Textual Complexity in Nonperiodic Disclosures and Investors' Use of Social Media as an Alternative Channel for Corporate Information

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Abstract

Textual complexity within corporate disclosures may reduce investors' comprehension of those disclosures. However, investors can rely on alternative sources of information to process textually complex disclosures. Unlike periodic disclosures, where various alternative sources (e.g., analysts and news media reports) are available to investors, there are limited alternative sources for unanticipated nonperiodic disclosures. Social media is one such source and has been shown to facilitate retail investors' access to information for investment decision-making. This leads to the question of how effective social media are for processing textually complex nonperiodic disclosures.

This thesis examines the connection between the causes and consequences of nonperiodic disclosures' textual complexity and whether social media can assist investors in processing such disclosures. The research consists of three empirical studies using corporate announcements from the Australian Securities Exchange and Hotcopper data, Australia's largest stock message board. The first study compares the textual complexity of nonperiodic and periodic disclosures and identifies whether they have different determinants. The second study examines the consequences of managers' strategic reporting on nonperiodic disclosures' textual complexity and their market outcomes. The third study examines the investors' use of alternative information from a regulated stock message board for complex disclosures and whether that improves stock price informativeness.

In the first study, evidence shows that nonperiodic disclosures are textually less complex than periodic disclosures, though both disclosures become less readable, lengthy and boilerplate over the sample period. Further, firms from the resource, finance, and regulated industries tend to produce more textually complex periodic

disclosures than nonperiodic due to their complex structure and business practices. In terms of determinants, compared to periodic disclosures, the textual complexity of nonperiodic disclosures is more influenced by time trends, market-to-book ratio, special items, and gearing, but not by poor performance. Besides firm-specific factors, the textual complexity of nonperiodic disclosure is also influenced by managers' strategic reporting, mainly when bad news is released after trading hours or on the week's last trading day.

The second study finds that after the GN8 revision of Listing Rule 3.1 by the Australian Securities Exchange, there is a significant reduction in the readability of nonperiodic disclosures among firms using boilerplate language in their disclosures. The boilerplate language, I argue, is used for reducing the litigation risks arising from the GN8 revision requirements for complete disclosures within strict time frames. The study also finds that the market returns of firms are negatively associated with the use of boilerplate language in nonperiodic disclosures, particularly for firms with more retail investors. These findings suggest that the GN8 revision has had unintended consequences. It has increased the use of boilerplate language in nonperiodic disclosures, which can adversely affect the readability of the disclosures and reduce their informativeness.

For the third study, I utilise the Australian Regulatory Guidance 162 within the GN8 revision environment. This guidance restricts CEOs' and experts' engagement on stock message boards. The results of my study reveal that less readable periodic and nonperiodic disclosures receive more views and discussions on the stock message board. Upon partitioning periodic and nonperiodic disclosures into subsamples, I find that longer and less readable nonperiodic disclosures attract greater stock message board views and discussions. Further, higher stock message board discussions are associated with lower stock price synchronicity for firms with

textually complex disclosures, particularly for those with lower institutional ownership. This implies that retail investors view the regulated stock message board as a credible and timelier alternative channel to process textually complex nonperiodic disclosures.

This thesis first contributes to the extant literature on textual complexity in corporate disclosures by adding an examination of the determinants and effects of textual complexity of nonperiodic disclosures. Next, it extends the social media literature by examining investors' use of regulated stock message boards to deal with textually complex nonperiodic disclosures.

Keywords: Textual complexity, Periodic disclosures, Nonperiodic disclosures, Strategic reporting, Information processing costs, Market reactions, Stock message boards, Stock price synchronicity.

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List of Abbreviations

ASIC	-	Australian Securities and Investments Commission
ASX	-	Australian Securities Exchange Ltd
ATH	-	After trading hours
ATHonLTD	-	After trading hours on the last trading day of the week
CASAC	-	Companies and Securities Advisory Committee
CDR	-	Continuous Disclosure Regulation
CLERP 9	-	Corporate Law Economic Reform Program
CSA	-	Chartered Secretaries Australia
D&Os	-	directors and officers
DiD	-	Difference-in-differences
ESMA	-	European Securities and Market Authority
FASB	-	Financial Accounting Standard Board
FCA	-	UK Financial Conduct Authority
FMA	-	Financial Market Authority NZ
FRC	-	Financial Reporting Council
GN8	-	Guidance Note 8
IASB	-	International Accounting Standards Board
I/B/E/S	-	Institutional Brokers' Estimate System
IDS	-	Internet discussion sites
IRH	-	Incomplete revelation hypothesis
LTD	-	Last trading day of the week
NSAs	-	Nonprofessional security analysts
RG162	-	Regulatory Guidance 162
SEC	-	US Securities and Exchange Commission

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which, to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signature:

Date: 21.03.2023

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Chapter One:

Introduction

1.1 Motivation and research questions

Textual complexity in corporate disclosures can hinder effective communication of valuation-relevant information, as readers may struggle to process and comprehend the written text. Extant studies suggest that higher processing costs for textually complex disclosures can influence investors' decisions to rely on alternative sources such as social media, analysts' reports and news media (Asay et al., 2017; Asay et al., 2018; Blankespoor et al., 2020). Recently, social media has been shown to facilitate investors' access to user-generated information for their investment decisions (Bartov et al., 2018; Chen et al., 2014; Lawrence, Ryans, & Sun, 2017; Lerman, 2020). However, investors can incur higher information processing costs for textually complex periodic (e.g., annual or quarterly reports) and nonearning/nonperiodic (e.g., 8-K filing in the US, Continuous Disclosure Regulation (CDR) in Australia) disclosures (Li, 2008; Li & Tan, 2022; Miller, 2010), leading to the question of whether investors substitute social media discussions for these textually complex disclosures. Further, the extent to which nonperiodic disclosure text affects investors' processing costs is unclear from existing literature, leaving it open to question whether and how investors may use social media differently for these disclosures compared to periodic disclosures. This thesis aims to provide a cohesive understanding of whether nonperiodic disclosures' textual complexity differs from periodic disclosures and how the difficulty of processing the information they carry may influence investors' demand for information from social media as an alternative channel.

This thesis comprises three independent but related empirical studies. The first study focuses on the supply side of disclosures by examining whether nonperiodic disclosures differ from periodic disclosures regarding textual complexity and their determinants. Despite regulatory initiatives,[1] the causes and consequences of growing textual complexity in periodic disclosures (Dyer et al., 2017) have received considerable attention from regulators and accounting literature. Unlike periodic disclosures, nonperiodic disclosures are unanticipated and cover a wide range of events that are material to investors (Carter & Soo, 1999).[2] Extant literature primarily focuses on the determinants of the timeliness and frequency of nonperiodic disclosures and their economic outcomes (Brown et al., 1999; Carter & Soo, 1999; Debreceny & Rahman, 2005; Jackson et al., 2015; Lerman & Livnat, 2010; McMullin et al., 2019). Recent studies have shown that variations in nonperiodic 8-K filings' textual content can negatively affect the market (Li & Tan, 2022; Watkins, 2022). However, when processing textual information from these nonperiodic disclosures, it is unclear if investors face similar challenges to those they face with periodic disclosures.

