013 sub-sample and the total sample, while the

Table 3 Regressions by CAPM with clustered standard error pre-2013

	Model 1	Model 2	Model 3	Model 4
(Intercept)	−0.0035	0.0300*	0.0096	0.0174
FOG	(0.0092) 0.0014**	(0.0167)	(0.0095)	(0.0116)
WORDCOMPLEXITY	(0.0006)	−0.0011		
SENTENCECOMPLEXITY		(0.0007)	0.0017**	
COMPLEXITYWORDSPERCENT			(0.0007)	−0.0042
RSMEPre	0.3893**	0.4103***	0.3831**	(0.0050) 0.4141***
AlphaPre	(0.1523) −0.8373	(0.1545) −0.8827	(0.1551) −0.8687	(0.1518) −0.8482
LogSize	(1.1729) −0.0013	(1.2176) −0.0012	(1.1675) −0.0013	(1.2031) −0.0009
	(0.0009)	(0.0009)	(0.0009)	(0.0007)
AbsAbR	0.0166	0.0197	0.0207	0.0141
	(0.0493)	(0.0466)	(0.0477)	(0.0503)
LogB2M	0.0002	−0.0001	0.0002	−0.0000
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
R^2	0.4789	0.4673	0.4891	0.4662
Adj. R^2	0.3193	0.3042	0.3326	0.3027
Num. obs	210	210	210	210

***$p<0.01$; **$p<0.05$; *$p<0.1$

The samples are for the Pre-2013 period, which contains 2011 to 2013. The dependent variable of the models is RMSE, the residual mean square error from CAPM representing the market volatility after the release of the financial reports. Each of the four included models uses a different measure to represent the complexity of financial reports, i.e., "FOG", "WORDCOMPLEXITY", "SENTENCECOMPLEXITY", and "COMPLEXITYWORDSPERCENT". The definitions of the variables are included in the Appendix A

Table 4 Regressions by CAPM with clustered standard error post-2013

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.0264	0.0108	0.0396**	0.0353**
	(0.0199)	(0.0179)	(0.0168)	(0.0159)
FOG	0.0006			
WORDCOMPLEXITY	(0.0008)	0.0024***		
SENTENCECOMPLEXITY		(0.0008)	−0.0006	
COMPLEXITYWORDSPERCENT			(0.0010)	−0.0057
RSMEPre	0.3490**	0.3526**	0.3517**	(0.0076) 0.3560**
	(0.1740)	(0.1741)	(0.1733)	(0.1737)
AlphaPre	0.1346	0.1126	0.0894	0.0847
LogSize	(0.5438) −0.0025***	(0.5262) −0.0025***	(0.5408) −0.0025***	(0.5140) −0.0022**
AbsAbR	(0.0009) 0.1043**	(0.0009) 0.1000*	(0.0009) 0.1019**	(0.0009) 0.1022**
	(0.0513)	(0.0513)	(0.0509)	(0.0518)
LogB2M	0.0005	0.0004	0.0004	0.0007
	(0.0007)	(0.0007)	(0.0007)	(0.0008)
R^2	0.5226	0.5257	0.5225	0.5234
Adj. R^2	0.4688	0.4723	0.4687	0.4697
Num. obs	574	574	574	574

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$

The samples are for the Post-2013 period, which contains 2014 to 2021. The dependent variable of the models is RMSE, the residual mean square error from CAPM representing the market volatility after the release of the financial reports. Each of the four included models uses a different measure to represent the complexity of financial reports, i.e., "FOG", "WORDCOMPLEXITY", "SENTENCECOMPLEXITY", and "COMPLEXITYWORDSPERCENT". The definitions of the variables are included in the Appendix A

pre-2013 subsample demonstrates a lower level of fit. This discrepancy suggests a discernible difference between the sub-samples representing periods before and after 2013, coinciding with the application of IFRS 13.

The divergence evident in the pre-2013 regressions in Table 3 is particularly notable regarding the impact of complexity measures. The Fog index (Model 1) and sentence complexity (Model 3) emerge as significant, whereas the measure representing complex words (Models 2) are rendered insignificant. This finding mirrors the observations in the US context (Loughran and McDonald 2014), in which the Fog index and sentence complexity are also found to be significant but the complex words not. Conversely, in Table 4 for the post-2013 regressions, the Fog index loses significance while complex words become significant predictors. This comparison underscores the significance of the year 2013 in shaping the influence of complex words within the examined context.

