



UNIVERSIDADE CATÓLICA PORTUGUESA

The Impact of the Brexit Vote on Financial Narratives

Evidence from UK

Maria Leonor Guedes Soares

Católica Porto Business School

2019



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Final Assignment in the modality of Dissertation
presented to *Universidade Católica Portuguesa*
to obtain the degree of Master in Finance

by

Maria Leonor Guedes Soares

under the supervision of
(PhD) Paulo Alexandre Pimenta Alves

Católica Porto Business School
October 2019

Acknowledgments

I would like to thank my supervisor, Professor Paulo Alves, for the support and availability.

Resumo

Estudamos o impacto do referendo do *Brexit* em empresas transacionadas na *London Stock Exchange (LSE)* através da análise de mudanças de certas características das suas narrativas financeiras nomeadamente, o tom, a incerteza, o *forward-looking* e a causalidade. Usando vários modelos de regressão linear, realizamos uma análise das características referidas a diferentes secções do relatório de gestão (*Management Discussion and Analysis – MD&A* –, mensagem do *Chairman* e mensagem do *CEO*).

Enquanto o tom não é explicado pelo referendo, as palavras de incerteza, de *forward-looking* e de causalidade tornam-se mais frequentes após o voto.

Os resultados mostram que as empresas reagiram ao referendo do *Brexit* e alteraram o seu discurso em consequência do resultado do voto.

Palavras-chave: Referendo do *Brexit*, *Natural Language Processing*, tom, incerteza, *forward-looking*, causalidade, empresas financeiras e não financeiras.

Abstract

We study the impact of the Brexit referendum on firms listed on the London Stock Exchange (LSE) by analysing the changes in some characteristics of their financial narratives, namely, tone, uncertainty, forward-looking and causal language. Using a multivariate model, we analyse these features on different sections of the management report (e.g. Management Discussion and Analysis, Chairman message and CEO message).

While tone is not explained by the referendum, uncertainty, forward-looking and causal words become more frequent after the vote.

Our results confirm companies reacted to the Brexit referendum and change their discourse as a consequence of the vote outcome.

Keywords: Brexit referendum, Natural Language Processing, tone, uncertainty, forward-looking, causality, financial and non-financial firms.

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1. Introduction

Natural Language Processing (NLP) can be defined as a “discourse analysis technique” and refers to automated methods used to process information from text collections (Xing, Cambria and Welsch, 2017). Through its application, it is possible to extract discourse characteristics, such as sentiment (or tone), complexity and readability.

Research on Accounting and Finance suggests that firm sentiment can be a predictor for earnings and stock returns (Bannier, Pauls and Walter, 2017; Price et al, 2012) or a proxy for firm performance (Smith and Taffler, 2000), reflecting not only current performance, but also, expectations towards the future. However, tone has been shown to be used as a mechanism to manipulate investors’ perception of performance (Huang, Teoh and Zhang, 2011). In addition, it has been documented that firms with lower earnings increase complexity, making discourse harder to understand as an attempt to difficult the process of analysing information. Furthermore, profitable firms with persistent earnings have lower complexity (Li, 2008).

Hence, tone and complexity are correlated with firm performance and can be used to more accurately analyse a company’s financial condition. Note that, the association between performance and tone can be used to analyse if a firm is looking to inform the market or engaging in perception manipulation.

Sentiment based research can be applied to different corporate disclosure vehicles, from conference calls and earnings press releases to annual reports. In this thesis, we focus on the Chairman’s, the CEO’s and Management Discussion and Analysis (MD&A) sections of the annual report¹. The study of these sections

¹ Alves et al. (2016) showed that different annual report sections carry different performance predictive ability. Given that, we conduct an analysis tone, uncertainty discourse, forward-looking speech and causal reasoning across different annual report sections.

is complementary to the Financial Statements' analysis (Karthik, Li and Yang, 2012), as investors are unable to fully analyse a company's financial performance by looking only to quantitative information (Huang, Teoh and Zhang, 2011).

Interest on the information that firm sentiment captures is increasing, which is evident in the growing importance of the narratives' sections both in terms of Accounting and Finance research (Clatworthy and Jones, 2003) but also in each firm's annual report. Lewis and Young (2019) showed that the median report size – measured by the number of words – grew by 122%², and the number of topics in the median table of contents of UK reports, related to the narratives sections was 50% higher from 2003 to 2016, considering a sample of 19,426 annual reports (3,252 firms).

We use the dataset³ generated by the CFIE–FRSE⁴ software which classifies annual report sections and extracts sentiment based on different lists of words developed for Accounting and Finance research. Using a sample of 6,821 annual reports (2,296 from financial firms and 4,525 from non-financial companies) from 2012 to 2017, we study the narratives tone – here defined as the number of positive words minus the negative ones, scaled by their sum –, but also, uncertainty, forward-looking and causality language. Positive and negative words are defined according to the list of words proposed by Loughran and McDonald (2011). Uncertainty is proxied with words that capture imprecision (Loughran and McDonald, 2011). Forward-looking words are the ones related with forecasts (Hussainey, Schleicher and Walker, 2003). Causal language is associated with words firms use to justify or explain something, such as performance or an event that affected it (Zhang and Aerts, 2015). Koonce, Seybert and Smith (2011) stated that causal language is a central dimension on financial

² This growth can be explained by the mandatory adoption of the IFRS in 2005 (Lewis and Young, 2019).

³ The dataset is available for download at [http://www.research.lancs.ac.uk/portal/en/datasets/uk-annual-report-narratives-dataset-cfiefrse-may-2019\(4443e5bd-38c4-45bf-ae96-a7d947e529ce\).html](http://www.research.lancs.ac.uk/portal/en/datasets/uk-annual-report-narratives-dataset-cfiefrse-may-2019(4443e5bd-38c4-45bf-ae96-a7d947e529ce).html)

⁴ The software is available for download at <https://drelhaj.github.io/CFIE-FRSE/>.

and voluntary report. However, there is a major gap on research on uncertainty, forward-looking and causal language in Accounting and Finance. We plan to contribute to the literature by studying these sentiments around an event that may influence companies' performance and, consequently, discourse. The Brexit referendum is an example of such event. We believe it will impact the discourse applied in each company's financial narratives.

The Brexit referendum had a major impact for the economy of the United Kingdom as the market fail to anticipate the outcome of the vote. Results to leave the European Union (EU) won by 51.9%⁵. Studies show this result created uncertainty (Bloom, 2019), it reduced companies' abnormal returns (Oehler, Horn and Wendt, 2017; Ramiah et al, 2017) and is expected to reduce the UK's long-term GDP growth rate (Dhingra et al, 2017; OECD, 2016; PwC, 2016). Having in account these effects and work on firm sentiment, we test whether firms' discourse changes as a consequence of the vote. We expect tone to become more negative (to decrease) and uncertainty, forward-looking and causal words to be more recurrent in the annual reports published in 2016 and 2017.

Our results show the vote does not affect tone. Uncertainty, forward-looking and causal words, on the contrary, become more frequent, which means the financial narratives incorporated the uncertainty created by the Brexit referendum.

To the best of our knowledge, the effects of the Brexit referendum have not yet been quantified using computational linguistics. We add a different perspective to analyse the effects of the vote. Moreover, we contribute to Accounting and Finance literature by conducting an analysis across annual report sections and by studying different sentiments. Furthermore, we add to the work on automated content analysis, a study applied to a non-US country, the UK. Work on these

⁵ See <https://www.electoralcommission.org.uk/howe-we-and-what-we-do/elections-and-referendums/past-elections-and-referendums/eu-referendum/results-and-turnout-eu-referendum>

matters shows there are many obstacles to the application of computational linguistics to non-US countries, mainly due to disclosure regulation.

The remainder of the thesis is organized as follows. Chapter 2 regards the literature review presenting a theoretical framework on financial narratives and the Brexit referendum. Chapter 3 is the methodology, where we describe the process of sample selection and variables included in the models. Chapter 4 presents and discusses the results. Chapter 5 concludes the thesis.

2. Literature review

As mentioned above we study the impact of the Brexit referendum through the application of computational linguistics. Therefore, we start the literature review by explaining the process used to extract tone from text collections and then, how it is applied to study the impact of the Brexit referendum.

2.1. Automated content analysis

The use of automated content analysis for Accounting and Finance discourse or as stated by Loughran and McDonald (2016) “the notion of parsing text for patterns has a long history”.

Computational linguistics, automated content analysis or Natural Language Processing (NLP) are commonly used across disciplines as aliases and refer to similar textual analysis approaches (Loughran and McDonald, 2011 and 2016). These concepts are used to define the “idea of automatically analysing textual information” (Xing, Cambria and Welsch, 2018).

NLP is a subdiscipline of Artificial Intelligence (El-Haj et al, 2019b) and refers to methods such as, Naïve-Bayes classifications, term weighting and cosine similarity. Each one is a machine learning method. Their application is complex and hard to replicate across studies, which makes the process to validate their accuracy harder than the methods to be presented further – see Loughran and McDonald, 2011 and 2016; Xing, Cambria and Welsch, 2018; Lewis and Young, 2019 and El-Haj et al, 2019b for additional details.

On the other hand, there is word categorization, which is a dictionary-based approach and the most common method to extract tone in Accounting and Finance research (Loughran and McDonald, 2011). Bag of words – or word

categorization – is the method in which words are divided into several categories, according to the sentiment they capture. This method has the advantage to be easily replicated across papers however, in contrast to some machine-learning methods, it does not capture semantics, which means it ignores the sequence of words (El-Haj et al, 2019b).

There are four different lists of words commonly used for Accounting and Finance research: Henry (2008), Harvard's GI (General Inquirer), Diction and Loughran and McDonald (2011) – also known as LM dictionary.

Loughran and McDonald (2011) developed a list of words to be applied to Accounting and Finance research, with positive, negative and uncertainty meaning, after showing that the Harvard IV-4 dictionary – a list of positive and negative words created for psychology and sociology – is not appropriate for Accounting and Finance discourse since it classifies common words (considering this kind of speech) such as “tax” and “liability” as negative. In addition, it does not include words with a positive sentiment (and commonly used in financial disclosures) such as “strong” and “record” (Henry, 2009). The authors also studied Diction dictionaries and found that the software's word classification is not suitable for Accounting and Finance discourse. They applied word lists to manager's writing in 10-K files and found the following, “83% of the Diction optimism and 70% of the Diction pessimism frequencies are misclassified, based on LM classifications” (Loughran and McDonald, 2015).

These methods can be applied to “corporate press releases; webpage content; analyst reports; (...) pressure groups and politicians; media commentary; and speeches by policymakers, regulators and politicians:” (Lewis and Young, 2019). In Accounting and Finance research, tone has been shown to be related with stock returns, trading volume and earnings. Sentiment and performance's connection has been documented by applying automated content analysis methods to analyst reports (Huang, Zang and Zheng, 2014), social media (Kothari, Li and

Short, 2009) and corporate disclosures such as, earnings press releases (Henry, 2008; Huang, Teoh and Zhang, 2011; Price et al, 2012; Zhou, 2014) and annual reports (Li, 2008) or sections on it (Abrahamson and Amir, 1996; Li, 2010b; Lo, Ramos and Rogo, 2016; Smith and Taffler, 2000).

Bannier, Pauls and Walter (2017) studied the CEO's speech at the Annual General Meeting from German firms between 2008 and 2016. They developed a list of German words based on the lists proposed by Loughran and McDonald (2011). Cumulative abnormal returns decreased with the decrease of the difference between positive and negative tone.

Kothari, Li and Short (2009) using word lists from GI, quantified the effects of favorable or unfavorable disclosures from MD&A, analyst reports and business press, on the cost of capital, return volatility and analyst dispersion from 1996 to 2001. Considering the aggregated sources, they found that favorable (unfavorable) disclosures are associated with a decreasing (increasing) cost of capital, stock return volatility and analyst forecast dispersion. For each source of disclosure individually, they showed that the MD&A only affects stock return volatility, by increasing it, if the tone is unfavorable. This result reflects some credibility issues regarding the managers speech. By reacting only to unfavorable disclosures, the market is recognizing and acknowledging the existence of management bias. Analyst report's sentiment has no effects on cost of capital. The business press carries the same results as the combined sources.

Li (2010b) analysed forward-looking statements in the MD&A. She manually classified sentences as forward-looking and then applied Naïve-Bayes classifier to classify those sentences as positive, negative and neutral. She found that smaller firms with higher performance, lower accruals and less growth opportunities (high book-to-market ratio) have more positive forward-looking sentences.

In this thesis, the sentiments used to explain the impact of the Brexit referendum are extracted from the financial narratives of the companies who compose our sample.

2.2. Financial narratives

Ingram and Frazier (1983) defined an annual report as “undisguised advertisement”. It allows “management to present a serial, annual description of corporate financial performance” – Clatworthy and Jones, 2012. There are two main parts, the Financial Statements (FS) and the narratives’ sections – hereafter mentioned as the narratives. The FS are composed by the balance sheet, the income statement, statement of changes of equity, the cash–flow statement and the explanatory notes. Their disclosure is mandatory by the IFRS⁶ and, in contrast, to some parts of the narratives these ones are audited. Even though, they allow for corporate financial analysis, they are highly influenced by accounting standards and conventions, forecast errors and managers accounting choices (Palepu, Healy and Peek, 2013). The Chairman’s statement (also known as President’s Letter, Chairman’s Letter or Letter to Shareholders), the Management Commentary⁷ (also known as MD&A or Operating and Financial Review), the Governance report, the remuneration review, the audit review and a residual commentary, on the other hand, are included in the narratives.

In contrast, in the US, following the SEC’s (Securities and Exchange Commission) terms, firms are required to submit a part of the annual report on HTML format, which constitutes the 10–K files. Here, there is a very standardized

⁶ International Financial Reporting Standards (<https://www.ifrs.org/>)

⁷ IFRS Practice Statement 1: Management Commentary. “(...) Should be consistent with the following principles: Provide management’s view of entity’s performance, position and progress (including forward looking information)”. See <https://www.ifrs.org/issued-standards/management-commentary-practice-statement/> for the complete definition of the Management Commentary.

It may include one or more sections such as the CEO’s review, a business review or strategic review (Alves et al, 2016).

format associated with a standard set of headings, that all public firms must follow, which “enables more straightforward selection of relevant sections for further analysis” (El-Haj, Rayson, Alves and Young, 2018). In addition, the SEC’s EDGAR system, allows the extraction of a large sample of files. UK annual reports’ lack standardization and are not as easily available. Still, while following the requirements imposed by IAS Regulation, UK firms still hold some discretionary power regarding content and structure and so, they can choose where they present the information in the annual report and the titles for each section (El-Haj, Alves, Rayson, Walker and Young, 2019a). This together with the fact that in UK, annual reports are published as PDF files represents a major obstacle to retrieve and process information, as the first step to analyse the narratives involves to automatically determine the structure of the annual report.