In Australia, Listing Rule 3.1 of CDR plays a crucial role in maintaining the integrity of the financial market. In general, listed entities must immediately notify the Australian Securities Exchange (ASX) of any anticipated and unanticipated

[1] For example, the regulatory initiatives to combat financial reporting complexity include SEC's "Plain English Rule" in 1998, Financial Accounting Standard Board (FASB)'s "Disclosure Framework" in 2009 and "Simplification Initiative" in 2014, the SEC's "Disclosure Effectiveness Initiative" in 2013, the International Accounting Standards Board (IASB)'s "Disclosure Initiative" in 2013, the Australian Financial Reporting Council (FRC)'s "Managing Complexity Task Force" in 2012, and the UK Financial Reporting Council's "Cutting Clutter" initiative in 2011.

[2] For example, prior studies find that more frequent and timelier 8-K filings for nonperiodic material events are associated with significant market reactions (Lerman & Livnat, 2010) and improved price formation (McMullin et al., 2019), and act as a more informative substitute for voluntary guidance by broadening the flow of material information (Noh et al., 2019).

information that is expected to materially affect the price or value of the entities' securities (known as 'price-sensitive information'). Despite timeliness, Australian regulators comparatively put more emphasis on the contents of the nonperiodic announcements than periodic, as evidenced by ASX queries, Australian Securities and Investments Commission (ASIC) actions, and securities class actions (Chapple et al., 2021; Hsu, 2009), which is different from that of the US setting where there is no such regulations for the content of 8-K fillings.[3] Therefore, the Australian CDR provides a unique setting to examine how the textual complexity of nonperiodic disclosures may vary from periodic disclosures in terms of the determinants for two reasons. Firstly, nonperiodic disclosures play a crucial role in supplying a continuous stream of corporate information[4] between scheduled periodic disclosures within the reporting cycle (Carter & Soo, 1999; Lerman & Livnat, 2010; Noh et al., 2019). Since the Australian Securities Exchange (ASX) and the Australian Securities and Investments Commission (ASIC) emphasise that both disclosures are to be written in plain English,[5] examining and understanding the overall level of textual complexity across both disclosures is important, particularly in relation to investors' information processing costs. Secondly, managers' choices in regard to textual complexity can also affect investors' costs of processing information (Blankespoor,

[3] For example, out of 51 regulatory actions from 2005 to 2019 for breaching Listing Rule 3.1, 37 regulatory actions related to nonperiodic disclosures and 14 were for periodic disclosures. Besides public enforcement, nonperiodic disclosures also attract a significant number of class actions over the past few years for misleading and deceptive conduct. A more detailed discussion can be found in section 2.4.

[4] The major material events covered by nonperiodic announcements include takeovers, shareholders' detail, issued capital, asset acquisition and disposal, stock exchange announcements, progress reports, company administration, ASX Query, others, etc.

[5] Section 4.15 of GN8 states that "an announcement must be couched in language that is appropriate for release to the market. It should be factual, relevant and expressed in a clear and objective manner".

2018; Blankespoor et al., 2020), but existing literature provides little idea of whether textual complexity across both types of disclosures may vary due to managerial incentives. Despite the strict application of the timeliness requirements of ASX Listing Rules 3.1, managers have discretion in language choice (Price, 2015), providing a stronger setting to capture the impact of managers' incentives on textual complexity besides firm-specific factors. I use a broad set of textual complexity metrics, including readability, length and boilerplate text, that prior studies have identified as key textual characteristics that significantly influence investors' processing costs (Blankespoor et al., 2020).

Thus, the first study builds upon this institutional setting and predicts that because of their unanticipated nature, the factors affecting the textual complexity of nonperiodic disclosures may not necessarily be the same as those affecting periodic disclosures. With increasing business complexity, firms are expected to have more material events over a year (Cazier & Pfeiffer, 2016). Thus, nonperiodic disclosure complexity could be influenced more by firm-specific factors and time trends than by managers' incentives. Alternatively, nonperiodic disclosure complexity could be driven by managers' incentives to hide bad news or take advantage of investors' inattention when disclosure is released after trading hours (*ATH*), on the last trading day of the week (*LTD*) or after trading hours on the last trading day of the week (*ATHonLTD*). This is because the lack of additional information about unanticipated events aggravates investors' ability to spot potential manager bias on nonperiodic disclosures text. Given the lack of consensus on how economic factors and time trends may differently affect the textual complexity of nonperiodic disclosures in comparison to periodic disclosures, this thesis begins with the following research question:

RQ1: Do the determinants of textual complexity of nonperiodic disclosures differ from that of periodic disclosures?

The second study extends the analysis of textual complexity in nonperiodic disclosures by examining how managers' strategic reporting may lower the readability of their disclosures and result in weaker market reactions due to increased processing costs. I focus on one particular regulatory event, the GN8 revision of Listing Rule 3.1. ASX revised GN8 of Listing Rule 3.1 in 2013 in response to market confusion to clarify what constitutes a breach of immediate and complete nonperiodic disclosure requirements while emphasising plain English writing. In the GN8 revision, ASX took the more practical view of 'immediately' but cited previous infringement notices as examples of the standard of promptness without a stated filing deadline, unlike in the US for 8-K filings.[6] This worried directors because they felt that the clarification of 'immediately' may not lead to a different outcome. Rather, it might put more pressure in terms of time on managers to meet the 'complete' disclosures requirement to mitigate litigation risk post-GN8 revision because nonperiodic disclosures are unanticipated and require time to verify (Watkins, 2022).