The effect of IFRS 13 in the context of consumer discretionary disclosures

Table 5 presents the results of regressions conducted using the Difference-in-Difference (DiD) method (as specified in Eq. 2), aimed at verifying Hypothesis 2. This methodological approach seeks to ascertain the impact of IFRS 13, which was introduced in 2013. In addition to incorporating a dummy variable for the year 2013, indicative of the standard's release, the effect of the IFRS standard is further captured by an industry dummy variable. This variable assumes a value of 1 if the company under examination operates within the consumer discretionary industry, as defined by the ICB standard. Notably, the consumer discretionary sector is particularly susceptible to the influence of the Fair Value standard.

Our analysis reveals an increase in the impact of complex words following the implementation of IFRS 13 in 2013. The DiD regression design not only seeks to identify this trend across all industries but also aims to specifically examine its effect within an industry heavily impacted by the IFRS standard.

In Model 1 of Table 5, the "Word Complexity" metric serves as the chosen complexity measure. The coefficient "WORDCOMPLEXITY" exhibits insignificant impact prior to the treatment year 2013. This finding aligns with the results observed in the Pre-2013 sub-sample analysis as depicted in Table 3. The coefficients associated with the complexity metrics involving three types of dummies all demonstrate statistical significance. Firstly, the "YearInteractionDummy" coefficient captures the general trend of impact post-2013 across all industries except for the consumer discretionary sector, which serves as the treatment

Table 5 DiD regression with treatment defined by consumer discretionary by ICB

	Model 1	Model 2
(Intercept)	-0.0141^{*}	-0.0141^{*}
WORDCOMPLEXITY	(0.0078) -0.0004	(0.0078)
WORDCOMPLEXITY_YearInteractionDummy	(0.0005) 0.0030^{***}	
WORDCOMPLEXITY_IndusInteractionDummy	(0.0009) -0.0002^{***}	
WORDCOMPLEXITY_YearIndusInteractionDummy	(0.0001) 0.0004^{**}	
PERCENTCOMPLEXWORDS	(0.0002)	-0.0002
PERCENTCOMPLEXWORDS_YearInteractionDummy		(0.0002) 0.0012^{***}
PERCENTCOMPLEXWORDS_IndusInteractionDummy		(0.0003) -0.0001^{***}
PERCENTCOMPLEXWORDS_YearIndusInteractionDummy		(0.0000) 0.0002^{**}
RSMEPre	0.4582^{***}	(0.0001) 0.4582^{***}
AlphaPre	(0.1195) -0.4340	(0.1195) -0.4340
LogSize	(0.5098) -0.0012^{***}	(0.5098) -0.0012^{***}
AbsAbR	(0.0004) 0.0842^{**}	(0.0004) 0.0842^{**}
LogB2M	(0.0368) 0.0009^{***}	(0.0368) 0.0009^{***}
	(0.0003)	(0.0003)
R^2	0.4782	0.4782
Adj. R^2	0.4650	0.4650
Num. obs	775	775

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$

The DiD (Difference-in-Difference) models have the dummies multiplied by the complexity variables, i.e., "WORDCOMPLEXITY", and "PERCENTCOMPLEXWORDS", to measure their effects. "YearInteractionDummy" defines periods before and after the treatment, i.e., Pre-2013 and Post-2013 periods. "IndusInteractionDummy" is the treatment dummy defined by the consumer discretionary industry. "YearIndusInteractionDummy" is the dummy when the sample is both after 2013 and within the consumer discretionary industry. The industry classification is according to ICB (Industry Classification Benchmark). The dependent variable of the models is RMSE, the residual mean square error from CAPM representing the market volatility after the release of the financial reports. The definitions of the variables are included in the Appendix A

industry. Secondly, the "IndusInteractionDummy" coefficient signifies a discernible difference between the treatment industry and the remaining samples prior to the introduction of the Fair Value standard. Lastly, the "YearIndusInteractionDummy" coefficient indicates a heightened influence of complex words within the consumer discretionary industry. This positive significance suggests that the Fair Value standard contributes to valuation volatility, as companies introduce more complex language into their financial reporting practices.