Karthik, Li and Yang (2012) state that financial reporting and voluntary disclosure are complementary, since FS represent supportable evidence, while the narratives improve the FS’s credibility. Still, the narratives can also be subjected to management bias, since there is an opportunity for firms to manipulate the market perception of their financial performance or corporate accomplishments. Likewise, they can act as proxy for firm performance.

Merkel-Davies and Brennan (2007) showed that impression management⁸ is one incentive for voluntary narrative disclosures. Huang, Teoh and Zhang (2011) demonstrated that managers use tone management⁹ to mislead investor’s perception. Clatworthy and Jones (2003) proved that not only companies with improving performance present more good news and emphasize them, but also, there is a tendency to attribute improving performance on themselves and blame the environment in case of bad news. Li (2010a) evidenced the existence of

⁸ “Impression management, the process by which people control the impressions others form of them” — Leary and Kowalski, 1990.

⁹ Tone management is defined by Huang, Teoh and Zhang (2011) as the “choice of the tone level in qualitative text that is incommensurate with the concurrent quantitative information”.

managerial SAB (self-attribution bias) – managers take responsibility for positive results and fault someone or something else for poor results – when she found a more recurrent use of first-person pronouns, in MD&A from 10-K files, for improving performance. In addition, the author showed that companies with lower earnings presented more complex¹⁰ annual reports, and the ones associated with more persistent positive earnings have annual reports with higher levels of readability – they are easier to understand (Li, 2008). Lo, Ramos and Rogo (2016) showed that the MD&A section from 10-K files studied from 2000 to 2012 are more complex if the firm is more likely to have engaged in earnings management to overcome the previous year earnings.

Still, financial narratives can also be a source of incremental information. For instance, Smith and Tafler (2000) found that the chairman's statement can be a predictor for financial distressed firms, "reinforcing the argument that such unaudited narrative disclosures contain important information associated with the future of the company".

Ji, Talavera and Yin (2018) studied the Independent Directors Reports from Chinese listed firms from 2004–2012 by applying Naïve-Bayes classifiers. The authors found that positive (negative) tone is associated with improving (decreasing) firm performance (proxied by abnormal returns).

Price et al (2012) analysed earnings conference calls from the 4th quarter of 2004 to the 3rd quarter of 2007 using the GI list of words. The authors showed that the tone from quarterly earnings conference calls are a predictor of abnormal returns and trading volume.

¹⁰ For the mentioned paper, complexity is measured with the Fog index, which tell us the number of years of formal education required for an average intelligence person to understand a text collection after reading it once. It can be calculated with the following formula: Fog index = (words per sentence + proportion of complex words)×0,4
Words with more than three syllables are defined as complex. High levels of the fog index (more than 14 years of formal education) indicate for high levels of complexity and low levels of readability. A fog index higher than 21 stands for unreadable discourses.
See Li (2008) for further details.

Overall, tone may be positive reflecting good performance, or it may signal positive expectations regarding future performance that quantitative disclosures do not reflect due to regulation. In both cases, tone is a source of incremental information. Nevertheless, it can also represent an attempt for managers to hide poor performance, which, in this case, is an example of tone management (Huang, Teoh and Zhang, 2011).

Following, we discuss the effects of the Brexit referendum and explain why we believe it will affect a company's financial narratives.

2.3. The Brexit referendum

Brexit stands for British exit.

On June 23rd, 2016 the UK voted to leave the EU. The EU was formally notified regarding the UK's intention to no longer be a member by March 29th, 2017. According to Article 50 n° 3 on the Treaty on European Union¹¹, withdrawal negotiations may last two years. If the UK and the EU do not reach an agreement in that period, the UK will cease to be a member of the EU automatically. However, this period may be extended if the remaining EU state members unanimously approve. The deadline was set at 31st October 2019 and, until then, the UK is a member of the EU. The withdrawal process is still being negotiated.

When studying the effects of Brexit, literature focuses on the consequences of leaving the EU considering two possible scenarios, a Hard Brexit and a Soft Brexit. A Soft Brexit is considered an optimistic scenario. It assumes the UK remains in the European's Union single market¹², keeping the free movement of goods, services, capital and labor. A Hard Brexit means total isolation of the UK.

¹¹ Available at <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=OJ:C:2012:326:FULL&from=EN>.

¹² European Economic Area (EEA). By staying in the single market, the UK becomes a non-EU member with a similar agreement with the EU like Norway, Liechtenstein and Iceland. These countries have a free-trade agreement with the EU allowing the free trade of goods, services, labor and capital. They still contribute to the EU budget. Contributions are not as large as if they were EU members, though (Chang, 2017).

Considering this scenario, trades between the UK and the EU are regulated under the WTO – World Trade Organization – terms. This is the same as a non-agreement Brexit.

In addition, work regarding Brexit also studies the market's reaction to the vote.

By analysing a firm's narratives, we want to understand if the effects of the Brexit referendum and the expectations towards the consequences of Brexit, are reflected and absorbed by the firms that compose our sample.

2.3.1. The market reaction to the Brexit referendum

On June 24th, 2016, the day after the vote, the pound sterling registered its higher drop against the US Dollar since 1985. At the end of the day, the market closed with a nearly 8% drop in the GBP (see figure 1) while the EUR fell by, approximately, 2%. Against the EUR, the GBP reported a similar behavior, Exchange rates fell by 6% (see figure 2).

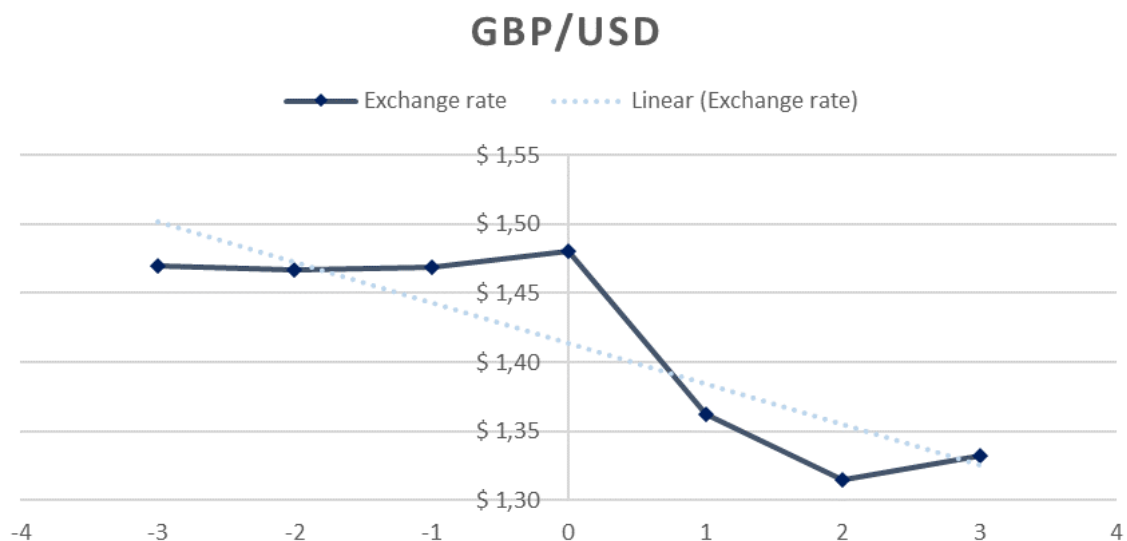


Figure 1 – GBP and USD exchange rate around the Brexit vote

Note: The x-axis is the number of working days before ($t < 0$) or following the Brexit referendum ($t > 0$). Day zero is the day of the vote, June 23rd, 2016. The y-axis tells us how many USD 1 GBP can buy. Source: Datastream.



Figure 2 – GBP and EUR exchange rate around the Brexit vote

Note: The x-axis is the number of working days before ($t < 0$) or following the Brexit referendum ($t > 0$). Day zero is the day of the vote, June 23rd, 2016. The y-axis tells us how many EUR 1 GBP can buy. Source: Datastream.

The index FTSE100, FTSE250 and LSE closed the day with a loss higher than 3%, 7% and 9% respectively (see figure 3).

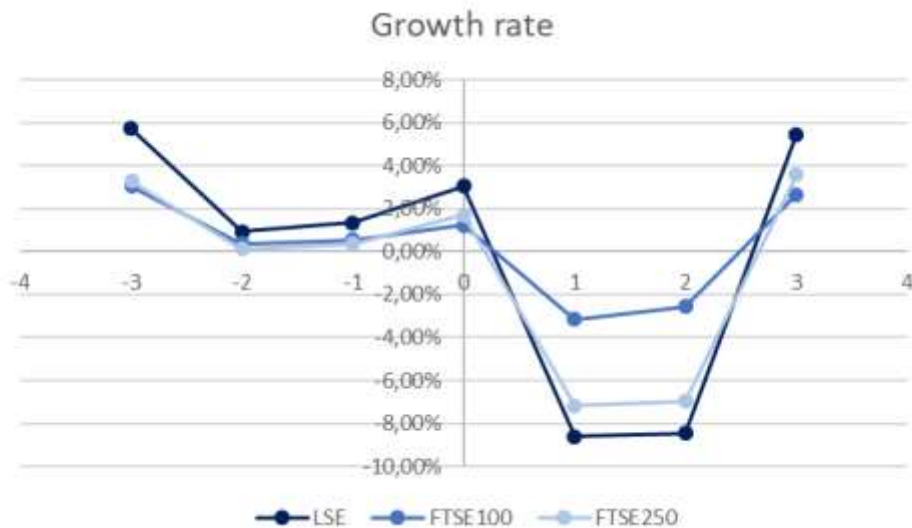


Figure 3 – Growth rate of the indexes around the Brexit vote

Note: The x-axis is the number of working days before ($t < 0$) or following the Brexit referendum ($t > 0$). Day zero is the day of the vote, June 23rd, 2016. The y-axis is the growth rate. Source: Datastream.

The credit rating agencies downgraded the UK's debt rating. Standard & Poor's lowered UK's credit rating to AA. Fitch ratings changed it from AA+ to AA. Moody's who had previously classified the UK's debt rating as stable, downgraded it to negative (Aristeidis and Elias, 2018; Oehler, Horn and Wendt, 2017).

Ramiah et al (2017) showed that the impact of the vote differs between sectors. However, most of them registered negative abnormal returns following the Brexit referendum. Banking was the most affected one. They also documented variations in the short-term systematic risk following the vote.

Bloom et al (2019) stated that the Brexit referendum started a period of high uncertainty. The authors found that nearly 40% of UK companies described Brexit as one of the top three causes of uncertainty in the two years following the referendum. Also, uncertainty is higher for firms who are more dependent on both trades or migrant labor from the EU, such as the ones from Wholesale & Retail and the Manufacturing industries. This finding is consistent with Oehler, Horn and Wendt (2017) who found that firms with lower levels of internationalization diversification – proxied by the weight of domestic sales – reported more negative abnormal returns the day following the vote, than the ones with high levels of diversification.

2.3.2. Consequences of Brexit

Brexit is a major source of uncertainty, particularly towards the potential existence of trade barriers, affecting both imports and exports. Uncertainty from the possibility of loss of passporting rights¹³, which may have a significant impact

¹³ For the UK, having passporting rights allows UK firms to trade services with any country from the EEA without the need of authorization from the country it is trading with, it reduces "red tap". Ramiah et al (2017) showed that Banking was the most affected sector following the vote, registering a high drop on abnormal returns. This is consistent with the concern to lose passporting rights. Note that, the banking sector is responsible to generate 54% of income from financial services trades between the EU and the UK (Armour, 2017).

on services exports. Uncertainty from the regulation of matters that so far were of shared or of exclusive competence of the EU, such as agriculture and fishery, trade agreements, immigration and financial regulation (Chang, 2017).

Uncertainty is a major issue because both people and firms do not know what to expect. If they do not recognize with a reasonable amount of certainty what is to come, they are unable to hedge themselves against future issues.

Considering this, Dhingra et al (2017) estimated a drop on the consumption of UK goods and services per capita by 1.3% and 2.7% with a Soft and Hard Brexit, respectively. Leaving the single market is expected to result in a decrease of exportations and an increase in the price of importations, due to the imposition of trade barriers. Consequently, a drop in UK's long-term GDP growth rate is anticipated. PwC (2016) and OECD (2016) estimated a 3.5% and a 5% decrease, respectively. Dhingra et al (2017) predicted more than a 7% drop.

So far, we have reported potential outcomes resulting from UK leaving the EU. Literature identifies both advantages and disadvantages of the Brexit. But for the matter of this thesis, the important subject here, is to understand that the market's reaction to the vote suggests a negative sentiment towards Brexit. Yet, and as a lot of work highlights, estimates are based on assumptions characterized by high uncertainty, that may or may not be accurate and verified in the future, since there are so many questions and doubts. Lehmann and Zetsche (2016) stated "(...) The only certainty for now is that it is impossible to predict the exact outcome of the negotiation process."

This uncertainty and reaction are what we look to capture in our study.

In addition to the work mentioned throughout the thesis, see Craig (2016) for a review of the process to get to the Brexit referendum; Belke, Dubova and Osowski (2018) who studied the consequences of Brexit to the UK and non-UK countries; Steinberg (2019) that documented the impact of uncertainty on trade policies following the vote; Driffield and Karoglou (2018) to understand the

effects of Brexit on foreign investment in the UK and Bockli et al (2017) who wrote “The Consequences of Brexit for Companies and Company Law”.

2.4. Research question: the effect of the Brexit vote on a firm’s discourse

Studies show that the annual report and individual sections, such as the Chairman’s and MD&A’s, carry predictive ability of a company’s future performance. Alves et al (2016) proposed three arguments that support the hypothesis that each section carries different predictive ability of firm performance, giving strength to the need to perform a simultaneous analysis of several annual report sections. First, each section, by definition, has one purpose and information may differ depending on the one it belongs to. Second, the whole annual report is not written by the same person or team. Furthermore, different authors may have a different profile – academic background and personality, for instance – which as shown by Argamon et al (2009) is reflected on linguistic style. Third, Ball, Robin and Wu (2003) showed that preparers’ incentives are a determinant of financial reporting quality. Moreover, Osma and Guillamón-Saorín (2011) documented that governance mechanisms impact management disclosures. Companies with strong governance policies are associated with higher quality disclosures.

Our goal is to understand if a company’s tone and discourse characteristics are affected by the Brexit referendum event. Given that, we compare its impact on different sentiments and sections. Thus, we not only care to explain tone, but also, uncertainty, forward-looking and causality as speech characteristics and sentiments in an annual report. Each one is studied for the Chairman’s, the CEO’s and the narratives’ sections.