However, extant literature suggests that firms that are sufficiently concerned about litigation add boilerplate disclosures to reduce the risk of lawsuits. This is because firms that add boilerplate text to lengthen disclosures to be 'complete' incur lower costs and require less time (Brown & Tucker, 2011), and are more likely to have favourable judicial and regulatory assessments (Cazier et al., 2021). Thus, I

[6] In the US, the filing deadline for mandatory nonperiodic 8-K items is four business days after the triggering nonperiodic event. However, despite the clarification about the term 'immediately' in the revised GN8, there is no specific deadline for filing nonperiodic price-sensitive announcements in Australia. More detailed discussion on the revised GN8 can be found in section 2.1.

expect firms to strategically use boilerplate disclosures to prepare 'complete' nonperiodic disclosures to meet time pressure post-GN8 revision while minimising the litigation risk. But the reduced readability and increased processing costs could be the downside because extracting relevant information about firms producing more boilerplate disclosures might be difficult (Blankespoor et al., 2020), thus leading to weaker market reaction post-GN8 revision. On the contrary, ASIC believes that firms with a sufficiently strong internal system are less likely to face pressure to respond to the GN8 revision, as most nonperiodic material events are well-known to listed firms (McGrath, 2013; Nicholson, 2011; Price, 2012). Thus, the GN8 revision is less likely to pressure firms. To investigate whether managers' strategic reporting drives the textual complexity of nonperiodic disclosures within a highly litigious environment, this thesis establishes its second and third research questions as follows:

RQ2: Does managers' strategic use of boilerplate post-GN8 revision reduce the readability of nonperiodic disclosures?

RQ3: Does the market react less strongly to nonperiodic disclosures that use more boilerplate disclosure post-GN8 revision?

The third and final study explores the role of social media in processing textually complex periodic and nonperiodic disclosures as an alternative channel from the investors' demand side. With the emergence of social media, the use of collective intelligence, known as the 'wisdom of crowds',[7] for real-time information processing has become increasingly prevalent in the financial markets (Bartov et al., 2018; Chen et al., 2014; Lawrence, Ryans, & Sun, 2017; Lerman, 2020). Despite social media's positive role, they are unregulated, and the use of this information can

[7] The 'Wisdom of Crowds' phenomenon proposes that the aggregated judgement of many individuals (non-expert) can be more accurate than the judgement of individual experts.

bias investors' collective information processing (Campbell et al., 2019; Farrell et al., 2021; Jia et al., 2020; Lei et al., 2019; Sabherwal et al., 2011; Xu et al., 2021). On the one hand, regulating these platforms can minimise biases, but on the other hand, too much restriction can offset processing benefits (Blankespoor, 2018; Campbell et al., 2019; Drake et al., 2022; Lei et al., 2019).

I use data from HotCopper, Australia's largest stock message board site, to examine the information processing role of the regulated stock message board. My choice of HotCopper is motivated by its operation under Regulatory Guidance 162 (RG162), which restricts CEOs and experts from engaging in stock message boards, and by the GN8 revision, which required listed firms to start to monitor for potential rumours and misinformation across all social media. Therefore, if investors view regulated stock message boards as a more credible information processing channel, I expect more stock message board views and discussions around textually complex disclosures. Further, if RG162 diminishes CEOs' and experts' biases and GN8 regulates misinformation, higher numbers of stock message board discussions may lower stock price synchronicity by facilitating access to more credible information at lower costs for the processing of textually complex disclosures. Because firms' choice of textual complexity for periodic and nonperiodic disclosures can affect investors' processing costs, it remains unclear how these information costs could affect social media activity. To address the information processing role of regulated stock message boards for firms with textually complex disclosures, the fourth and fifth research questions of the thesis are as follows:

RQ4: Do textually complex disclosures affect the extent to which investors engage in stock message board activity?

RQ5: Do higher levels of discussion on a regulated stock message board reduce stock price synchronicity for firms with textually complex disclosures?

1.2 Summary of the main findings

This thesis addresses five research questions in three self-contained but related empirical studies in Chapters 3, 4 and 5. The investigation delves into the impact of the textual complexity in periodic and nonperiodic disclosures on investors' tendency to rely on a regulated stock message board when they incur higher processing costs. Table 1.1 in Section 1.4 depicts an overview of the thesis structure with empirically tested hypotheses, research designs and key findings.

Chapter 3, entitled "Textual Complexity of Periodic and Nonperiodic Disclosures and Their Determinants", addresses the first research question. Descriptive analysis shows that nonperiodic disclosures are generally more readable, shorter and contain less boilerplate than periodic disclosures, and the significant mean difference further supports the idea that these two types of disclosures are distinct in terms of textual complexity. Both disclosures became more complex over time, but nonperiodic disclosures underwent more pronounced changes post-GN8 revision in 2013. However, industry analysis reveals that firms from the resource, finance, and regulated industries tend to produce more complex periodic than nonperiodic disclosures due to their complex structure and business practices. Furthermore, multivariate analysis documents that certain factors, such as time trends (e.g., a dummy variable that increments by 1 each year), market-to-book, gearing and special items, have a greater impact on the textual complexity of nonperiodic than periodic disclosures. Besides firm-specific factors, I also find evidence that managers' strategic reporting influences the textual complexity of

nonperiodic disclosures more than periodic disclosures, mainly when they consist of bad news released on *ATH*, *LTD* and *ATHonLTD* when investors pay less attention.

Chapter 4, entitled "Does Managers' Strategic Use of Textual Content to Meet Regulatory Pressure Make Nonperiodic Disclosures Less Readable?" investigates the second and third research questions. I use the GN8 revision as an exogenous shock to examine how managers' use of boilerplate to achieve the completeness of their disclosures within a strict timeframe to ease litigation risk may impact the readability of nonperiodic disclosures. I use readability as a proxy of textual complexity and find that nonperiodic disclosures became less readable post-GN8 revision. The difference-in-differences (DiD) analysis further confirms that firms that displayed greater increases in the use of boilerplate in nonperiodic disclosures appear to face the largest reduction in readability as these disclosures became less specific and had lower information content. The findings also show the negative association between market reactions and firms making greater use of boilerplate post-GN8 revision, and such association is only significant for firms with lower institutional ownership. These results indicate that adding boilerplate to nonperiodic disclosures to ease litigation made them less readable and harder for retail investors to process post-GN8 revision.

Chapter 5, entitled "Textual Complexity of Corporate Announcements and Information Processing Role of Regulated Stock Message Board", addresses the last two research questions. Chapters 3 and 4 established that investors incur higher processing costs for complex nonperiodic disclosures despite being textually different from periodic disclosures regarding determinants. This chapter examines how investors' reliance on a regulated stock message board for processing textually complex periodic and nonperiodic disclosures can lower stock price synchronicity. Using the HotCopper data, I show that less readable periodic and nonperiodic disclosures receive more views and discussions on the stock message board, but this

is not associated with announcement length after controlling for news media and analyst coverage. Partitioning periodic and nonperiodic disclosures into subsamples, I find that less readable and longer nonperiodic disclosures drive greater stock message board views and generate more discussions. Next, higher levels of discussion on the regulated stock message board reduce stock price synchronicity as investors can incorporate more credible information at a lower cost to process textually complex disclosures. However, such an association is stronger for nonperiodic disclosures with lower institutional ownership.