In Model 2 of Table 5, the "PERCENTCOMPLEXWORDS" metric is employed as an alternative to "WORDCOMPLEXITY," aiming to demonstrate the meaning in the magnitude of the significant coefficients, as the latter is just the weighted version of the former to act as a component of the Fog index. The "PERCENTCOMPLEXWORDS" directly represents the percentage of the complex words in a financial report. Every 1 percent increase in the use of complex words due to the application of the IFRS 13 standard, the additional volatility cause by this is 2 basis points, indicated by the significant coefficient "YearIndusInteractionDummy".

To contextualize this effect, consider the summary statistics of RMSE in the sample: the median is 0.01098 and the first quartile is 0.00808, resulting in a median–quartile range of 0.0029. Since this range reflects 25% of the overall volatility variation, the 2-basis point (0.0002) impact from complexity accounts for approximately 0.0002/0.0029 = 6.9% When scaled by the 25% share of total volatility, this implies that a 1 percentage point increase in PERCENTCOMPLEXWORDS contributes approximately 1% to the overall volatility, indicating a near 1—to—1 relationship between textual complexity and its marginal effect on daily return volatility.

In both Model 1 and 2 of Table 5, we find that the overall goodness-of-fit of the models remains consistent with previous analyses, such as the overall sample regressions in Table 2 and the Post-2013 sample regressions in Table 4, where the adjusted-R^2 is maintained at level around 0.47. Notably, in comparison to these prior models, the control variables in the current DiD models exhibit the same signed coefficients but demonstrate improved significance. Alongside "RMSEPre," "LogSize," and "AbsAbR," the variable "LogB2M" also emerges as statistically significant. The positive coefficient associated with "LogB2M" indicates that a larger book value is more likely to contribute to valuation volatility, highlighting yet another distinctive feature of the UK market. This enhanced significance underscores the robustness of the current DiD models and provides valuable insights into the factors driving valuation dynamics in the UK market.

Robustness test using GICS and others

GICS is an alternative standard to categorise the FTSE companies into industries. The ICB was developed by Dow Jones and the Financial Times Stock Exchange (FTSE) in 2005, whereas the GICS is an industry taxonomy developed in 1999 by MSCI and Standard and Poor's. The comparison of the samples by the two standards are shown in the Table 6. There are differences between the two standards, especially in terms of the Consumer Discretionary and Telecommunications/Communication Services industries. This section verifies the robustness of the identified effect by the Fair Value standard by running the DiD regressions using the alternative GICS classification standard.

Table 6 Samples by ICB and GICS

ICB INDUSTRY	NO.Samples	GICS INDUSTRY	NO. Samples
Financials	101	Financials	101
Industrials	118	Industrials	106
Energy	38	Energy	43
Basic Materials	51	Materials	69
Technology	16	Information Tech	26
Consumer Staples	58	Consumer Staples	58
Health Care	27	Health Care	24
Consumer Discretionary	113	Consumer Discretionary	76
Real Estate	19	Real Estate	12
Telecommunications	16	Communication Services	52
Utilities	7	Utilities	7

The table shows the breakdown of companies in our sample by industries according to the ICB (Industry Classification Benchmark) and GICS (Global Industry Classification Standard) respectively

Table 7 presents similar results to ICB regressions as in Table 5. The complexity term and the related dummies show similar result in terms of both significance and the directions. The DiD term "YearIndusInteractionDummy" is a positive term with significant at the level of 5%. All the control variables but the pre-filing alpha, i.e., "AlphaPre", show significance. The overall fitness of the models, indicated by "Adj.R2", is at the same level as the models in Table 5. The results by the GICS confirms the robustness of the identified DiD effect.

Additional robustness tests were conducted for the regressions in Table 5. These included parallel trend tests using the two pre-treatment years (2011 and 2012), applying different clustering methods for standard errors, and testing for additional fixed effects. The outcomes, presented in Appendix B, are consistent with our main findings.

Conclusion

This study examines narrative obfuscation as operationalised in the association between financial report complexity and the subsequent market volatility post issuance of company annual reports. It investigates this as narrative obfuscation by examining the relationship between the use of complex language in annual reports and subsequent market volatility following the issuance of these reports. We present three key findings: (i) confirmation of a positive association between linguistic word complexity and market volatility in the UK FTSE 100 stocks, (ii) amplification of this relationship following the application of IFRS 13 in the consumer discretionary industry, and (iii) robustness of the findings when tested using different industry classification standards. Our results indicate that increased complexity in financial reports significantly hinders the interpretation of financial information, as evidenced by heightened post-issuance market volatility in the UK. Moreover, the adoption of IFRS 13 in 2013 further intensifies the impact of report complexity on market volatility. These findings are robust across industry classification schemes, whether using the Industry Classification Benchmark (ICB) or the Global Industry Classification Standard (GICS).