To test if the Brexit referendum influenced companies, we formulated the following hypotheses:

H_{1a}) *Brexit has a negative impact on tone in the Chairman's letter.*

H_{1b}) *Brexit has a negative impact on tone in the CEO's review.*

H_{1c}) *Brexit has a negative impact on the MD&A's¹⁴ tone.*

Considering the negative effect, the Brexit referendum had on firms' abnormal returns for most sectors (Ramiah et al, 2017), we believe a company's tone will decrease, consequently. These hypotheses are formulated under the assumption that tone and firm performance are positively associated, meaning that decreasing performance is reflected with a more negative tone.

H_{2a}) *Brexit has a positive impact on the level of uncertainty in the Chairman's section.*

H_{2b}) *Brexit has a positive impact on the level of uncertainty in the CEO's section.*

H_{2c}) *Brexit has a positive impact on the MD&A's level of uncertainty.*

Uncertainty words are defined as the ones related with the notion of imprecision (Loughran and McDonald, 2011). As mentioned throughout the thesis, one of the major consequences of the referendum is the uncertainty it brought and created for firms in the UK. Given that, we expect the referendum to increase the use of uncertainty words on the firm's annual report.

Still, we must highlight that literature on the study of uncertainty discourse, forward-looking speech and causal reasoning as speech dimensions for Accounting and Finance research is sparse and limited. For this reason, this assumes an exploratory character.

H_{3a}) *Brexit has a positive impact on the use of forward-looking words in the Chairman's section.*

H_{3b}) *Brexit has a positive impact on the use of forward-looking words in the CEO's section.*

H_{3c}) *Brexit has a positive impact on the MD&A's use of forward-looking words.*

¹⁴ As mentioned on page 8, the MD&A or Management Commentary, may include several annual report sections' and, as so, it is commonly used to refer to the narratives. Given that, hereinafter when we use the term MD&A we are referring to the narratives.

Hussainey et al (2003) identified forward-looking words as the ones “associated with forecasts and predictions”.

Although the study of forward-looking discourse undertakes an experimental character – and, given that, there is some doubt towards the expected impact of the vote on forward-looking discourse – following the work from Bozanic et al (2018), we believe the vote has positive effect on forward-looking words. The authors found that when uncertainty is high, the issuance of forward-looking statements with a non-forecast-like dimension (non-quantitative earnings-related reports) increases. Furthermore, Athanasakou and Hussainey (2014) showed that firms make more disclosures on forward-looking performance – measured by an index of reports regarding expected performance – when they increase levels of debt or if they are to announce bad news.

H_{4a}) Brexit has a positive impact on the use of causal words in the Chairman’s section.

H_{4b}) Brexit has a positive impact on the use of causal words in the CEO’s section.

H_{4c}) Brexit has a positive impact on the MD&A’s use of causal words.

Causal words are the ones used when we are explaining or justifying something. Zhang and Aerts (2015) stated it is the kind of language used when the firm is explaining “why” and “how” of its performance. Their paper studies the use of causality words on the Management Commentary, as an impression management mechanism firms use when they fail to meet earnings thresholds. They found a positive relationship between the use of causal reasoning words and not meeting earnings thresholds, “such as positive earnings, earnings change and analyst earnings consensus”. Li (2008) found that companies with less persistent earnings use causal words more frequently.

Considering the impact of the Brexit referendum documented related with the decrease on cumulative abnormal returns and abnormal returns, the expectations towards the UK’s GDP, the evolution of consumption of UK goods and services,

but also UK exports, we believe the use of causal language will become more recurrent following the vote.

3. Methodology

3.1. Sample selection

The digital PDF annual reports are processed by the software CFIE–FRSE, which generates the dataset of textual analysis. It includes one dummy variable (DR_AR_IGNORE) that takes the value one if the annual report classification accuracy is questionable. To collect the sample, we drop those observations (DR_AR_IGNORE=1) and the ones with no data. Next, we delete the ones prior to 2012 and utility firms as well.

Due to the presence of outliers, we drop the extreme bottom and top one percentiles for the following variables: ROA, market value and book–to–market ratio. For the returns, earnings yield, change in ROA and ROA and returns volatility we only drop the observations above percentile 99.

Our sample comprises a total of 6,821 annual reports. The number of observations varies across annual report section.

3.2. Research design

To test our hypotheses, we formulate several OLS regression models. To understand the impact of the referendum, first, we regress tone, uncertainty, forward–looking and causality on tone determinants and industry–fixed effects which control for firm features. Then, we formulate a second regression model and add the Brexit indicator variable.

Each sentiment is regressed for three sections, the CEO’s, the Chairman’s and the MD&A’s, according to the hypothesis being tested.

Tests on our hypotheses focus on estimates of β_{14} from the following regression model:

Narratives' characteristics

$$\begin{aligned} &= \beta_0 + \beta_1 ROA_{it} + \beta_2 Ch_ROA_{it} + \beta_3 Ret_{it} + \beta_4 EY_{it} \\ &+ \beta_5 Ch_EY_{it} + \beta_6 Size_{it} + \beta_7 BTM_{it} + \beta_8 RetVol_{it} \\ &+ \beta_9 ROAVol_{it} + \beta_{10} Age_{it} + \beta_{11} GeoSeg_{it} \\ &+ \beta_{12} BusSeg_{it} + \beta_{13} Loss_{it} + \beta_{14} Brexit_{it} \\ &+ industry - fixed\ effects + \varepsilon_{it} \end{aligned} \quad (1 - 12)$$

Note that, the independent variables are the same regardless of the sentiment and annual report section. The only difference among the regression models used to test our hypotheses, are the dependent variables, which vary according to the sentiment and section.

The dependent variable for model (1) is the tone of the Chairman's section from the annual report published by firm *i* in year *t*; for model (2) is the tone of the CEO's section from the annual report published by firm *i* in year *t*; for model (3) is the tone of the MD&A from the annual report published by firm *i* in year *t*; for model (4) is the uncertainty of the Chairman's section from the annual report published by firm *i* in year *t*; for model (5) is the uncertainty from the CEO's section, from the annual report published by firm *i* in year *t*; for model (6) is the uncertainty of the MD&A from the annual report published by firm *i* in year *t*; for model (7) is the forward-looking of the Chairman's section from the annual report published by firm *i* in year *t*; for model (8) is the forward-looking of the CEO's section from the annual report published by firm *i* in year *t*; for model (9) is the forward-looking of the MD&A from the annual report published by firm *i* in year *t*; for model (10) is the causal reasoning of the Chairman's section from the annual report published by firm *i* in year *t*; for model (11) is the causal reasoning of the CEO's section from the annual report published by firm *i* in year *t*; for model (12) is the causal reasoning of the MD&A from the annual report published by firm *i* in year *t*.

Following the literature by Li (2008 and 2010) we run panel data regression models on tone determinants suggested by the author. ROA and change in ROA are proxies for profitability. Market and financial performance are measured by the returns, earnings yield and its change. The logarithm of the companies' equity market value controls for firm dimension. The book-to-market ratio is a proxy for growth opportunities. The ROA and returns volatility control for operational and business risk. Age captures the life cycle of the firm. The number of geographic segments and business segments controls for the firm's operating complexity. Loss controls for an event of decreasing earnings yield.

Apart from the Brexit indicator variable, our models differ from hers, since we do not control for special items and firm events (seasoned equity offerings and mergers and acquisitions). Also, we add the variables earnings yield and its change and dummy variable loss, to control for situations of changes in earnings and its decline. Each variable is defined in table 16 in appendix.

ROA_{it} is return on assets of firm i in year t ; Ch_ROA_{it} is the change in the return on assets of firm i in year t ; Ret_{it} is the 12-month stock return of firm i in year t ; $Earnings\ Yield_{it}$ is the earnings yield of firm i in year t ; Ch_EY_{it} is the change in the earnings yield of firm i in year t ; $Size_{it}$ is the logarithm of market capitalization at fiscal year-end of firm i in year t ; BTM_{it} is the book-to-market ratio of firm i in year t ; $RetVol_{it}$ is the returns' volatility of firm i in year t ; $ROAVol_{it}$ is the ROA volatility of firm i in year t ; Age_{it} is the $\log(1+age)$ of firm i in year t ; $GeoSeg_{it}$ is the $\log(1 + \text{number of geographic segments})$ of firm i in year t ; $BusSeg_{it}$ is the $\log(1 + \text{number of business segments})$ of if firm i in year t ; $Loss_{it}$ is the dummy variable that takes the value 1 if the EY from firm i in year t is lower than zero, or zero otherwise; $Brexit_{it}$ is the indicator variable that takes the value one if the annual report from firm i is published in 2016 or 2017 and zero otherwise. Since the referendum happened in June 2016, we believe this year's annual report can capture its effect, once they are typically disclosed at the end

of the year, which makes us believe, firms had time to react to the vote and reflect that reaction and expectations in the annual report.

4. Results

Table 1 presents the descriptive statistics of the sample including both financial and non-financial firms.

The median firm has one geographic and business segments. It has 16 years, a market capitalization of 100, a book to market ratio of 0.61; a 12-month stock return of 7.5%; an earnings yield of 4.6%; a ROA of 3.6% and both have changes of, approximately, 0.6%. It has a return and ROA volatility of, approximately, 0.08 and 0.07, respectively. Also, the median firm has a positive tone (tone is higher than zero) and the CEO's section is the one with the higher levels (0.42). Uncertainty words follow the same pattern, being the CEO's section the one with the highest level (approximately 0.05). Forward-looking discourse is higher for the Chairman's statement (0.02), while causal words are more frequent in the narratives (0.01).

Results are presented as follows. For tone – models (1), (2) and (3) – see table 2; for uncertainty – models (4), (5) and (6) – see table 5; for forward-looking – models (7), (8) and (9) – see table 8; for causal reasoning – models (10), (11) and (12) – see table 11.

Table 1 – Descriptive statistics

PANEL A – TONE MEASURES								
Variable name	N	Mean	St. Dev.	Min.	P25	Median	P75	Max.
<i>Tone_Chair</i>	5,833	0.2807	0.3050	−1.0000	0.0581	0.3333	0.5152	1.0000
<i>Tone_CEO</i>	3,155	0.3817	0.2414	−1.0000	0.2500	0.4184	0.5524	1.0000
<i>Tone_MD&A</i>	6,821	0.0076	0.2047	−1.0000	−0.1507	0.0357	0.1581	0.6091
<i>Change_Tone</i>	2,686	0.0000	0.1900	−1.0558	−0.1150	0.0076	0.1223	0.7993
<i>Uncertainty_Chair</i>	5,833	0.0484	0.0158	0.0000	0.0380	0.0479	0.0582	0.1476
<i>Uncertainty_CEO</i>	3,155	0.0535	0.0161	0.0000	0.0438	0.0539	0.0636	0.2225
<i>Uncertainty_MD&A</i>	6,821	0.0328	0.0073	0.0000	0.0278	0.0329	0.0377	0.1027
<i>Change_Uncertainty</i>	2,686	0.0000	0.0136	−0.0590	−0.0085	−0.0006	0.0079	0.7899
<i>Forwardlooking_Chair</i>	5,833	0.0175	0.0066	0.0000	0.0132	0.0172	0.0216	0.0701
<i>Forwardlooking_CEO</i>	3,155	0.0150	0.0066	0.0000	0.0106	0.0143	0.0188	0.0636
<i>Forwardlooking_MD&A</i>	6,821	0.0120	0.0029	0.0000	0.0102	0.0118	0.0136	0.0429
<i>Change_Forwardlooking</i>	2,686	0.0000	0.0063	−0.0189	−0.0041	−0.0004	0.0039	0.0243
<i>Causal_Chair</i>	5,833	0.0122	0.0053	0.0000	0.0087	0.0120	0.0153	0.0413
<i>Causal_CEO</i>	3,155	0.0128	0.0053	0.0000	0.0092	0.0123	0.0159	0.0520
<i>Causal_MD&A</i>	6,821	0.0138	0.0029	0.0000	0.0120	0.0138	0.0157	0.0367
<i>Change_Causal</i>	2,686	0.0000	0.0051	−0.0148	−0.0034	−0.0003	0.0029	0.0292

PANEL B – TONE DETERMINANTS/ FIRM SPECIFICS								
Variable name	N	Mean	St. Dev.	Min.	P25	Median	P75	Max.
<i>ROA</i>	6,821	−0.0110	0.2135	−1.7136	−0.0415	0.0360	0.0927	0.3903
<i>Change ROA</i>	6,821	0.0224	0.3028	−0.8096	−0.0358	0.0056	0.0472	11.8066
<i>Returns</i>	6,821	0.0983	0.4360	−1.0000	−0.1506	0.0747	0.2966	2.4211
<i>Earnings Yield</i>	6,821	−0.0237	0.4491	−18.0000	−0.0472	0.0459	0.0942	0.5855
<i>Change Earnings Yield</i>	6,821	0.0537	1.0341	−32.1786	−0.0338	0.0061	0.0584	43.0127
<i>Market Value</i>	6,821	959	3,191	1	21	100	505	37,937
<i>BTM</i>	6,821	0.4282	1.4194	−14.0037	0.2424	0.6102	1.0297	4.2778
<i>Return Volatility</i>	6,821	0.0995	0.0709	0.0031	0.0514	0.0796	0.1259	0.5068
<i>ROA Volatility</i>	6,821	0.1332	0.2549	0.0002	0.0283	0.0656	0.1395	3.8501
<i>Age</i>	6,821	21.4454	14.9918	0.0000	11.0000	16.0000	29.0000	53.0000
<i>Number geographic seg.</i>	6,821	2.4130	1.9554	1.0000	1.0000	1.0000	4.0000	10.0000
<i>Number business seg.</i>	6,821	2.2466	1.6895	1.0000	1.0000	1.0000	3.0000	10.0000
<i>Loss</i>	6,821	0.3271	0.4692	0.0000	0.0000	0.0000	1.0000	1.0000
<i>Brexit</i>	6,821	0.3168	0.4653	0.0000	0.0000	0.0000	1.0000	1.0000

The sample comprises firm-years for firms listed in the London Stock Exchange with fiscal year-ends between January 2012 and December 2017. Source: market and accounting data is extracted from Datastream. Tone variables belong to the dataset available for download at [http://www.research.lancs.ac.uk/portal/en/datasets/uk-annual-report-narratives-dataset-cfiefrse-may-2019\(4443e5bd-38c4-45bf-ae96-a7d947e529ce\).html](http://www.research.lancs.ac.uk/portal/en/datasets/uk-annual-report-narratives-dataset-cfiefrse-may-2019(4443e5bd-38c4-45bf-ae96-a7d947e529ce).html)

4.1. Tone

Table 2 presents the regression models on tone from the CEO's, the Chairman's and the MD&A's sections of the annual report. Each one is shown with and without the Brexit indicator variable.