Overall, the findings show that nonperiodic disclosures are generally less textually complex than periodic disclosures. Firm-specific factors, managerial incentives and the risk of litigation impact the textual complexity of nonperiodic disclosures, leading to negative market outcomes due to the increased processing costs associated with these disclosures. Further, investors demand more information on regulated stock message boards in response to complex textual disclosures. The credible stock message board discussions available at lower cost appear to improve price informativeness, particularly when processing unanticipated material events.

1.3 Contributions to the literature

My first study primarily contributes to the broader literature on nonperiodic disclosures and the existing accounting research that uses textual analysis. First, I show that nonperiodic disclosures are more readable, shorter and contain less boilerplate than periodic disclosures in terms of textual complexity, adding to the literature that primarily focuses on the textual complexity of periodic disclosures (Cazier & Pfeiffer, 2016; Cazier et al., 2021; Dyer et al., 2017; Lang & Stice-Lawrence, 2015; Lee, 2012; Li, 2008; Merkley, 2013; Yekini et al., 2016). Second, the existing literature on nonperiodic disclosure primarily focuses on their

determinants of timeliness and frequency and provides less understanding of its textual complexity (Brown et al., 1999; Carter & Soo, 1999; Debreceny & Rahman, 2005; Jackson et al., 2015; Lerman & Livnat, 2010; McMullin et al., 2019; Segal & Segal, 2016). I contribute to this literature by showing that nonperiodic disclosures have become increasingly textually complex over time and that factors such as market-to-book, high gearing, and special items have a greater impact on their language compared to periodic disclosures. Third, existing literature shows managers strategically time nonperiodic disclosures that come with bad news (Li & Tan, 2022; Rubin et al., 2017; Segal & Segal, 2016). But within a strict timeframe setting in Australia, I show that, for nonperiodic disclosures containing negative information released on *ATH*, *LTD* and *ATHonLTD*, managers are prompted to present them in more complex language.

The second study further adds to the literature on nonperiodic disclosures and studies on the influence of managers' strategic reporting on textual complexity in three dimensions. Firstly, prior studies highlight the positive role of regulation in the improved timeliness and frequency of nonperiodic disclosures (Brown et al., 1999; Lerman & Livnat, 2010; McMullin et al., 2019; Noh et al., 2019). My results contribute to the existing research by highlighting the unintended effects of the revision of GN8 by examining how managers' use of boilerplate disclosure to ease litigation risk may reduce readability, leading to unfavourable market outcomes. Secondly, I contribute to the studies that examine the managers' strategic use of textual complexity (Cazier & Pfeiffer, 2017; Cazier et al., 2021; H. Li, 2019) and its associated impact on disclosure readability and capital market outcomes (Dyer et al., 2017; Lang & Stice-Lawrence, 2015; McClane, 2019). I contribute to this literature by showing that, besides periodic disclosure, the strategic use of lengthy boilerplate disclosure as 'complete' disclosure is particularly useful to nonperiodic disclosures in

providing better protection against litigation within a strict timeframe. However, the downside is that investors with firms that use boilerplate disclosure tend to find the information has lower readability. Thus, they face higher information processing costs, leading to negative market reactions. Finally, my research offers valuable insights for regulators on the effects of the Treasury Laws Amendment (2021 Measures No. 1) Bill 2021 passed by the Australian Federal Government. The bill aimed to alleviate directors' fears of facing speculative lawsuits for misleading and deceptive conduct. In response to the bill that is expected to reduce litigation risk, regulators can expect firms to rely less on boilerplate disclosure and hedging with complex legal terminology, leading to less textually complex periodic disclosures.

My third study primarily contributes to the literature related to investors' complex disclosure processing, social media, stock price synchronicity literature and the social media policy debate. First, I demonstrate that complex texts like lengthy and less readable disclosures can cause investors to turn to lower-cost alternative sources for comprehension. This contribution expands on previous research examining how investors process information from textually complex disclosures (Asay et al., 2017: Blankespoor, 2018; Blankespoor et al., 2020; Miller, 2010). Second, my findings on higher numbers of stock message board views and discussions around textually complex disclosures add to the growing literature that examines the determinants and production of user-generated information on social media (Blankespoor, 2018; Lawrence, Ryans, & Sun, 2017; Lawrence, Ryans, Sun, & Soni, 2017; Lei et al., 2019; Lerman, 2020). In addition, I find that the association between stock message board activity and textually complex disclosures is more pronounced for nonperiodic material events. This finding implies that prior evidence on higher message board activity around nonperiodic 8-Ks in a US setting (Debreceny et al., 2021; Lawrence, Ryans, Sun, & Soni, 2017; Lerman, 2020) may

be driven by retail investors using them as a more effective and timelier channel to process longer and less readable unanticipated material information. Third, this study responds to the policy debate about regulating social media, adding to the literature that highlights the negative role of unregulated social media (Campbell et al., 2019; Chen et al., 2014; Farrell et al., 2021; Jia et al., 2020; Lei et al., 2019). I utilise an Australian stock message board where RG162 restricts experts' opinions from being shared, and the GN8 regulates misinformation, and I show that higher levels of discussion on the regulated stock message board can lower stock price synchronicity for firms with textually complex disclosures by facilitating the production of more credible firm-specific information at a lower cost. My findings provide valuable insights for ASIC, along with a collection of international securities regulators, to evaluate and set regulations that would enable retail investors to use nonprofessional experts' research posted on stock message boards as a complement to or substitute for professional experts' commentary. Finally, I provide new insights into the determinants of stock price synchronicity (Ding et al., 2020; Huang et al., 2022; Jin & Myers, 2006; Morck et al., 2000; Roll, 1988) by highlighting the incremental role of regulated stock message boards. Notably, my paper adds to the work of Ding et al. (2019) and Huang et al. (2022) by highlighting the information processing role of the regulated stock message board, particularly for processing textually complex nonperiodic disclosures rather than the opaque discretionary accruals, and by confirming inferences made in a more regulated setting as a complementary information processing channel for formal disclosure.

1.4 Thesis structure

The remainder of this thesis is organised as follows. Chapter 2 discusses the definition of textual complexity, the institutional background, its current regulatory issue, and finally, the research framework.

Chapters 3 to 5 report the empirical studies. Chapter 3 examines the textual complexity across periodic and nonperiodic disclosures and their determinants. Chapter 4 investigates managers' strategic use of nonperiodic disclosure text to mitigate litigation risk for regulatory pressure and its market consequences. Chapter 5 examines the information processing role of a regulated stock message board for firms with textually complex disclosures. Each empirical study attempts to examine identified research questions by developing hypotheses, theorising the relations between the variables of interest, detailing empirical models, defining the sample selection process and presenting descriptive statistics, followed by regression results and additional analyses.

Chapter 6 concludes and summarises the findings from the previous chapters and discusses the potential implications of the three empirical studies. Also, study limitations are identified, and directions for future research are provided.