However, several caveats apply to our results. First, the sample is restricted to FTSE 100 firms, suggesting the need for future research to explore smaller companies and broader markets. We acknowledge that our findings, based on FTSE-100 firms characterised by their size, visibility, and strong governance oversight may not generalise to smaller firms, such as those listed on AIM, or to settings with weaker regulatory enforcement, and we caution readers to interpret the results within this context. Second, alternative measures of the impact of linguistic complexity could provide additional

Table 7 DiD regression with treatment defined by consumer discretionary by GICS

	Model 1	Model 2
(Intercept)	−0.0157*	−0.0157*
WORDCOMPLEXITY	(0.0080) −0.0003	(0.0080)
WORDCOMPLEXITY_YearInteractionDummy	(0.0006) 0.0030***	
WORDCOMPLEXITY_IndusInteractionDummy	(0.0009) −0.0003**	
WORDCOMPLEXITY_YearIndusInteractionDummy	(0.0001) 0.0005**	
PERCENTCOMPLEXWORDS	(0.0002)	−0.0001
PERCENTCOMPLEXWORDS_YearInteractionDummy		(0.0002) 0.0012***
PERCENTCOMPLEXWORDS_IndusInteractionDummy		(0.0004) −0.0001**
PERCENTCOMPLEXWORDS_YearIndusInteractionDummy		(0.0001) 0.0002**
RSMEPre	0.4615***	(0.0001) 0.4615***
AlphaPre	(0.1150) −0.2696	(0.1150) −0.2696
LogSize	(0.4938) −0.0012***	(0.4938) −0.0012***
AbsAbR	(0.0004) 0.0779**	(0.0004) 0.0779**
LogB2M	(0.0374) 0.0008***	(0.0374) 0.0008***
	(0.0003)	(0.0003)
R2	0.4777	0.4777
Adj. R2	0.4647	0.4647
Num. obs.	784	784

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$

The DiD (Difference-in-Difference) models have the dummies multiplied by the complexity variables, i.e., "WORDCOMPLEXITY", and "PERCENTCOMPLEXWORDS", to measure their effects. "YearInteractionDummy" defines periods before and after the treatment, i.e., Pre-2013 and Post-2013 periods. "IndusInteractionDummy" is the treatment dummy defined by the consumer discretionary industry. "YearIndusInteractionDummy" is the dummy when the sample is both after 2013 and within the consumer discretionary industry. The industry classification is according to GICS (Global Industry Classification Standard). The dependent variable of the models is RMSE, the residual mean square error from CAPM representing the market volatility after the release of the financial reports. The definitions of the variables are included in the Appendix A

insights. For instance, Kim et al. (2019) examines the relationship between complexity and crash risk, positing that managers' accumulation of hidden information may lead to sudden price crashes. They use a modified fog measure to capture linguistic readability.

Overall, this article increases our understanding of the financial reporting effect on the general debate surrounding its impact on market outcomes, specifically market volatility in this case and how textual characteristics can impact on investors behaviour. Critically we document that this impact which we observe is emphasised by application of accounting standards in this case, fair value and in the context of the consumer discretionary industry. Our findings may help standard setters to reassess the application of fair value accounting and how this impacts on narrative disclosures in the associated financial reporting narratives. It will also support practitioners in considering where narrative complexity can be debunked through voluntary disclosures that can allow users of reports to easily assess the detailed explanations of fair value assumptions. These can help standard setters and practitioners to explore the provision of more usable fair value information in financial narrative disclosures.

Appendix A: Definition of variables

See (Table 8).