Table 2 – OLS coefficients estimates of tone

	Tone											
	Chairman			CEO				MD&A				
	1.1	1.2		2.1	2.2			3.1		3.2		
<i>Intercept</i>	0.3232 *** (0.0000)	0.3196 *** (0.0000)		0.3735 *** (0.0000)	0.3694 *** (0.0000)			0.1116 *** (0.0000)		0.1120 *** (0.0000)		
<i>ROA</i>	0.0271 (0.2890)	0.0264 (0.3030)		0.0254 (0.4130)	0.0241 (0.4370)			0.0004 (0.9780)		0.0005 (0.9720)		
<i>Change ROA</i>	-0.0364 *** (0.0000)	-0.0365 *** (0.0000)		0.0195 (0.3030)	0.0190 (0.3180)			-0.0229 *** (0.0010)		-0.0228 *** (0.0010)		
<i>Returns</i>	0.0773 *** (0.0000)	0.0776 *** (0.0000)		0.0540 *** (0.0000)	0.0544 *** (0.0000)			0.0399 *** (0.0000)		0.0399 *** (0.0000)		
<i>Earnings Yield</i>	0.0302 *** (0.0090)	0.0301 *** (0.0090)		0.0397 *** (0.0050)	0.0398 *** (0.0040)			0.0127 ** (0.0320)		0.0127 ** (0.0320)		
<i>Change Earnings Yield</i>	-0.0017 (0.6850)	-0.0018 (0.6700)		-0.0031 (0.5110)	-0.0033 (0.4830)			-0.0029 ** (0.0460)		-0.0029 ** (0.0460)		
<i>Size</i>	0.0238 *** (0.0000)	0.0234 *** (0.0000)		0.0248 *** (0.0000)	0.0244 *** (0.0000)			0.0030 *** (0.0050)		0.0030 *** (0.0050)		
<i>BTM</i>	-0.0143 *** (0.0000)	-0.0136 *** (0.0000)		-0.0069 (0.1160)	-0.0061 (0.1720)			-0.0073 *** (0.0000)		-0.0074 *** (0.0000)		
<i>Return Volatility</i>	0.1392 ** (0.0250)	0.1375 ** (0.0260)		-0.2065 *** (0.0050)	-0.2059 *** (0.0050)			0.0016 (0.9670)		0.0017 (0.9630)		
<i>ROA Volatility</i>	0.0006 (0.9710)	0.0011 (0.9430)		-0.0147 (0.4660)	-0.0146 (0.4680)			-0.0232 ** (0.0140)		-0.0232 ** (0.0140)		
<i>Age</i>	-0.0480 *** (0.0000)	-0.0472 *** (0.0000)		-0.0298 *** (0.0000)	-0.0288 *** (0.0000)			-0.0303 *** (0.0000)		-0.0304 *** (0.0000)		
<i>GeoSeg</i>	0.0237 *** (0.0010)	0.0242 *** (0.0010)		-0.0126 (0.1440)	-0.0124 (0.1520)			0.0176 *** (0.0000)		0.0175 *** (0.0000)		
<i>BusSeg</i>	0.0758 *** (0.0000)	0.0763 *** (0.0000)		0.0103 (0.2520)	0.0105 (0.2400)			0.0637 *** (0.0000)		0.0637 *** (0.0000)		
<i>Loss</i>	-0.1118 *** (0.0000)	-0.1118 *** (0.0000)		-0.0453 *** (0.0000)	-0.0459 *** (0.0000)			-0.0669 *** (0.0000)		-0.0669 *** (0.0000)		
<i>Brexit</i>		0.0091 (0.1620)			0.0102 (0.2050)					-0.0011 (0.7830)		
<i>Industry fixed effects</i>	Yes	Yes		Yes	Yes			Yes		Yes		
<i>F statistic</i>	229.3100	219.2100		42.8500	41.4500			339.1700		323.7100		
<i>Adjusted R²</i>	44.26%	44.28%		24.05%	24.09%			48.38%		48.38%		
<i>N</i>	5,833	5,833		3,155	3,155			6,821		6,821		

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients.

OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

Brexit seems to not explain tone as H_{1a} , H_{1b} and H_{1c} are rejected. The indicator variable has no statistical significance. We identify two reasons to explain this result. Firstly, companies do not react to the vote, suggesting it has no effect on their expectations of future performance. We find this unlikely considering the results to be presented further and literature on the market reaction to the vote. Secondly, firms do not identify a positive or negative dimension in result of the Brexit referendum. This finding is consistent with the uncertainty hypothesis. Since companies are unable to identify which scenario will result from the Brexit event, they do not attribute a positive or negative sentiment to the vote, which explains why the Brexit variable adds no value (to the regression model without the Brexit dummy variable) when explaining tone. Note that, the scenario in which the UK leaves the EU has a major impact on companies. In addition, the reaction to the vote varies significantly across industry.

Bouoiyour and Selmi (2018) showed that Financial and Technology firms reported stronger stock price declines as a reaction to the referendum than industries such as Consumer Goods and Oil and Gas. Even though, all industries studied reacted negatively to the vote, these last two were much less sensible.

Furthermore, with the sterling depreciation exports are expected to become cheaper (*ceteris paribus*), explaining why Consumer Goods do not react as badly (as Technology and Financial firms). Oil and Gas companies trade mostly in US Dollars and for that reason, are considered in this scenario, as “safe haven” (Bouoiyour and Selmi, 2018). Knowing this, and once our sample includes those industries, we conduct this analysis on financial and non-financial firms traded in the LSE. We chose to analyse the financial industry individually due to its importance in the UK and the studies suggesting it was one of the most affected industry by the referendum. In 2018, the financial sector accounted for 7% of UK’s GDP and 23% of all services exports in the UK, which, in 2017, 43% of those were to EU countries (Rhodes, 2019). Tables 17 and 18 in appendix present the

descriptive statistics of non-financial and financial firms, respectively. Our results are presented on the tables 3 and 4.

While the tone from financial firms is not explained by the Brexit referendum, the tone from non-financial companies became more positive following the vote.

Before discussing these results, we must highlight that our sample is composed by traded firms on the LSE, not necessarily firms based in the UK. These firms may react positively as they identify the possibility to win market share by the UK exit from the EU.

Note that, while one sample only includes financial firms, the other is a diversified sample, including seven different industries – Basic Materials, Consumer Goods, Consumer Services, Healthcare, Industrials, Oil and Gas, Technology and Telecommunications – which may explain the positive tone following the referendum.

Last of all, Bouoiyour and Selmi (2018) also concluded that when firms announced projects related with product diversification, abnormal returns become positive. In exception to Consumer Goods firms', this was reported for all sectors in-sample. At least 25% of our sample of non-financial institutions is composed by firms with geographic segments – proxy for diversification – between 4 and 10. This means the impact of Brexit, even if negative, it is lower for these firms. In contrast, only 5% of financial firms have, at least, 4 geographic segments, which shows this sample has a much lower weight of diversified companies (when compared to non-financial firms). The ones with less diversification – less than 4 geographic segments (95%) – are more exposed to the potential consequences from Brexit, which, consequently, explains the results obtained.

Table 3 – Non-financial firms: OLS coefficients estimates of tone

	Tone											
	Chairman				CEO				MD&A			
	1.1		1.2		2.1		2.2		3.1		3.2	
<i>Intercept</i>	0,4375	***	0,4325	***	0,4096	***	0,4036	***	0,2073	***	0,2064	***
	(0,0000)		(0,0000)		(0,0000)		(0,0000)		(0,0000)		(0,0000)	
<i>ROA</i>	0,0606	**	0,0605	**	0,0283		0,0267		0,0062		0,0061	
	(0,0280)		(0,0290)		(0,3800)		(0,4090)		(0,6940)		(0,7010)	
<i>Change ROA</i>	-0,0380	***	-0,0382	***	0,0224		0,0215		-0,0193	***	-0,0193	***
	(0,0000)		(0,0000)		(0,2430)		(0,2620)		(0,0090)		(0,0080)	
<i>Returns</i>	0,0806	***	0,0807	***	0,0555	***	0,0556	***	0,0429	***	0,0429	***
	(0,0000)		(0,0000)		(0,0000)		(0,0000)		(0,0000)		(0,0000)	
<i>Earnings Yield</i>	0,0273	**	0,0271	**	0,0449	***	0,0452	***	0,0154	**	0,0154	**
	(0,0170)		(0,0180)		(0,0040)		(0,0040)		(0,0170)		(0,0180)	
<i>Change Earnings Yield</i>	0,0003		0,0002		-0,0033		-0,0036		-0,0017		-0,0018	
	(0,9320)		(0,9650)		(0,4780)		(0,4300)		(0,3600)		(0,3520)	
<i>Size</i>	0,0239	***	0,0235	***	0,0226	***	0,0221	***	0,0035	***	0,0034	***
	(0,0000)		(0,0000)		(0,0000)		(0,0000)		(0,0050)		(0,0060)	
<i>BTM</i>	-0,0067	**	-0,0058	*	-0,0033		-0,0020		-0,0022		-0,0020	
	(0,0300)		(0,0640)		(0,4600)		(0,6550)		(0,2210)		(0,2640)	
<i>Return Volatility</i>	-0,2109	***	-0,2117	***	-0,3088	***	-0,3067	***	-0,2318	***	-0,2319	***
	(0,0020)		(0,0020)		(0,0000)		(0,0000)		(0,0000)		(0,0000)	
<i>ROA Volatility</i>	0,0206		0,0215		-0,0205		-0,0200		-0,0174		-0,0173	
	(0,2360)		(0,2140)		(0,3700)		(0,3800)		(0,1140)		(0,1160)	
<i>Age</i>	-0,0404	***	-0,0392	***	-0,0249	***	-0,0233	***	-0,0329	***	-0,0326	***
	(0,0000)		(0,0000)		(0,0000)		(0,0000)		(0,0000)		(0,0000)	
<i>GeoSeg</i>	0,0057		0,0062		-0,0032		-0,0030		0,0086	*	0,0087	*
	(0,4630)		(0,4240)		(0,7180)		(0,7330)		(0,0660)		(0,0650)	
<i>BusSeg</i>	-0,0036		-0,0034		-0,0207	**	-0,0208	**	0,0126	**	0,0126	**
	(0,6600)		(0,6770)		(0,0280)		(0,0280)		(0,0100)		(0,0100)	
<i>Loss</i>	-0,0837	***	-0,0838	***	-0,0393	***	-0,0404	***	-0,0618	***	-0,0619	***
	(0,0000)		(0,0000)		(0,0030)		(0,0020)		(0,0000)		(0,0000)	
<i>Brexit</i>			0,0126	*			0,0154	*			0,0023	
			(0,0900)				(0,0550)				(0,5960)	
<i>Industry fixed effects</i>	Yes		Yes		Yes		Yes		Yes		Yes	
<i>F statistic</i>	64,6300		61,6100		35,3700		34,2800		68,1900		64,9000	
<i>Adjusted R²</i>	27,50%		27,55%		23,31%		23,41%		25,10%		25,10%	
<i>N</i>	3,826		3,826		2,588		2,588		4,525		4,525	

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients. OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

Table 4 – Financial firms: OLS coefficients estimates

	Tone							
	Chairman		CEO		MD&A			
	1.1	1.2	2.1	2.2	3.1	3.2		
<i>Intercept</i>	−0.1712 *** (0.0000)	−0.1765 *** (0.0000)	0.0777 (0.2760)	0.0809 (0.2620)	−0.3111 *** (0.0000)	−0.3092 *** (0.0000)		
<i>ROA</i>	0.0865 (0.2580)	0.0820 (0.2860)	0.0045 (0.9760)	0.0046 (0.9750)	0.0520 (0.2350)	0.0536 (0.2230)		
<i>Change ROA</i>	−0.0518 (0.2560)	−0.0521 (0.2560)	−0.0337 (0.8240)	−0.0331 (0.8260)	−0.0604 ** (0.0240)	−0.0605 ** (0.0230)		
<i>Returns</i>	0.0606 ** (0.0230)	0.0623 ** (0.0200)	0.0491 (0.1080)	0.0475 (0.1380)	0.0260 * (0.0900)	0.0254 * (0.0980)		
<i>Earnings Yield</i>	0.0419 *** (0.0050)	0.0418 *** (0.0050)	−0.0038 (0.9450)	−0.0028 (0.9590)	0.0090 (0.5450)	0.0090 (0.5440)		
<i>Change Earnings Yield</i>	−0.0164 (0.2120)	−0.0164 (0.2140)	0.0158 (0.4270)	0.0155 (0.4390)	−0.0035 * (0.0630)	−0.0035 * (0.0620)		
<i>Size</i>	0.0167 *** (0.0000)	0.0162 *** (0.0000)	0.0296 *** (0.0000)	0.0299 *** (0.0000)	−0.0016 (0.4610)	−0.0014 (0.5230)		
<i>BTM</i>	−0.0198 *** (0.0000)	−0.0189 *** (0.0010)	−0.0160 (0.1970)	−0.0166 (0.1910)	−0.0125 *** (0.0000)	−0.0128 *** (0.0000)		
<i>Return Volatility</i>	1.0455 *** (0.0000)	1.0393 *** (0.0000)	0.4517 (0.1480)	0.4555 (0.1460)	0.6634 *** (0.0000)	0.6654 *** (0.0000)		
<i>ROA Volatility</i>	−0.0525 (0.1220)	−0.0516 (0.1290)	0.0552 (0.2340)	0.0557 (0.2300)	−0.0476 *** (0.0050)	−0.0479 *** (0.0050)		
<i>Age</i>	−0.0382 *** (0.0000)	−0.0373 *** (0.0000)	−0.0358 ** (0.0280)	−0.0362 ** (0.0270)	−0.0096 * (0.0780)	−0.0099 * (0.0700)		
<i>GeoSeg</i>	0.0524 *** (0.0020)	0.0534 *** (0.0020)	−0.0407 (0.1180)	−0.0414 (0.1220)	0.0307 *** (0.0050)	0.0304 *** (0.0060)		
<i>BusSeg</i>	0.2288 *** (0.0000)	0.2298 *** (0.0000)	0.1069 *** (0.0000)	0.1061 *** (0.0000)	0.1629 *** (0.0000)	0.1625 *** (0.0000)		
<i>Loss</i>	−0.1429 *** (0.0000)	−0.1427 *** (0.0000)	−0.0907 ** (0.0140)	−0.0909 ** (0.0140)	−0.0733 *** (0.0000)	−0.0734 *** (0.0000)		
<i>Brexit</i>		0.0095 (0.4180)		−0.0059 (0.8190)		−0.0036 (0.6110)		
<i>F statistic</i>	73.6300	68.4400	8.5000	7.8900	66.1700	61.6200		
<i>Adjusted R²</i>	32.53%	32.56%	16.02%	16.03%	27.57%	27.58%		
<i>N</i>	2,007	2,007	567	567	2,296	2,296		

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients. OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

4.2. Uncertainty

Table 5 presents the regression models on uncertainty language from the CEO's, the Chairman's and the MD&A's sections of the annual report. Each one is shown with and without the Brexit indicator variable.