Table 1.1: Thesis structure and summary of the main findings

Chapter 2: Textual complexity, Institutional Background and Research Framework		
Chapter 3: Textual Complexity of Periodic and Nonperiodic Disclosures and Their Determinants		
RQs and Hypotheses	**Research Design**	**Key Findings**
***RQ1*: Do the determinants of textual complexity of nonperiodic disclosures differ from that of periodic disclosures?** **$H_{3.1}$:** Nonperiodic disclosures are less textually complex than periodic disclosures. **$H_{3.2a}$**: Textual complexity of nonperiodic disclosures is more influenced by time trends than periodic disclosures. **$H_{3.2b}$**: Textual complexity of nonperiodic disclosures is more influenced by firm-specific factors than periodic disclosures. **$H_{3.3}$**: Nonperiodic disclosures with bad news are more textually complex when they are released after trading hours, on the week's last trading day, and after trading hours on the last trading day of the week.	Sample: All S&P/ASX 200 firms with 17,080 firm-announcement observations based on periodic and nonperiodic announcements. Period: 2010 to 2018. Approach: OLS regression. Dep var: Readability (Bog Index), Length, Boilerplate as textual complexity measures and Tone for both periodic and nonperiodic disclosures. Indep var: Firms' size, Leverage, Market-to-Book, Age, Loss, Big4, special items, geographic and operational complexity. In addition, a time trend variable that increments by 1 each year starting from 2010 is added to capture the time-series trend in textual attributes.	▪ Nonperiodic disclosures are comparatively more readable, shorter, less boilerplate and more positive in tone than periodic disclosures. ▪ Factors such as time trends, market-to-book, gearing and special items appear to have a greater impact on the textual complexity of nonperiodic disclosures than on periodic disclosures. ▪ Managers tend to strategically report more textually complex nonperiodic disclosures when they contain bad news and are released after trading hours, on the last trading day of the week and after trading hours on the last trading day of the week when investors are less attentive.
Chapter 4: Does Managers' Strategic Use of Textual Content to Meet Regulatory Pressure Make Nonperiodic Disclosures Less Readable?		
RQs and Hypotheses	**Research Design**	**Key Findings**
***RQ2*: Does managers' strategic use of boilerplate post-GN8 revision reduce the readability of nonperiodic disclosures?**	Sample: All S&P/ASX 200 firms with 9,995 firm-announcement observations based on nonperiodic announcements.	▪ The decreased readability of nonperiodic disclosures post-GN8 revision is more

$H_{4.1}$: The decrease in nonperiodic disclosures' readability post-GN8 revision is more pronounced for firms with greater use of boilerplate text in the document. ***RQ3*: Does the market react less strongly to nonperiodic disclosures that use more boilerplate disclosure post-GN8 revision?** **$H_{4.2}$**: There is a negative association between *CAR* and greater use of boilerplate text in disclosures post-GN8 revision.	Period: 2010 to 2017. Approach: Difference-in-differences (DiD) using propensity score matching, OLS regression. Dep var: Readability (Bog Index)/Cumulative abnormal returns (*CARs*). Indep var: Post GN8 revision dummy is set to 1 if the observation is after the effective date of the GN8 revision (1 May 2013). Firms' size, Leverage, Return on assets, Market-to-Book, Age, Special items, Volatility, Geographic and Operational complexity, Big4, No. of analysts, and News coverage. Dummy variables for firms that are involved in merger & acquisition and season equity offerings and belong to high-tech, regulated or resource industries.	pronounced for firms that displayed a greater increase in the use of boilerplate disclosure. ▪ The negative market reactions around nonperiodic disclosures are more pronounced for firms with a greater increase in the use of boilerplate disclosure post-GN8 revision.

Chapter 5: Textual Complexity of Corporate Announcements and Information Processing Role of Regulated Stock Message Board

RQs and Hypotheses	Research Design	Key Findings
***RQ4*: Do textually complex disclosures affect the extent to which investors engage in stock message board activity?** **$H_{5.1a}$**: There is a negative association between stock message board activity and the readability of disclosures. **$H_{5.1b}$**: There is a positive association between stock message board activity and longer disclosures.	Sample: All S&P/ASX 200 firms with 17,080 firm-announcement observations based on periodic and nonperiodic announcements. Period: 2010 to 2018. Approach: OLS regression, instrumental variables.	▪ There are higher numbers of stock message board views and discussions around less readable periodic and nonperiodic disclosures, but these are not associated with announcement length. ▪ Partitioning the periodic and nonperiodic disclosures, the higher numbers of stock message board views and discussions are mainly driven by less readable and longer nonperiodic disclosures.

$H_{5.2a}$: The negative association between stock message board activity and the readability of disclosures is stronger around unanticipated events. **$H_{5.2b}$**: The positive association between stock message board activity and longer disclosures is stronger around unanticipated events. ***RQ5:*** **Do higher levels of discussion on a regulated stock message board reduce stock price synchronicity for firms with textually complex disclosures?** **$H_{5.3a}$**: The higher the number of stock message board discussions for less readable and longer disclosures, the lower the stock price synchronicity. **$H_{5.3b}$**: The negative association between the number of stock message board discussions and stock price synchronicity is more pronounced for firms with less readable and longer nonperiodic disclosures.	Dep var: stock message board activity- views and discussions/Stock price synchronicity. Indep var: Readability (Bog Index) and Length as textual complexity measures. Daily control variables include News coverage, No. of analysts, announcement tone and pre-announcement Return, Turnover and Volatility. Yearly firm control variables include Firms' size, Leverage, Return on assets, Market-to-Book, zero returns, no of firms in the industry and Herfindahl index of industry-level concentration and dummy variables for high-tech firms, regulated firms and resource firms, and firms that are involved with merger & acquisition and season equity offerings.	▪ The number of Stock message board discussions are significantly negatively associated with stock price synchronicity for firms with longer and less readable disclosures, and this association is more pronounced for nonperiodic disclosures.

Chapter 6: Conclusion and Future Research Directions

Chapter Two:
Textual Complexity, Institutional Background and Research Framework

2.1 Introduction

This chapter first defines textual complexity and discusses several textual complexity characteristics that have been identified by prior research as potentially affecting the informativeness of disclosure. Next, an overview of the institutional background to the thesis, focusing on the CDR and regulation for social media in Australia. I begin by discussing the CDR (Section 2.3.1), followed by the rules and enforcement of Listing Rule 3.1 (Section 2.3.2), shareholder class action for breaching the CDR (Section 2.3.3) and Regulatory Guidance 162 (RG162) for social media regulation in Australia (Section 2.3.4). Section 2.4 depicts the current issues with the CDR and social media regulation. Building on this institutional setting, Section 2.5 sets out the research framework of the thesis.