Table 8 Variable definitions

Variables	Definitions
Readability measures	
Fog index	[(WordComplexity + WordPerSentence)*0.4]. "The interpretation of the fog index is score ≤ 18 = unreadable text, 14–18 = difficult text, 12–14 = ideal, 10–12 = acceptable, and 8–10 = childish text" (Li 2008)
WordComplexity	0.4*Percentage of complex words in the annual report. Complex words are words with three or more syllables
PercertComplexWords	[(Number of complex words in the annual report/total number of words in the same report)*100]. Complex words are words with three or more syllables
SentenceComplexity	0.4*Average word number of words per sentence
ComplexityWordsPercent The count of complexity words (Loughran and McDonald 2023), divided by the total number of words in the annual report × 100	
Dependent variables	
Post-filing RSME	The RMSE from a market model estimated using trading weeks [1, 4] relative to annual report announcement date (approximately one calendar month). There must be a minimum of 10 observations to be included in the sample
Control Variables	
AlphaPre	The alpha from a market model using trading weeks [-51, -1]. At least 60 observations of daily returns must be available to be included in the sample
RMSEPre	The RMSE from a market model using trading weeks [-51, -1]. At least 60 observations of daily returns must be available to be included in the sample
AbsAbR	The absolute value of the filing week excess return, measured by the buy- and-hold cumulative return between filing date (day 0) and day + 5 minus the buy-and-hold return of the FTSE 100 index over the same one-day period
LogSize	The natural logarithm of the reported market capitalisation of stock from Bloomberg on the day prior to annual report announcement date
LogB2M	The natural log of reversed price-to-book ratio offered by Bloomberg on the day prior to annual report announcement date

Appendix B: Additional robustness tests

Table 9 presents the results of the parallel trend tests, which were conducted to ensure the robustness of the DiD regressions reported in the main analysis.

Table 10 provides two robustness checks for our main findings. The results are consistent when using an alternative standard error clustering method, and F-tests show that additional industry- and firm-level fixed effects are not jointly significant.

Table 9 Parallel trend tests

Tested Component		WORDCOM	PLEXITY	PERCENTCOM	PLEXWORDS
		Pre-Treat Year 2011	Pre-Treat Year 2012	Pre-Treat Year 2011	Pre-Treat Year 2012
Intercept	Statistic	0.0130	0.0055	0.0130	0.0055
	p-value	0.6153	0.8598	0.6153	0.8598
Complexity	Statistic	−0.0012	−0.0006	−0.0005	−0.0002
	p-value	0.6296	0.8378	0.6296	0.8378

The parallel trend assumption was tested using two pre-treatment years (2011–2012) for DiD models with WORDCOMPLEXITY and PERCENTCOMPLEXWORDS. The results support the parallel trend assumption. *P*-values were above the 10% significance level, meaning we fail to reject the null hypothesis of parallel trends for both the intercept (trend in RMSE) and the coefficient of the complexity measure

Table 10 DiD regressions with different clustering and tests for fixed effects

	Model 1	Model 2
(Intercept)	-0.0141^{**}	-0.0141^{*}
WORDCOMPLEXITY	(0.0059)	(0.0074)
	-0.0004	
WORDCOMPLEXITY_YearInteractionDummy	(0.0007)	
	0.0030^{***}	
WORDCOMPLEXITY_IndusInteractionDummy	(0.0010)	
	-0.0002^{***}	
WORDCOMPLEXITY_YearIndusInteractionDummy	(0.0001)	
	0.0004^{*}	
PERCENTCOMPLEXWORDS	(0.0002)	-0.0002
PERCENTCOMPLEXWORDS_YearInteractionDummy		(0.0003)
		0.0012^{***}
PERCENTCOMPLEXWORDS_IndusInteractionDummy		(0.0004)
		-0.0001^{***}
PERCENTCOMPLEXWORDS_YearIndusInteractionDummy		(0.0000)
		0.0002^{*}
RSMEPre	0.4582^{***}	(0.0001)
		0.4582^{***}
AlphaPre	(0.0946)	(0.0906)
	-0.4340	-0.4340
LogSize	(0.5363)	(0.5226)
	-0.0012	-0.0012
AbsAbR	(0.0007)	(0.0008)
	0.0842^{***}	0.0842^{***}
LogB2M	(0.0245)	(0.0234)
	0.0009^{***}	0.0009^{***}
	(0.0002)	(0.0002)
R^2	0.4782	0.4782
Adj. R^2	0.4650	0.4650
Num. obs	775	775
F-test for Industry Level Fixed Effect	0.8506	0.8506
P-value	0.8401	0.8401
F-test for Firm Level Fixed Effect	-8.2677	-8.2677
P-value	1	1

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$

These models are identical to those in the main text but use two-way clustered stan- dard errors (by firm and year with Wild bootstrapping) for robustness. Key findings remain significant. F-tests for industry- and firm-level fixed effects yield high p-values, indicating the additional fixed effects are not jointly significant. This supports using the more parsimonious model specification presented

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