Table 5 – OLS coefficients estimates of uncertainty

	Uncertainty									
	Chairman		CEO				MD&A			
	4.1	4.2	5.4	5.5	6.1	6.2				
<i>Intercept</i>	0.0477 *** (0.0000)	0.0472 *** (0.0000)	0.0397 *** (0.0000)	0.0391 *** (0.0000)	0.0299 *** (0.0000)	0.0294 *** (0.0000)				
<i>ROA</i>	0.0038 *** (0.0050)	0.0037 *** (0.0060)	0.0018 (0.2890)	0.0016 (0.3410)	0.0003 (0.5830)	0.0002 (0.7450)				
<i>Change ROA</i>	-0.0014 *** (0.0040)	-0.0014 *** (0.0030)	0.0000 (0.9740)	-0.0001 (0.9570)	-0.0006 ** (0.0110)	-0.0006 *** (0.0080)				
<i>Returns</i>	0.0028 *** (0.0000)	0.0029 *** (0.0000)	0.0016 ** (0.0230)	0.0017 ** (0.0190)	0.0008 *** (0.0000)	-0.0001 (0.7780)				
<i>Earnings Yield</i>	0.0011 * (0.0520)	0.0011 * (0.0570)	0.0004 (0.5070)	0.0004 (0.4860)	0.0000 (0.8300)	-0.0001 (0.3640)				
<i>Change Earnings Yield</i>	-0.0003 (0.1810)	-0.0003 (0.1550)	-0.0001 (0.6060)	-0.0001 (0.4640)	-0.0001 (0.4560)	0.0009 *** (0.0000)				
<i>Size</i>	0.0012 *** (0.0000)	0.0011 *** (0.0000)	0.0022 *** (0.0000)	0.0022 *** (0.0000)	0.0008 *** (0.0000)	0.0008 *** (0.0000)				
<i>BTM</i>	-0.0008 *** (0.0000)	-0.0007 *** (0.0000)	-0.0008 *** (0.0000)	-0.0007 *** (0.0030)	-0.0005 *** (0.0000)	-0.0004 *** (0.0000)				
<i>Returns Volatility</i>	-0.0019 (0.5980)	-0.0021 (0.5510)	-0.0071 (0.1480)	-0.0071 (0.1540)	0.0015 (0.3290)	0.0013 (0.3890)				
<i>ROA Volatility</i>	0.0000 (0.9810)	0.0001 (0.9340)	-0.0036 *** (0.0010)	-0.0036 *** (0.0010)	-0.0007 ** (0.0490)	-0.0007 * (0.0600)				
<i>Age</i>	-0.0019 *** (0.0000)	-0.0018 *** (0.0000)	-0.0014 *** (0.0010)	-0.0012 *** (0.0030)	-0.0011 *** (0.0000)	-0.0010 *** (0.0000)				
<i>GeoSeg</i>	0.0021 *** (0.0000)	0.0022 *** (0.0000)	0.0024 *** (0.0000)	0.0025 *** (0.0000)	0.0017 *** (0.0000)	0.0017 *** (0.0000)				
<i>BusSeg</i>	0.0034 *** (0.0000)	0.0035 *** (0.0000)	0.0009 (0.1070)	0.0010 (0.0950)	* (0.0000)	0.0020 *** (0.0000)				
<i>Loss</i>	-0.0041 *** (0.0000)	-0.0041 *** (0.0000)	-0.0020 *** (0.0060)	-0.0021 *** (0.0040)	-0.0013 *** (0.0000)	-0.0013 *** (0.0000)				
<i>Brexit</i>		0.0013 *** (0.0010)		0.0015 *** (0.0070)		0.0011 *** (0.0000)				
<i>Industry fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes				
<i>F statistic</i>	86.7100	83.8600	44.0000	43.0200	139.3700	137.4300				
<i>Adjusted R²</i>	23.89%	24.03%	22.67%	22.84%	28.84%	29.33%				
<i>N</i>	5,833	5,833	3,155	3,155	6,821	6,821				

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients.

OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

Results seem to indicate that the vote led to an increase on the use of uncertainty words for the sections studied, which is consistent with our expectations and confirms H_{2a}, H_{2b} and H_{2c}. Brexit is a source of uncertainty and, as a result, annual reports from 2016 and 2017 show a more recurrent use of imprecision-related words than the ones from 2012 to 2015. See tables 6 and 7 for the results on non-financial and financial firms.

Tests on those companies document the same results. On the matter of uncertainty, there is no difference between financial and non-financial firms and across annual report sections. Note that, only the CEO's section from a financial firm reports a Brexit indicator variable with no statistical significance. This is also reported for the sentiments presented further, which can be explained by the lack of observations on this specific section.

Table 6 – Non-financial firms: OLS coefficients estimates of uncertainty

	Uncertainty									
	Chairman		CEO				MD&A			
	4.1	4.2	5.4	5.5	6.1	6.2				
<i>Intercept</i>	0.0515 *** (0.0000)	0.0510 *** (0.0000)	0.0405 *** (0.0000)	0.0398 *** (0.0000)	0.0331 *** (0.0000)	0.0326 *** (0.0000)				
<i>ROA</i>	0.0036 ** (0.0170)	0.0036 ** (0.0180)	0.0017 (0.3390)	0.0015 (0.3950)	0.0003 (0.6150)	0.0002 (0.7210)				
<i>Change ROA</i>	-0.0015 *** (0.0010)	-0.0015 *** (0.0010)	0.0001 (0.9430)	0.0000 (0.9780)	-0.0007 *** (0.0010)	-0.0008 *** (0.0010)				
<i>Returns</i>	0.0033 *** (0.0000)	0.0033 *** (0.0000)	0.0020 *** (0.0090)	0.0020 *** (0.0090)	0.0010 *** (0.0000)	0.0001 (0.7160)				
<i>Earnings Yield</i>	0.0013 * (0.0520)	0.0013 * (0.0560)	0.0002 (0.7670)	0.0002 (0.7290)	0.0001 (0.6540)	0.0001 (0.5060)				
<i>Change Earnings Yield</i>	-0.0001 (0.7290)	-0.0001 (0.6730)	-0.0001 (0.6620)	-0.0001 (0.4780)	0.0001 (0.4070)	0.0010 (0.0000)				
<i>Size</i>	0.0012 *** (0.0000)	0.0012 *** (0.0000)	0.0021 *** (0.0000)	0.0020 *** (0.0000)	0.0007 *** (0.0000)	0.0006 *** (0.0000)				
<i>BTM</i>	-0.0008 *** (0.0000)	-0.0007 *** (0.0000)	-0.0008 *** (0.0030)	-0.0007 ** (0.0150)	-0.0004 *** (0.0000)	-0.0003 *** (0.0010)				
<i>Returns Volatility</i>	-0.0107 *** (0.0090)	-0.0108 *** (0.0080)	-0.0125 ** (0.0210)	-0.0123 ** (0.0230)	-0.0055 *** (0.0010)	-0.0056 *** (0.0010)				
<i>ROA Volatility</i>	-0.0004 (0.6700)	-0.0003 (0.7430)	-0.0040 *** (0.0010)	-0.0039 *** (0.0010)	-0.0008 * (0.0560)	-0.0007 * (0.0720)				
<i>Age</i>	-0.0024 *** (0.0000)	-0.0023 *** (0.0000)	-0.0008 * (0.0740)	-0.0007 (0.1540)	-0.0012 *** (0.0000)	-0.0010 *** (0.0000)				
<i>GeoSeg</i>	0.0018 *** (0.0010)	0.0019 *** (0.0000)	0.0025 *** (0.0000)	0.0025 *** (0.0000)	0.0015 *** (0.0000)	0.0015 *** (0.0000)				
<i>BusSeg</i>	0.0019 *** (0.0010)	0.0019 *** (0.0010)	0.0002 (0.7750)	0.0002 (0.7840)	0.0008 *** (0.0000)	0.0009 *** (0.0000)				
<i>Loss</i>	-0.0039 *** (0.0000)	-0.0039 *** (0.0000)	-0.0016 ** (0.0460)	-0.0017 ** (0.0320)	-0.0012 *** (0.0000)	-0.0012 *** (0.0000)				
<i>Brexit</i>		0.0012 ** (0.0180)		0.0017 *** (0.0050)		0.0014 *** (0.0000)				
<i>Industry fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes				
<i>F statistic</i>	56.7900	54.7000	38.0700	37.1800	69.8200	69.7400				
<i>Adjusted R²</i>	20.47%	20.58%	22.25%	22.47%	22.80%	23.60%				
<i>N</i>	3,826	3,826	2,588	2,588	4,525	4,525				

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients.
 OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

Table 7 – Financial firms: OLS coefficients estimates of uncertainty

	Uncertainty											
	Chairman			CEO				MD&A				
	4.1		4.2		5.4		5.5		6.1		6.2	
<i>Intercept</i>	0.0313	***	0.0304	***	0.0375	***	0.0374	***	0.0210	***	0.0207	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
<i>ROA</i>	0.0066	*	0.0059		0.0008		0.0008		0.0018		0.0015	
	(0.0610)		(0.7500)		(0.7550)		(0.7540)		(0.7590)		(0.7640)	
<i>Change ROA</i>	−0.0007		−0.0007		−0.0018		−0.0019		−0.0004		−0.0003	
	(0.7620)		(0.7500)		(0.7550)		(0.7540)		(0.7590)		(0.7640)	
<i>Returns</i>	0.0002		0.0005		−0.0013		−0.0012		0.0002		−0.0003	
	(0.8910)		(0.7140)		(0.3720)		(0.4150)		(0.7320)		(0.4740)	
<i>Earnings Yield</i>	0.0014	*	0.0014	*	0.0046	*	0.0045	*	−0.0003		−0.0003	**
	(0.0530)		(0.0530)		(0.0510)		(0.0530)		(0.4770)		(0.0160)	
<i>Change Earnings Yield</i>	−0.0012	*	−0.0012	*	0.0000		0.0000		−0.0003	**	0.0003	
	(0.0740)		(0.0770)		(0.9780)		(0.9690)		(0.0150)		(0.6120)	
<i>Size</i>	0.0009	***	0.0008	***	0.0026	***	0.0026	***	0.0011	***	0.0010	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
<i>BTM</i>	−0.0006	**	−0.0005	*	−0.0010	**	−0.0010	**	−0.0006	***	−0.0006	***
	(0.0220)		(0.0890)		(0.0210)		(0.0270)		(0.0000)		(0.0000)	
<i>Returns Volatility</i>	0.0243	***	0.0232	***	0.0244	**	0.0243	**	0.0189	***	0.0186	***
	(0.0030)		(0.0040)		(0.0460)		(0.0480)		(0.0000)		(0.0000)	
<i>ROA Volatility</i>	0.0001		0.0002		−0.0001		−0.0001		−0.0006		−0.0006	
	(0.9700)		(0.8770)		(0.9670)		(0.9610)		(0.3770)		(0.4160)	
<i>Age</i>	−0.0006		−0.0004		−0.0031	***	−0.0031	***	−0.0007	***	−0.0006	***
	(0.2110)		(0.3780)		(0.0000)		(0.0000)		(0.0010)		(0.0020)	
<i>GeoSeg</i>	0.0029	***	0.0031	***	0.0024	*	0.0024	*	0.0022	***	0.0022	***
	(0.0010)		(0.0010)		(0.0580)		(0.0600)		(0.0000)		(0.0000)	
<i>BusSeg</i>	0.0069	***	0.0071	***	0.0030	**	0.0030	**	0.0040	***	0.0041	***
	(0.0000)		(0.0000)		(0.0120)		(0.0120)		(0.0000)		(0.0000)	
<i>Loss</i>	−0.0042	***	−0.0042	***	−0.0036	*	−0.0036	*	−0.0013	***	−0.0013	***
	(0.0000)		(0.0000)		(0.0510)		(0.0520)		(0.0010)		(0.0010)	
<i>Brexit</i>			0.0017	***			0.0002				0.0006	***
			(0.0060)				(0.8810)				(0.0000)	
<i>F statistic</i>	28.1800		26.8100		28.0900		26.0900		76.1900		71.3600	
<i>Adjusted R²</i>	16.05%		16.36%		26.31%		26.32%		28.16%		28.31%	
<i>N</i>	2,007		2,007		567		567		2,296		2,296	

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients.
 OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

4.3. Forward-looking

Table 8 presents the regression models on the forward-looking language from the CEO's, the Chairman's and the MD&A's sections of the annual report. Each one is shown with and without the Brexit indicator variable.