2.2 Textual complexity

Defining textual complexity is not simple (Loughran & McDonald, 2014a, 2016). Extant literature in accounting defines the textual complexity within a disclosure document as the degree of difficulty in understanding the written text within the disclosure and links it closely to the costs of information processing. The underlying notion is that a more difficult-to-read document requires greater cognitive effort to process, which can impede the reader's ability to locate and extract useful information efficiently (Lee, 2012; Li, 2008; Loughran & McDonald, 2016; Miller, 2010).

Applying textual analysis, several metrics have been developed to capture specific textual complexity characteristics of financial reporting and received substantial attention from regulators, standard setters and practitioners. The suitability of different methods for measuring textual complexity varies depending on the specific context of use. Measures of readability, such as the Fog and Bog index scores, focus on assessing the clarity component of writing, whereas document length (i.e., number of words) captures the quantity component of textual information within documents (Bonsall et al., 2017). Loughran and McDonald (2014a) further propose incorporating document file size as a quantity-based measure, as it aligns with the concept of overwriting. Previous research has shown that annual reports that are longer and less readable can increase the processing costs for investors (Bloomfield, 2002), leading to delayed market reactions (Miller, 2010; You & Zhang, 2009), increased idiosyncratic volatility (Loughran & McDonald, 2014a), and subsequent changes in stock price (Lee, 2012).

Similarly, regulators and standard setters have further identified the growing standardisation of annual reports (often called 'boilerplate') as problematic (FASB, 2012; FRC, 2012) because the unnecessary length added by boilerplate (Henry & Peytcheva, 2020) may impede investors' ability to separate relevant from irrelevant information (Blankespoor et al., 2020; Dyer et al., 2017; Henry & Peytcheva, 2020). Consistent with this notion, Brown and Tucker (2011) recommend using cosine similarity to measure consistency between documents across different periods and discover a link between changes in management discussion and analysis ('MD&A') language and economic activity and stock returns. Lang and Stice-Lawrence (2015) found that companies commonly using more boilerplate disclosure across the firm experience reduced liquidity, institutional ownership, and analyst coverage. There is some evidence, as discovered by Cazier and Pfeiffer (2017) that repeated phrases

within a 10-K filing may result in slower price responses. However, standardising the format through boilerplate language might aid in locating relevant data, and repeated information within particular sections of an annual report may benefit investors focusing on a specific section. Additionally, using consistent language over time could simplify the identification of new information when comparing different periods.

Prior studies on textual complexity are primarily based on periodic disclosures and provide less understanding of how the textual complexity of nonperiodic disclosures could influence investors' processing costs in relying on social media for clarification. My analysis focuses on a diverse range of textual complexity measures because no single measure can fully capture all aspects of textual complexity. In Chapter Three, I focus on all the textual complexity characteristics discussed above – readability, length and boilerplate – to provide a broader understanding of the textual complexity across periodic and nonperiodic disclosures and their determinants. In Chapter Four, I rely on boilerplate measures to capture the managers' strategic textual reporting incentives for nonperiodic disclosures to meet regulatory pressure while using readability measures to show how boilerplate disclosure can compromise the investors' understanding. Boilerplate is used because more boilerplate disclosures are less likely to be considered inadequate under judicial and regulatory review, though the downside is that investors incur higher processing costs for decreased readability (Cazier & Pfeiffer, 2017; Cazier et al., 2021). Finally, I employ readability and length measures in Chapter Five to investigate how a regulated stock message board can improve stock price informativeness by facilitating investors' processing of textually complex disclosures at a lower cost. My choice of these two measures is motivated by theoretical support for these textual characteristics since they depict that information that is more costly to extract from

public data is less completely revealed in market prices (Blankespoor et al., 2020). However, I acknowledge that the interpretation of these characteristics is limited since I do not directly measure the usefulness of the disclosed content. Furthermore, different users may be influenced by the same attributes in different ways, and certain types of information may require disclosure using distinct features.

2.3 Institutional background

2.3.1 The evolution of disclosure regulation in Australia

The Australian Securities Exchange (ASX) had long-standing regulations requiring listed companies to disclose material information frequently and in a timely fashion. However, the effectiveness of these regulations were criticised in the early 1990s due to several high-profile corporate failures in the late 1980s, such as those of Rothwells Limited, Hooker Corporation, and Qintex Australia Limited.[8] In response, the government asked the Companies and Securities Advisory Committee (CASAC) to investigate the need for a legislation-based Listing Rule 3.1. CASAC's report in 1991 suggested that a legally backed disclosure regulation could improve enforceability and restore investor confidence, which was perceived to be low due to these corporate failures. Following these recommendations, a legislation-backed Listing Rule 3.1, referred to as the CDR, was introduced on 5 September 1994 in Australia to enhance enforceability.

Since 1994, the CDR has subsequently been amended on several occasions. On 1 July 1998, ASIC was granted the power to impose enforceable undertakings on listed firms for CDR non-compliance (Section 93AA of ASIC Act 2001) to help firms to minimise the likelihood of future CDR breaches. On 11 March 2002, the Financial

[8] Prior to 1994, regulatory authorities had limited investigative powers and could not pursue criminal or civil liability with firms for breaching Listing Rule 3.1.

Service Reform Act 2001 (Cth) came into effect, and CDR provisions were included in the civil penalty regime under Section 674(2) of the Corporations Act 2001. On 1 January 2003, the introduction of Listing Rule 3.1B authorised ASX to ask listed firms to provide all necessary information to correct or prevent a false market situation. The introduction of the Corporate Law Economic Reform Program (CLERP 9) on 1 July 2004 further strengthened ASX's ability to impose civil penalties on individuals involved in a contravention of the CDR, including on-the-spot fines.

On 1 May 2013, ASX revised its Guidance Note 8 (GN8) on the CDR in response to public consultation. The public consultation reflected the listed firms' concerns about balancing the timeliness and completeness of disclosure without triggering regulatory action. The revised GN8 attempted to clarify a few major areas, such as the definition of "immediately" as "promptly and without delay" to disclose information and the use of a trading halt to manage a firm's continuous disclosure obligations. On 9 March 2018, ASX further revised its listing rule to improve market disclosure in some key areas, including additional guidance on Section 4.15 for drafting material contracts and Section 5.10 for the insolvent trading safe harbour for directors. Lastly, with increasing concerns about companies' ability to comply with the CDR at the peak of the COVID-19 pandemic, Bill 2021 (Cth) ('the Bill') was introduced with temporary modifications of the CDR by the Federal Government in May 2020 to provide relief to firms and officers from opportunistic shareholder class actions. Later, on 17 February 2021, Bill 2021 was introduced into Parliament to make the changes permanent and on 10 August 2021, the Senate amended and passed the Bill, which took effect on 14 August 2021. Figure 2.1 summarises the evolution of the Australian CDR.

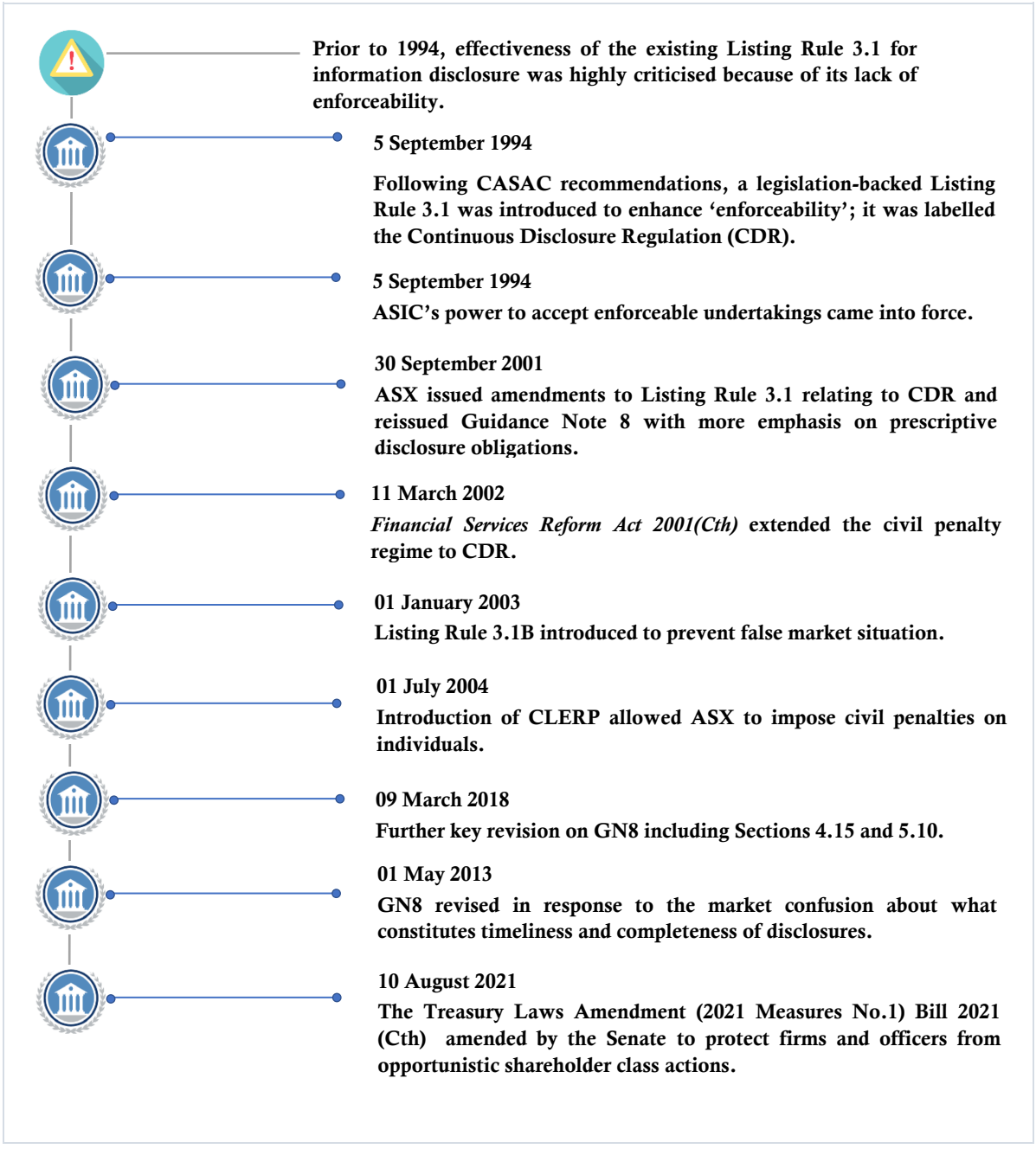
2.3.2 *Rules and enforcement of Listing Rule 3.1*

The centrepiece of the Australian CDR is Listing Rule 3.1. I describe the current rules of Listing Rule 3.1 based on ASX's GN8 published in 2019. ASX Listing Rule 3.1 requires listed firms to immediately disclose any information that a reasonable person would expect to have a material effect on the price or value of the entity's securities. Further, the test of whether the information is material or not is set out by Section 677 of the Corporations Act. It states that information likely to influence general investors in deciding whether to acquire or dispose of the security is considered to have a material effect.

Further, Section 674(2)(c) of the Corporations Act provides an additional obligation for listed firms to notify the market operator of information according to the relevant listing rules if the information is not already available. However, in a false market situation driven by market speculation or media comment, ASX may ask listed firms to provide additional information to correct or prevent a false market under Listing Rule 3.1B.[9] Besides the CDR obligation in Section 674 of the Corporations Act for timely disclosures, statutory provisions also require disclosures not to be misleading and deceptive. If company disclosures are not clear, concise or effective, there is an increased risk that such disclosures could be deceptive and misleading to readers. Therefore, Section 4.15 of Listing Rule 3.1 emphasises that listed firms must prepare disclosure documents in a manner that is factual, relevant, complete and written in plain English. Finally, there are some exceptions in Rule 3.1A when information is confidential, and firms may apply carve-out provisions when disclosure is unnecessary.

[9] Listing Rule 3.1B states that "If ASX considers that there is or is likely to be a false market in an entity's securities and asks the entity to give it information to correct or prevent a false market, the entity must give ASX the information needed to correct or prevent the false market."

Figure 2.1: Evolution of continuous disclosure regulation



The Australian financial market is co-regulated by both ASIC and ASX. ASX governs the Listing Rules 3.1 and can suspend listed firms' security trading or even terminate their listing. In addition, ASX uses ASX Query as soft enforcement, asking firms to clarify any issues or concerns with ASX Listing Rule 3.1 compliance. ASIC, on the other hand, has the authority to investigate any potential breach under Section 674(2) of the Corporations Act for non-compliance with Listing Rule 3.1 obligations