Table 8 – OLS coefficients estimates of forward-looking

	Forward-looking									
	Chairman		CEO				MD&A			
	7.1	7.2	8.1	8.2	9.1	9.2				
<i>Intercept</i>	0.0168 *** (0.0000)	0.0167 *** (0.0000)	0.0150 *** (0.0000)	0.0151 *** (0.0000)	0.0107 *** (0.0000)	0.0106 *** (0.0000)				
<i>ROA</i>	0.0014 * (0.0500)	0.0014 * (0.0540)	-0.0005 (0.5260)	-0.0005 (0.5400)	0.0004 (0.1490)	0.0004 (0.1760)				
<i>Change ROA</i>	-0.0001 (0.8220)	-0.0001 (0.8100)	-0.0002 (0.6000)	-0.0002 (0.6100)	0.0004 ** (0.0210)	0.0004 ** (0.0230)				
<i>Returns</i>	-0.0002 (0.2710)	-0.0002 (0.2880)	-0.0005 (0.1030)	-0.0005 (0.1010)	-0.0002 * (0.0580)	-0.0002 * (0.0650)				
<i>Earnings Yield</i>	0.0004 * (0.0890)	0.0004 * (0.0940)	0.0006 ** (0.0330)	0.0006 ** (0.0340)	-0.0002 ** (0.0300)	-0.0002 ** (0.0290)				
<i>Change Earnings Yield</i>	0.0000 (0.8590)	0.0000 (0.8400)	0.0001 (0.4070)	0.0001 (0.3950)	0.0000 (0.1430)	0.0000 (0.1240)				
<i>Size</i>	-0.0001 *** (0.0090)	-0.0001 *** (0.0050)	0.0001 (0.1120)	0.0001 (0.1020)	0.0003 *** (0.0000)	0.0003 *** (0.0000)				
<i>BTM</i>	-0.0001 (0.1830)	-0.0001 (0.3110)	0.0001 (0.3300)	0.0001 (0.3920)	-0.0001 *** (0.0010)	-0.0001 ** (0.0100)				
<i>Returns Volatility</i>	0.0010 (0.5490)	0.0009 (0.5720)	0.0035 (0.1120)	0.0035 (0.1130)	0.0017 ** (0.0160)	0.0017 ** (0.0180)				
<i>ROA Volatility</i>	0.0001 (0.8010)	0.0001 (0.7680)	-0.0007 (0.1740)	-0.0007 (0.1730)	0.0002 (0.4010)	0.0002 (0.3800)				
<i>Age</i>	0.0001 (0.3020)	0.0002 (0.2180)	-0.0004 *** (0.0080)	-0.0005 *** (0.0060)	-0.0002 *** (0.0020)	-0.0001 ** (0.0100)				
<i>GeoSeg</i>	-0.0004 * (0.0700)	-0.0004 * (0.0840)	-0.0008 *** (0.0010)	-0.0008 *** (0.0010)	-0.0003 *** (0.0000)	-0.0003 *** (0.0010)				
<i>BusSeg</i>	-0.0007 *** (0.0020)	-0.0007 *** (0.0020)	0.0000 (1.0000)	0.0000 (0.9900)	-0.0004 *** (0.0000)	-0.0004 *** (0.0000)				
<i>Loss</i>	0.0008 *** (0.0070)	0.0008 *** (0.0070)	0.0009 ** (0.0190)	0.0009 ** (0.0180)	0.0006 *** (0.0000)	0.0006 *** (0.0000)				
<i>Brexit</i>		0.0003 (0.1040)		-0.0001 (0.6000)		0.0002 *** (0.0010)				
<i>Industry fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes				
<i>F statistic</i>	7.8400	7.5900	11.7200	11.2300	27.6200	26.7500				
<i>Adjusted R²</i>	2.79%	2.84%	8.05%	8.06%	8.67%	8.80%				
<i>N</i>	5,833	5,833	3,155	3,155	6,821	6,821				

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients. OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

Like the use of uncertainty words, the vote also has a positive effect on the use of forward-looking words on the MD&A from the annual reports from the year of the vote – 2016 – and the year after – 2017, however only H_3c is accepted.

This finding is consistent with our expectations but also, with literature that suggests that periods of high uncertainty lead to an increase in the issuance of forward-looking statements. Such reports are the ones related with future performance (Athanasakou and Hussainey, 2014) as the Management Commentary – or MD&A –, which may be the reason why Brexit does not explain forward-looking discourse on the Chairman's and CEO's section. This latter section (when it exists) can be included in the Management Commentary. By only analysing it, we are studying just a part of the Management Commentary. The narratives, on the other hand, cover all sections including other forward-looking statements, such as the ones studied by Athanasakou and Hussainey (2014).

Following, we present results on non-financial (table 9) and financial institutions (table 10).

While the uncertainty of financial and non-financial firms individually, reported similar results to the ones documented on the sample including both, this is not as straightforward on forward-looking discourse.

Results on non-financial firms suggest both the Chairman and the MD&A adopt a more recurrent forward-looking language. On the other hand, the Brexit variable on financial firms has no statistical significance on any section. Still, the Brexit estimates with statistical significance load with a positive and expected coefficient, allowing us to draw the same conclusions, which is a sign of robust and consistent results.

Table 9 – Non-financial firms: OLS coefficients estimates of forward-looking

	Forward-looking							
	Chairman		CEO				MD&A	
	7.1	7.2	8.1	8.2	9.1	9.2		
<i>Intercept</i>	0.0165 *** (0.0000)	0.0163 *** (0.0000)	0.0151 *** (0.0000)	0.0152 *** (0.0000)	0.0102 *** (0.0000)	0.0100 *** (0.0000)		
<i>ROA</i>	0.0005 (0.5040)	0.0005 (0.5070)	−0.0005 (0.5620)	−0.0005 (0.5770)	0.0000 (0.9550)	0.0000 (0.9080)		
<i>Change ROA</i>	−0.0003 (0.5030)	−0.0003 (0.4980)	−0.0004 (0.4390)	−0.0004 (0.4490)	0.0004 ** (0.0270)	0.0004 ** (0.0290)		
<i>Returns</i>	−0.0004 (0.1390)	−0.0004 (0.1420)	−0.0005 (0.1210)	−0.0005 (0.1210)	−0.0003 *** (0.0060)	−0.0003 *** (0.0060)		
<i>Earnings Yield</i>	0.0003 (0.2600)	0.0003 (0.2740)	0.0005 (0.1340)	0.0005 (0.1360)	−0.0001 ** (0.0470)	−0.0002 ** (0.0460)		
<i>Change Earnings Yield</i>	0.0001 (0.6180)	0.0001 (0.6460)	0.0001 (0.3080)	0.0001 (0.2940)	0.0000 (0.4140)	0.0000 (0.4980)		
<i>Size</i>	−0.0001 (0.1640)	−0.0001 * (0.0970)	0.0001 (0.1550)	0.0001 (0.1390)	0.0004 *** (0.0000)	0.0004 *** (0.0000)		
<i>BTM</i>	−0.0001 (0.2020)	−0.0001 (0.3790)	0.0000 (0.7490)	0.0000 (0.8380)	−0.0001 ** (0.0310)	−0.0001 (0.1210)		
<i>Returns Volatility</i>	0.0034 * (0.0650)	0.0034 * (0.0670)	0.0033 (0.1630)	0.0032 (0.1670)	0.0022 *** (0.0060)	0.0021 *** (0.0070)		
<i>ROA Volatility</i>	−0.0004 (0.3400)	−0.0004 (0.3840)	−0.0008 (0.1890)	−0.0008 (0.1860)	−0.0001 (0.6550)	−0.0001 (0.6990)		
<i>Age</i>	−0.0001 (0.4310)	−0.0001 (0.6160)	−0.0004 ** (0.0220)	−0.0005 ** (0.0190)	−0.0002 ** (0.0260)	−0.0001 * (0.0780)		
<i>GeoSeg</i>	−0.0001 (0.6220)	−0.0001 (0.6830)	−0.0007 ** (0.0100)	−0.0007 ** (0.0100)	−0.0003 *** (0.0020)	−0.0003 *** (0.0030)		
<i>BusSeg</i>	−0.0005 * (0.0690)	−0.0005 * (0.0740)	−0.0002 (0.5720)	−0.0002 (0.5730)	−0.0005 *** (0.0000)	−0.0005 *** (0.0000)		
<i>Loss</i>	0.0006 * (0.0790)	0.0006 * (0.0820)	0.0008 ** (0.0440)	0.0008 ** (0.0420)	0.0006 *** (0.0000)	0.0006 *** (0.0000)		
<i>Brexit</i>		0.0005 ** (0.0350)		−0.0002 (0.5580)		0.0003 *** (0.0020)		
<i>Industry fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes		
<i>F statistic</i>	5.7200	5.6600	11.8100	11.3000	26.6100	25.6300		
<i>Adjusted R²</i>	3.00%	3.11%	9.04%	9.05%	10.49%	10.66%		
<i>N</i>	3,826	3,826	2,588	2,588	4,525	4,525		

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients.
 OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

Table 10 – Financial firms: OLS coefficients estimates of forward-looking

	Forward-looking									
	Chairman		CEO				MD&A			
	7.1	7.2	8.1	8.2	9.1	9.2				
<i>Intercept</i>	0.0189 *** (0.0000)	0.0190 *** (0.0000)	0.0152 *** (0.0000)	0.0152 *** (0.0000)	0.0120 *** (0.0000)	0.0119 *** (0.0000)				
<i>ROA</i>	0.0035 ** (0.0430)	0.0036 ** (0.0410)	-0.0028 (0.5810)	-0.0028 (0.5810)	0.0024 *** (0.0040)	0.0023 *** (0.0060)				
<i>Change ROA</i>	0.0021 *** (0.0070)	0.0021 *** (0.0070)	0.0039 (0.2210)	0.0039 (0.2210)	-0.0002 (0.6580)	-0.0002 (0.6610)				
<i>Returns</i>	0.0000 (0.9910)	0.0000 (0.9630)	-0.0006 (0.5240)	-0.0005 (0.5390)	0.0000 (0.9020)	0.0001 (0.8360)				
<i>Earnings Yield</i>	0.0011 ** (0.0160)	0.0011 ** (0.0160)	0.0023 (0.2500)	0.0023 (0.2490)	-0.0002 (0.2720)	-0.0002 (0.2760)				
<i>Change Earnings Yield</i>	-0.0013 *** (0.0000)	-0.0013 *** (0.0000)	-0.0006 (0.3210)	-0.0006 (0.3220)	-0.0001 *** (0.0080)	-0.0001 *** (0.0080)				
<i>Size</i>	-0.0002 ** (0.0120)	-0.0002 ** (0.0160)	0.0001 (0.5400)	0.0001 (0.5620)	0.0000 (0.7370)	0.0000 (0.9220)				
<i>BTM</i>	-0.0002 (0.1880)	-0.0002 (0.1630)	0.0003 (0.1940)	0.0003 (0.1960)	-0.0001 ** (0.0170)	-0.0001 ** (0.0400)				
<i>Returns Volatility</i>	-0.0095 ** (0.0130)	-0.0094 ** (0.0140)	0.0045 (0.5380)	0.0044 (0.5390)	0.0009 (0.5570)	0.0009 (0.5930)				
<i>ROA Volatility</i>	0.0013 (0.1730)	0.0013 (0.1760)	-0.0002 (0.8640)	-0.0002 (0.8630)	0.0008 (0.1360)	0.0008 (0.1350)				
<i>Age</i>	0.0004 ** (0.0400)	0.0004 * (0.0500)	-0.0005 (0.1960)	-0.0005 (0.1990)	-0.0002 *** (0.0090)	-0.0002 *** (0.0160)				
<i>GeoSeg</i>	-0.0009 ** (0.0280)	-0.0009 ** (0.0260)	-0.0011 ** (0.0440)	-0.0011 ** (0.0470)	-0.0005 *** (0.0040)	-0.0005 *** (0.0050)				
<i>BusSeg</i>	-0.0004 (0.3020)	-0.0004 (0.2860)	0.0005 (0.3580)	0.0005 (0.3610)	0.0001 (0.4450)	0.0001 (0.3960)				
<i>Loss</i>	0.0014 *** (0.0050)	0.0014 *** (0.0050)	0.0013 (0.2200)	0.0013 (0.2200)	0.0005 *** (0.0050)	0.0006 *** (0.0050)				
<i>Brexit</i>		-0.0001 (0.6520)		0.0000 (0.9790)		0.0001 (0.2030)				
<i>F statistic</i>	7.0300	6.5500	1.2300	1.1500	3.9100	3.8900				
<i>Adjusted R²</i>	3.94%	3.95%	3.14%	3.14%	2.70%	2.76%				
<i>N</i>	2,007	2,007	567	567	2,296	2,296				

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients. OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01

4.4. Causality

Table 11 presents the regression models on causal reasoning language from the CEO's, the Chairman's and the MD&A's sections of the annual report. Each one is shown with and without the Brexit indicator variable.

Table 11 – OLS coefficients estimates of causality

	Causal											
	Chairman				CEO				MD&A			
	10.1		10.2		11.1		11.2		12.1		12.2	
<i>Intercept</i>	0,0120	***	0,0119	***	0,0120	***	0,0119	***	0,0110	***	0,0107	***
	(0,0000)		(0,0000)		(0,0000)		(0,0000)		(0,0000)		(0,0000)	
<i>ROA</i>	0,0016	***	0,0016	***	0,0016	**	0,0016	**	0,0012	***	0,0011	***
	(0,0010)		(0,0020)		(0,0190)		(0,0240)		(0,0000)		(0,0000)	
<i>Change ROA</i>	-0,0011	**	-0,0011	**	-0,0011	***	-0,0011	***	-0,0002	**	-0,0003	**
	(0,0160)		(0,0140)		(0,0020)		(0,0020)		(0,0160)		(0,0120)	
<i>Returns</i>	-0,0006	***	-0,0006	***	-0,0006	**	-0,0006	**	-0,0004	***	-0,0004	***
	(0,0030)		(0,0040)		(0,0100)		(0,0120)		(0,0000)		(0,0000)	
<i>Earnings Yield</i>	-0,0005		-0,0005		-0,0005	*	-0,0005	*	-0,0004	***	-0,0004	***
	(0,5210)		(0,4800)		(0,0730)		(0,0730)		(0,0000)		(0,0000)	
<i>Change Earnings Yield</i>	0,0002		0,0002		0,0002	*	0,0002	*	0,0000	*	0,0000	
	(0,6100)		(0,6550)		(0,0540)		(0,0670)		(0,0720)		(0,1290)	
<i>Size</i>	-0,0002	***	-0,0002	***	-0,0002	***	-0,0002	***	0,0004	***	0,0004	***
	(0,0000)		(0,0000)		(0,0010)		(0,0010)		(0,0000)		(0,0000)	
<i>BTM</i>	0,0001		0,0002		0,0001		0,0002	*	-0,0001	***	0,0000	
	(0,6530)		(0,9470)		(0,1900)		(0,0940)		(0,0030)		(0,2140)	
<i>Returns Volatility</i>	0,0006		0,0006		0,0006		0,0006		0,0016	**	0,0015	**
	(0,9300)		(0,8740)		(0,7280)		(0,7180)		(0,0160)		(0,0230)	
<i>ROA Volatility</i>	-0,0006	***	-0,0006	***	-0,0006		-0,0006		-0,0008	***	-0,0008	***
	(0,0000)		(0,0000)		(0,1410)		(0,1460)		(0,0000)		(0,0000)	
<i>Age</i>	0,0003	**	0,0003	***	0,0003	**	0,0003	**	0,0000		0,0000	
	(0,0240)		(0,0070)		(0,0310)		(0,0150)		(0,7240)		(0,3580)	
<i>GeoSeg</i>	0,0006	***	0,0006	***	0,0006	***	0,0006	***	0,0008	***	0,0008	***
	(0,0000)		(0,0000)		(0,0020)		(0,0020)		(0,0000)		(0,0000)	
<i>BusSeg</i>	0,0000		0,0000		0,0000		0,0000		0,0004	***	0,0004	***
	(0,3890)		(0,3170)		(0,8820)		(0,8470)		(0,0000)		(0,0000)	
<i>Loss</i>	0,0000	*	0,0000	*	0,0000		0,0000		0,0002	**	0,0002	**
	(0,0540)		(0,0520)		(0,9720)		(0,9130)		(0,0180)		(0,0200)	
<i>Brexit</i>			0,0004	***			0,0004	**			0,0007	***
			(0,0000)				(0,0430)				(0,0000)	
<i>Industry fixed effects</i>	Yes		Yes		Yes		Yes		Yes		Yes	
<i>F statistic</i>	10,0900		10,3900		5,3300		5,3300		86,5400		88,7000	
<i>Adjusted R²</i>	3,74%		3,94%		3,12%		3,24%		20,23%		21,31%	
<i>N</i>	5833		5833		3155		3155		6821		6821	

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients. OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

The Brexit indicator variable loads with a positive coefficient. Consistent with our expectations the vote led firms to use causal words more recurrently and thus hypothesis H_{4a}, H_{4b} and H_{4c} are accepted.

Financial and non-financial firms report similar results. Both document an increase in the use of causal words following the referendum. However, similarly to the forward-looking regression models', the coefficient of the Brexit indicator variable from the CEO's section of financial firms is not significant. Yet, the results with statistical significance are aligned with our prospects. Following the vote, both financial and non-financial firms applied a more explanatory and justifying kind of speech. This is consistent with our results and the literature that suggests the use of causal words to be negatively associated with performance, a relationship we document as well, as the returns – a proxy of market and financial performance – share with causality a negative association.

Table 12 – Non-financial firms: OLS coefficients estimates of causality

	Causality											
	Chairman				CEO				MD&A			
	10.1		10.2		11.1		11.2		12.1		12.2	
<i>Intercept</i>	0.0120	***	0.0117	***	0.0115	***	0.0113	***	0.0111	***	0.0108	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
<i>ROA</i>	0.0019	***	0.0019	***	0.0017	**	0.0016	**	0.0015	***	0.0014	***
	(0.0010)		(0.0010)		(0.0210)		(0.0250)		(0.0000)		(0.0000)	
<i>Change ROA</i>	−0.0004	**	−0.0004	**	−0.0010	***	−0.0011	***	−0.0002	**	−0.0002	**
	(0.0310)		(0.0300)		(0.0030)		(0.0020)		(0.0410)		(0.0330)	
<i>Returns</i>	−0.0005	**	−0.0005	**	−0.0005	**	−0.0005	*	−0.0004	***	−0.0004	***
	(0.0180)		(0.0190)		(0.0490)		(0.0500)		(0.0000)		(0.0000)	
<i>Earnings Yield</i>	−0.0001		−0.0001		−0.0005	*	−0.0005	*	−0.0004	***	−0.0004	***
	(0.7450)		(0.7070)		(0.0870)		(0.0890)		(0.0000)		(0.0000)	
<i>Change Earnings Yield</i>	0.0000		0.0000		0.0002	***	0.0002	**	0.0001		0.0000	
	(0.5950)		(0.6470)		(0.0080)		(0.0120)		(0.1090)		(0.1950)	
<i>Size</i>	−0.0004	***	−0.0004	***	−0.0002	***	−0.0002	***	0.0004	***	0.0003	***
	(0.0000)		(0.0000)		(0.0030)		(0.0020)		(0.0000)		(0.0000)	
<i>BTM</i>	−0.0001		0.0000		0.0002		0.0002	*	0.0000		0.0000	
	(0.5430)		(0.8720)		(0.1380)		(0.0710)		(0.3000)		(0.6810)	
<i>Returns Volatility</i>	0.0005		0.0005		−0.0003		−0.0002		0.0003		0.0002	
	(0.7330)		(0.7490)		(0.8860)		(0.9080)		(0.7140)		(0.7470)	
<i>ROA Volatility</i>	−0.0012	***	−0.0011	***	−0.0003		−0.0003		−0.0006	***	−0.0006	***
	(0.0040)		(0.0050)		(0.5150)		(0.5350)		(0.0020)		(0.0030)	
<i>Age</i>	0.0004	***	0.0005	***	0.0006	***	0.0006	***	0.0003	***	0.0003	***
	(0.0010)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
<i>GeoSeg</i>	0.0007	***	0.0007	***	0.0007	***	0.0007	***	0.0006	***	0.0006	***
	(0.0000)		(0.0000)		(0.0020)		(0.0020)		(0.0000)		(0.0000)	
<i>BusSeg</i>	0.0002		0.0002		−0.0001		−0.0001		0.0000		0.0000	
	(0.2760)		(0.2570)		(0.6480)		(0.6420)		(0.9210)		(0.8160)	
<i>Loss</i>	0.0002		0.0002		0.0003		0.0003		0.0003	***	0.0003	***
	(0.4070)		(0.4220)		(0.3780)		(0.4240)		(0.0050)		(0.0090)	
<i>Brexit</i>			0.0006	***			0.0004	*			0.0008	***
			(0.0020)				(0.0660)				(0.0000)	
<i>Industry fixed effects</i>	Yes		Yes		Yes		Yes		Yes		Yes	
<i>F statistic</i>	9.1400		9.3700		6.0500		6.0000		56.8400		59.3300	
<i>Adjusted R²</i>	4.92%		5.14%		3.95%		4.07%		19.49%		20.84%	
<i>N</i>	3,826		3,826		2,588		2,588		4,525		4,525	

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients.
 OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01

Table 13 – Financial firms: OLS coefficients estimates of causality

	Causal											
	Chairman				CEO				MD&A			
	10.1		10.2		11.1		11.2		12.1		12.2	
<i>Intercept</i>	0.0133 ***		0.0131 ***		0.0152 ***		0.0150 ***		0.0109 ***		0.0106 ***	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
<i>ROA</i>	0.0016		0.0014		0.0032		0.0031		0.0007		0.0005	
	(0.3120)		(0.3750)		(0.2410)		(0.2450)		(0.2870)		(0.4760)	
<i>Change ROA</i>	−0.0005		−0.0005		−0.0017		−0.0017		−0.0004		−0.0003	
	(0.5100)		(0.4960)		(0.5100)		(0.5020)		(0.3150)		(0.3220)	
<i>Returns</i>	−0.0009 *		−0.0009 *		−0.0015 **		−0.0014 *		−0.0007 ***		−0.0006 **	
	(0.0600)		(0.0830)		(0.0320)		(0.0550)		(0.0040)		(0.0120)	
<i>Earnings Yield</i>	−0.0001		−0.0001		−0.0003		−0.0003		−0.0002		−0.0002	
	(0.7330)		(0.7270)		(0.8260)		(0.7860)		(0.2410)		(0.2330)	
<i>Change Earnings Yield</i>	0.0000		0.0000		−0.0005		−0.0005		0.0000		0.0000	
	(0.8830)		(0.8890)		(0.2740)		(0.2970)		(0.5900)		(0.6280)	
<i>Size</i>	−0.0001		−0.0001		−0.0002		−0.0002		0.0005 ***		0.0004 ***	
	(0.1770)		(0.1020)		(0.1230)		(0.1070)		(0.0000)		(0.0000)	
<i>BTM</i>	0.0000		0.0000		−0.0001		0.0000		−0.0002 ***		−0.0001 **	
	(0.9980)		(0.7790)		(0.7540)		(0.8960)		(0.0010)		(0.0200)	
<i>Returns Volatility</i>	−0.0029		−0.0031		0.0056		0.0053		0.0045 ***		0.0042 ***	
	(0.3620)		(0.3220)		(0.3290)		(0.3550)		(0.0040)		(0.0060)	
<i>ROA Volatility</i>	−0.0016 **		−0.0015 **		−0.0021 *		−0.0021 *		−0.0010 ***		−0.0010 ***	
	(0.0350)		(0.0380)		(0.0640)		(0.0590)		(0.0040)		(0.0040)	
<i>Age</i>	−0.0002		−0.0002		−0.0006 **		−0.0006 **		−0.0005 ***		−0.0004 ***	
	(0.2590)		(0.3680)		(0.0370)		(0.0450)		(0.0000)		(0.0000)	
<i>GeoSeg</i>	0.0009 ***		0.0009 ***		0.0005		0.0005		0.0010 ***		0.0010 ***	
	(0.0090)		(0.0070)		(0.3280)		(0.2970)		(0.0000)		(0.0000)	
<i>BusSeg</i>	−0.0002		−0.0001		0.0004		0.0004		0.0009 ***		0.0009 ***	
	(0.6230)		(0.7180)		(0.4360)		(0.3870)		(0.0000)		(0.0000)	
<i>Loss</i>	0.0007 **		0.0008 **		−0.0010		−0.0010		0.0001		0.0001	
	(0.0490)		(0.0460)		(0.2130)		(0.2190)		(0.7700)		(0.7080)	
<i>Brexit</i>			0.0004 *				0.0004				0.0005 ***	
			(0.0970)				(0.4630)				(0.0000)	
<i>F statistic</i>	2.3800		2.4100		1.8600		1.7300		42.6700		41.8200	
<i>Adjusted R²</i>	1.49%		1.63%		3.78%		3.89%		21.36%		22.09%	
<i>N</i>	2,007		2,007		567		567		2,296		2,296	

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients.
 OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

4.5. Further analysis

Alves et al (2016) captured inconsistency in performance-related narratives. Our models differ from theirs, since we capture inconsistency in the CEO's section (while they used the business review, instead) and Chairman's discourse.

We capture discourse inconsistencies for tone, uncertainty, forward-looking and causality, by regressing the Chairman's speech on the CEO's discourse. The inconsistency is captured by the error term of each model – μ_{it} . The error term captures everything related with the Chairman speech that is not explained by the CEO's discourse – see table 14 and equation 13.

$$\begin{aligned} & \text{Narratives' characteristics_Chair}_{it} \\ & = \alpha_0 + \alpha_1 \text{Narratives' characteristics_CEO}_{it} + \mu_{it} \end{aligned} \quad (13-16)$$

Table 14 – Regression models that capture discourse inconsistencies

	Tone_Chair		Uncertainty_Chair		Forwardlooking_Chair		Causal_Chair	
<i>Intercept</i>	0.2305	***	0.0326	***	0.0135	***	0.0093	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
<i>Tone_CEO</i>	0.5024	***						
	(0.0000)							
<i>Uncertainty_CEO</i>			0.3893	***				
			(0.0000)					
<i>Forwardlooking_CEO</i>					0.2333	***		
					(0.0000)			
<i>Causal_CEO</i>							0.1977	***
							(0.0000)	
<i>F statistic</i>	638.4100		219.2300		143.2300		82.1800	
<i>Adjusted R²</i>	27.74%		17.01%		5.75%		3.99%	
<i>N</i>	2,686		2,686		2,686		2,686	

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients. OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

After capturing inconsistency – the residuals from the models shown in table 14 –, we regress it on tone determinants (identified in chapter 2), the Brexit dummy and industry indicator variables – equation 17.

$$\begin{aligned} & \text{Ch_Narratives' characteristics}_{it} \\ & = \beta_0 + \beta_1 \text{ROA}_{it} + \beta_2 \text{Ch_ROA}_{it} + \beta_3 \text{Ret}_{it} + \beta_4 \text{EY}_{it} \\ & + \beta_5 \text{Ch_EY}_{it} + \beta_6 \text{Size}_{it} + \beta_7 \text{BTM}_{it} + \beta_8 \text{RetVol}_{it} \\ & + \beta_9 \text{ROAVol}_{it} + \beta_{10} \text{Age}_{it} + \beta_{11} \text{GeoSeg}_{it} \\ & + \beta_{12} \text{BusSeg}_{it} + \beta_{13} \text{Loss}_{it} + \beta_{14} \text{Brexit}_{it} \\ & + \text{industry} - \text{fixed effects} + \varepsilon_{it} \end{aligned} \quad (17-20)$$

If the error term of the model of tone inconsistency is lower than zero, we expect the CEO is being optimistic, presenting a more positive discourse than the Chairman. On the contrary, if the error term is higher than zero, the CEO is being

pessimist, presenting a more negative, or less positive discourse than the Chairman. Both describe discourse inconsistencies'. However, our analysis focuses on the situations when CEO's are optimistic.

We expect managers to be optimistic and to use more uncertainty, forward-looking and causality words (than the Chairman) if they belong to firms with poor market and financial performance, which is proxied by the variable earnings yield, change in earnings yield, returns and loss. These variables are expected to load with a positive coefficient. Loss, on the other hand, with a negative one.

Variables are defined in table 16. Tone determinants and Brexit dummy variable keep the same interpretation as defined in Chapter 3 and table 16.

The median firm reports a positive change in tone, while the changes in uncertainty, forward-looking and causal words are negative. This suggests the CEO from the median firm applies a more uncertain, forward-looking and causal discourse than the Chairman.

Results are presented as follows (table 15).

Brexit loads with a positive and significant coefficient on tone, uncertainty and forward-looking language, suggesting the CEO's discourse after the referendum became less positive and applied less uncertainty and forward-looking words than the Chairman. In addition, we can also infer on the influence of firm features on optimism. The CEO uses a more positive and uncertain language (than the Chairman) if the firm is more mature and reports poor market and financial performance. On the contrary, he/she uses more causal reasoning words when performance increases. Regarding the use of forward-looking words, we can only infer the CEO uses these words more recurrently if it belongs to a larger firm with increasing profitability and decreasing performance.

Table 15 – Discourse inconsistencies

	Discourse Inconsistencies			
	Change_Tone	Change_Uncertainty	Change_Forwardlooking	Change_Causality
<i>Intercept</i>	0.0447 (0.1990)	0.0052 ** (0.0310)	−0.0008 (0.5220)	0.0004 (0.6120)
<i>ROA</i>	0.0226 (0.4720)	0.0055 ** (0.0240)	0.0019 (0.1210)	0.0029 *** (0.0010)
<i>Change ROA</i>	0.0322 (0.3520)	−0.0030 (0.1810)	−0.0023 ** (0.0380)	−0.0014 (0.1430)
<i>Returns</i>	0.0414 *** (0.0000)	0.0028 *** (0.0000)	0.0001 (0.8560)	−0.0008 *** (0.0030)
<i>Earnings Yield</i>	0.0371 *** (0.0000)	0.0024 *** (0.0000)	0.0002 (0.6420)	−0.0005 * (0.0970)
<i>Change Earnings Yield</i>	−0.0052 (0.1080)	−0.0003 (0.2940)	0.0003 *** (0.0010)	0.0001 (0.2060)
<i>Size</i>	0.0012 (0.5840)	−0.0003 * (0.0950)	−0.0003 *** (0.0000)	−0.0003 *** (0.0000)
<i>BTM</i>	−0.0035 (0.5440)	−0.0001 (0.7960)	0.0000 (0.8010)	0.0000 (0.9170)
<i>Returns Volatility</i>	−0.0741 (0.3120)	−0.0062 (0.2130)	0.0028 (0.2530)	0.0002 (0.9180)
<i>ROA Volatility</i>	0.0596 *** (0.0030)	0.0006 (0.5910)	−0.0003 (0.6460)	−0.0012 ** (0.0200)
<i>Age</i>	−0.0110 ** (0.0300)	−0.0012 *** (0.0030)	0.0002 (0.2960)	0.0003 ** (0.0280)
<i>GeoSeg</i>	−0.0048 (0.5290)	0.0004 (0.4570)	0.0000 (0.8790)	0.0004 ** (0.0460)
<i>BusSeg</i>	−0.0066 (0.4020)	0.0006 (0.3030)	−0.0001 (0.8460)	0.0003 (0.1690)
<i>Loss</i>	−0.0600 *** (0.0000)	−0.0020 ** (0.0170)	0.0006 (0.1680)	0.0005 (0.1540)
<i>Brexit</i>	0.0127 * (0.0960)	0.0015 *** (0.0060)	0.0007 *** (0.0050)	0.0003 (0.1450)
<i>Industry-fixed effects</i>	Yes	Yes	Yes	Yes
<i>F statistic</i>	10.6300	8.9900	4.5500	4.6800
<i>Adjusted R²</i>	8.03%	6.53%	3.37%	3.95%
<i>N</i>	2,686	2,686	2,686	2,686

P-values reported in parentheses are computed using the robust standard errors to obtain unbiased OLS coefficients. OLS coefficients estimates and its p-values in parentheses. *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

5. Conclusions

We examine the effects of the Brexit referendum on companies' financial discourse by studying the CEO's, the Chairman's and the MD&A's sections. Not only we analyse tone, but also the use of uncertainty, forward-looking and causal words.

Results show companies reacted to the vote. We compare the period following the referendum by studying annual reports published in 2016 and 2017 with the ones from 2012 to 2015. We conduct an analysis on a sample comprising 6,821 annual reports, including both financial and non-financial institutions. While tone is not explained by the vote, uncertainty, forward-looking and causal reasoning words are more frequent and positively associated with the vote.

To test our results' consistency and robustness we divide our sample between financial and non-financial companies. Only tone reports different results. The tone from financial firms is not explained by the vote. Non-financial firms, on the other hand, adopt a more positive discourse.

Even though our main objective is to understand the effects of the referendum on our companies' financial narratives, we also study which firm dimension influences each sentiment. The tone determinants used, control for profitability, market and financial performance, size, growth opportunities, operational and business risk, firm's operating complexity and we also add industry fixed - effects in models including non-financial companies. Both tone and uncertainty share a positive relationship with market and financial performance – the variable returns reports a positive and significant coefficient - and are negatively associated with profitability – change in ROA reports a negative and significant coefficient. These results suggest firms adopt a more positive but uncertain discourse when returns increase and changes in ROA are lower. Forward-

looking carries opposite results depending on the annual report section. While, the CEO and Chairman use these words more frequently when performance increases – positive and significant coefficient of the earnings yield – the MD&A is negatively associated with performance. Causal reasoning is also negatively associated with performance – proxied here by the returns.

Last of all, we also study discourse inconsistencies on the CEO's discourse. Following the referendum, the CEO became less positive and used less uncertainty forward-looking and causal words than the Chairman. Also, as expected, the CEO adopts a more positive and uncertainty language when firms' performance deteriorates. On the contrary, the CEO adopts a discourse with more causal words (than the Chairman) when performance increases and profitability decreases.

Our study faces some limitations, though. For instance, the CEO's section often reports a Brexit coefficient with no statistical significance. We believe this happens due to fewer observations on this section.

Furthermore, determination coefficients from forward-looking and causal language are significantly lower than the ones reported in tone and uncertainty regression models'. This is evidence that tone determinants, Brexit and industry controls are very limited on explaining these kinds of language.

Knowing this, we recommend future researchers to conduct studies on the incremental predictive power of the abnormal sentiment, which is everything that firm's dimensions do not explain. Likewise, to study these sentiments around the financial crisis period, looking for a connection between this period, (when many companies faced financial distress situations), and those sentiments.

In addition, we also recommend researchers to include a variable indicating if a firm is based in the UK or not. Being based or traded in the UK, for the matter of this thesis, may have a significant impact on the results. After controlling for tone determinants, Brexit and industry level, one would expect a UK-based firm

to react negatively to the referendum. Non-financial firms reacted positively, though. Not being based in the UK is a possible explanation for such result. Yet, most results reflect our expectations and robustness tests confirm their consistency.

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7. Appendix

Table 16 – Variables definition.

Variable name	Definition
<i>Tone_Chair</i>	Chairman's section: Net tone: The difference between the number of positive and negative words scaled by their sum. Words are defined as positive and negative according to Loughran and McDonald's list
<i>Tone_CEO</i>	CEO review: Net Tone: The difference between the number of positive and negative words scaled by their sum. Words are defined as positive and negative according to Loughran and McDonald's list
<i>Tone_MD&A</i>	MD&A: Net tone: The difference between the number of positive and negative words scaled by their sum. Words are defined as positive and negative according to Loughran and McDonald's lists
<i>Change_Tone</i>	Tone inconsistencies'
<i>Uncertainty_Chair</i>	Chairman's section: number of uncertainty words proposed by Loughran and McDonald words list
<i>Uncertainty_CEO</i>	CEO review: number of uncertainty words proposed by Loughran and McDonald words list
<i>Uncertainty_MD&A</i>	MD&A: number of uncertainty words proposed by Loughran and McDonald words list
<i>Change_Uncertainty</i>	Uncertainty inconsistencies'
<i>Forwardlooking_Chair</i>	Chairman's section: number of forward-looking words from an updated version of the list of words proposed by Hussainey et al (2003)
<i>Forwardlooking_CEO</i>	CEO review: number of forward-looking words from an updated version of the list of words proposed by Hussainey et al (2003)
<i>Forwardlooking_MD&A</i>	MD&A: number of forward-looking words from an updated version of the list of words proposed by Hussainey et al (2003)
<i>Change_Forwardlooking</i>	Forward-looking inconsistencies'
<i>Causal_Chair</i>	Chairman's section: number of causal reasoning words in performance commentary, based on a composite wordlist
<i>Causal_CEO</i>	CEO review: number of causal reasoning words in performance commentary, based on a composite wordlist
<i>Causal_MD&A</i>	MD&A: number of causal reasoning words in performance commentary, based on a composite wordlist
<i>Change_Causal</i>	Causality inconsistencies'
<i>ROA</i>	Return on assets: net income from accounting scaled by lagged total assets
<i>Change_ROA</i>	Change in return on assets: net income change (the difference between the current year and the previous one) scaled by lagged total assets
<i>Return</i>	12-month raw stock return ending four months after the fiscal year-end
<i>Earnings Yield</i>	Earnings per share scaled by lagged stock price
<i>Change Earnings Yield</i>	Change in earnings yield: earnings per share variation (the difference between the current year and the previous one) scaled by lagged stock price
<i>Market value</i>	Market value of equity at fiscal year-end
<i>Size</i>	Log (market value)
<i>BTM</i>	Book to market ratio: Firm's book value scaled by its market value
<i>Return Volatility</i>	Standard deviation over the last 12 months before year end
<i>ROA Volatility</i>	Standard deviation of ROA over the last five years
<i>Age</i>	Log (Age)
<i>GeoSeg</i>	Log (1+ number of geographic segments)

<i>BusSeg</i>	Log (1+ number of business segments)
<i>Loss</i>	Indicator variable that takes the value one if the earnings yield is lower than zero in the current year and zero otherwise
<i>Brexit</i>	Indicator variable that takes take value one if year is 2016 or 2017 and zero otherwise

Table 17 – Descriptive statistics: non-financial firms

PANEL A – TONE MEASURES								
Variable name	N	Mean	St. Dev.	Min.	P25	Median	P75	Max.
<i>Tone_Chair</i>	3,826	0.3935	0.2500	−1.0000	0.2609	0.4286	0.5660	1.0000
<i>Tone_CEO</i>	2,588	0.4078	0.2233	−1.0000	0.2886	0.4409	0.5652	1.0000
<i>Tone_MD&A</i>	4,525	0.0939	0.1600	−1.0000	0.0043	0.1054	0.1957	0.6091
<i>Uncertainty_Chair</i>	3,826	0.0514	0.0162	0.0000	0.0411	0.0512	0.0614	0.1476
<i>Uncertainty_CEO</i>	2,588	0.0541	0.0163	0.0000	0.0444	0.0541	0.0641	0.2225
<i>Uncertainty_MD&A</i>	4,525	0.0343	0.0070	0.0000	0.0301	0.0346	0.0388	0.1027
<i>Forwardlooking_Chair</i>	3,826	0.0172	0.0067	0.0000	0.0128	0.0169	0.0213	0.0701
<i>Forwardlooking_CEO</i>	2,588	0.0151	0.0067	0.0000	0.0106	0.0143	0.0190	0.0636
<i>Forwardlooking_MD&A</i>	4,525	0.0123	0.0030	0.0000	0.0104	0.0122	0.0140	0.0429
<i>Causal_Chair</i>	3,826	0.0121	0.0055	0.0000	0.0084	0.0117	0.0153	0.0413
<i>Causal_CEO</i>	2,588	0.0127	0.0053	0.0000	0.0091	0.0122	0.0158	0.0520
<i>Causal_MD&A</i>	4,525	0.0141	0.0029	0.0000	0.0123	0.0143	0.0161	0.0367

PANEL B – TONE DETERMINANTS/ FIRM SPECIFICS								
Variable name	N	Mean	St. Dev.	Min.	P25	Median	P75	Max.
<i>ROA</i>	4,525	−0.0419	0.2366	−1.7136	−0.0757	0.0295	0.0787	0.3851
<i>Change ROA</i>	4,525	0.0210	0.3446	−0.8096	−0.0334	0.0049	0.0375	11.8066
<i>Returns</i>	4,525	0.0919	0.4918	−1.0000	−0.2328	0.0474	0.3432	2.4211
<i>Earnings Yield</i>	4,525	−0.0496	0.4536	−18.0000	−0.0700	0.0340	0.0750	0.5855
<i>Change Earnings Yield</i>	4,525	0.0582	1.0229	−32.1786	−0.0250	0.0050	0.0406	31.9562
<i>Market Value</i>	4,525	1,014	3,216	1	17	87	529	36,275
<i>BTM</i>	4,525	0.2711	1.4799	−14.0037	0.1692	0.4357	0.8079	4.2383
<i>Return Volatility</i>	4,525	0.1184	0.0731	0.0069	0.0679	0.0981	0.1478	0.5068
<i>ROA Volatility</i>	4,525	0.1417	0.2803	0.0015	0.0255	0.0570	0.1392	3.8501
<i>Age</i>	4,525	21.2756	15.1496	0.0000	11.0000	16.0000	29.0000	53.0000
<i>Number geographic seg.</i>	4,525	2.8979	2.0462	1.0000	1.0000	2.0000	4.0000	10.0000
<i>Number business seg.</i>	4,525	2.5171	1.7001	1.0000	1.0000	2.0000	4.0000	10.0000
<i>Loss</i>	4,525	0.3708	0.4831	0.0000	0.0000	0.0000	1.0000	1.0000
<i>Brexit</i>	4,525	0.3165	0.4651	0.0000	0.0000	0.0000	1.0000	1.0000

Table 18 – Descriptive statistics: financial firms

PANEL A – TONE MEASURES								
Variable name	N	Mean	St. Dev.	Min.	P25	Median	P75	Max.
<i>Tone_Chair</i>	2,007	0.0655	0.2840	−1.0000	−0.1313	0.0286	0.2564	1.0000
<i>Tone_CEO</i>	567	0.2628	0.2820	−1.0000	0.1111	0.3065	0.4654	1.0000
<i>Tone_MD&A</i>	2,296	−0.1624	0.1744	−1.0000	−0.2814	−0.1975	−0.0482	0.4702
<i>Uncertainty_Chair</i>	2,007	0.0428	0.0133	0.0000	0.0342	0.0419	0.0512	0.0967
<i>Uncertainty_CEO</i>	567	0.0510	0.0151	0.0048	0.0412	0.0525	0.0611	0.0935
<i>Uncertainty_MD&A</i>	2,296	0.0299	0.0069	0.0000	0.0253	0.0290	0.0341	0.0552
<i>Forwardlooking_Chair</i>	2,007	0.0180	0.0062	0.0000	0.0139	0.0179	0.0221	0.0438
<i>Forwardlooking_CEO</i>	567	0.0145	0.0061	0.0000	0.0107	0.0141	0.0183	0.0416
<i>Forwardlooking_MD&A</i>	2,296	0.0114	0.0026	0.0000	0.0099	0.0113	0.0128	0.0268
<i>Causal_Chair</i>	2,007	0.0126	0.0048	0.0000	0.0095	0.0124	0.0153	0.0377
<i>Causal_CEO</i>	567	0.0131	0.0055	0.0000	0.0093	0.0125	0.0164	0.0385
<i>Causal_MD&A</i>	2,296	0.0132	0.0027	0.0000	0.0116	0.0131	0.0147	0.0248

PANEL B – TONE DETERMINANTS/ FIRM SPECIFICS								
Variable name	N	Mean	St. Dev.	Min.	P25	Median	P75	Max.
<i>ROA</i>	2,296	0.0500	0.1398	−0.9975	0.0013	0.0521	0.1197	0.3903
<i>Change ROA</i>	2,296	0.0251	0.1959	−0.6705	−0.0417	0.0080	0.0784	4.7547
<i>Returns</i>	2,296	0.1109	0.2963	−1.0000	−0.0247	0.0946	0.2403	2.2419
<i>Earnings Yield</i>	2,296	0.0273	0.4357	−9.0000	0.0038	0.0743	0.1508	0.5613
<i>Change Earnings Yield</i>	2,296	0.0449	1.0562	−13.3263	−0.0604	0.0116	0.1111	43.0127
<i>Market Value</i>	2,296	849	3,138	1	32	123	452	37,937
<i>BTM</i>	2,296	0.7377	1.2350	−11.2024	0.6799	0.9975	1.1229	4.2778
<i>Return Volatility</i>	2,296	0.0621	0.0480	0.0031	0.0334	0.0492	0.0749	0.4779
<i>ROA Volatility</i>	2,296	0.1165	0.1943	0.0002	0.0378	0.0813	0.1399	3.7890
<i>Age</i>	2,296	21.7801	14.6733	1.0000	11.0000	17.0000	27.0000	53.0000
<i>Number geographic seg.</i>	2,296	1.4573	1.3159	1.0000	1.0000	1.0000	1.0000	10.0000
<i>Number business seg.</i>	2,296	1.7134	1.5350	1.0000	1.0000	1.0000	1.0000	10.0000
<i>Loss</i>	2,296	0.2409	0.4277	0.0000	0.0000	0.0000	0.0000	1.0000
<i>Brexit</i>	2,296	0.3175	0.4656	0.0000	0.0000	0.0000	1.0000	1.0000