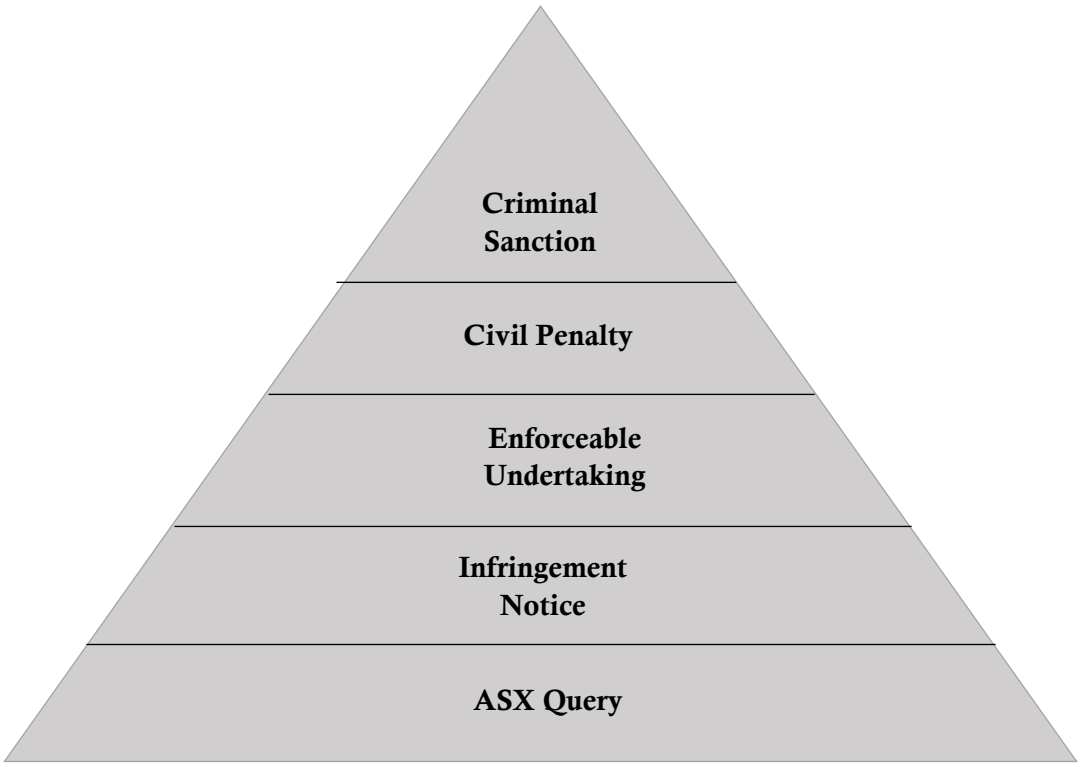
and can impose criminal (Section 1311) or civil penalties (Section 1317E) on liable firms. ASIC has a range of options to deal with non-compliance with Listing Rules 3.1, including infringement notices, enforceable undertaking and court actions. For an alleged contravention of Section 674(2), ASIC has the authority to issue an infringement notice under Section 1317DAC. This gives ASIC the power to impose a financial penalty ranging from $33,000 to $100,000[10] depending on the firms' market capitalisation and whether they have received any notice previously. The company must comply with the notice and pay the penalty within 28 days from the issuing day of the infringement notice.

ASIC uses enforceable undertakings as an administrative settlement with listed firms to deal with serious cases (rather than trivial situations). This regulatory tool was designed to achieve more effective compliance procedures via negotiated settlement than court or other regulatory actions. However, enforceable undertakings can be used to impose a penalty when it is combined with an infringement notice or court action. Finally, ASIC may initiate civil penalty and criminal proceedings to deal with severe contraventions of the Listing Rule 3.1. The provision of CLERP 9 allows ASIC not only to impose civil penalties on those responsible for the contravention but also to provide the most appropriate remedy for those who have suffered loss or damage (such as shareholders). If the court is satisfied with the standard of proof that a civil penalty provision has been contravened, then the court must make a declaration of the effect (Section 1317E). The consequence of such a declaration could lead to a pecuniary penalty of up to $1,000,000 for a corporate body under Section 1317 G or compensation to another person under Section 1317HA. Finally, ASIC can apply the criminal sanction as severe punishment of all enforcement options for a Listing Rule 3.1 breach. However, there have been no

[10] All dollar figures given throughout the thesis are in Australian dollars unless otherwise stated.

successful criminal prosecutions because of the evidential burden of successful criminal proceedings. In Figure 2.2, I show the CDR Listing Rule 3.1 enforcement pyramid as adapted from Boros (2009). The pyramid ranks regulatory enforcement options based on their ever-increasing intensiveness from bottom to top.

Figure 2.2: CDR Listing Rule 3.1 enforcement pyramid, modified from Boros (2009)



2.3.3 *The role of shareholder litigation in the CDR*

Though the CDR is primarily monitored and enforced by ASIC and ASX, shareholder class actions as private actions have also proved to be effective. Securities class actions generally allege that the respondent listed company engaged in misleading or deceptive conduct by its statements via announcements to the market and/or failed to disclose relevant information to the market (Section 1041H of the Corporations Act 2001 (Cth)) and breached its CDR obligations to provide material

information under ASX Listing Rules (Section 674 of the Corporations Act). Following the introduction of the misleading and deceptive conduct provisions of the Corporations Act 2001 (Cth) in 2002 for CDR breaches, 63 securities class actions were filed in 2017 (as shown in Appendix B). Specifically, shareholder class actions for misleading and deceptive conduct in respect of CDR obligations have become the most commonly filed class action in the Federal Court, representing 34% of all class actions filed in the five years 2013–2017. Interestingly, among these shareholder class actions, 9 out of 10 have proceeded to some form of settlement resulting in a cost to the defendants. While Australian lawyers are prohibited from engaging in class action using their clients' damages to calculate their fees, third-party litigation financiers are not subject to such restriction. As a result, litigation financiers can absorb the shareholder-victims' risk and adverse costs through a contract in exchange for a share of the damages, which may be settled later.[11] Despite the positive role of the shareholder class action in deterring future breaches of the CDR and protecting investors' rights, the threat of facing a class action in Australia is a huge exposure for companies and their directors and officers (D&Os). Even highly regarded and well-maintained listed firms can be brought to court by plaintiff lawyers representing a class of shareholders whenever there is a significant movement in the share price following an announcement. Therefore, Australia is a country where firms and their D&Os face a very high risk of being subject to a shareholder class action (second highest risk in the world, behind only the US).

2.3.4 Regulation for social media in Australia

In Australia, Section 15.7 of ASX Listing Rule 3.1 strictly prohibits listed firms from releasing any material information to any other channels, including analysts

[11] For details, see Lumsden, (2018).

and social media, until it has been released via the ASX website. This minimises the firm's potential selective and strategic disclosure via non-corporate channels. Thus, Australian firms predominantly use social media as a channel for re-broadcasting or disseminating material information rather than providing new information (Prokofieva, 2015).

Furthermore, ASIC and other regulators view 'internet discussion sites' (IDSs), such as stock message boards, as an area of concern. Accordingly, ASIC amended Regulatory Guide 162 (RG162) under the Corporations Act 2001 on 5 July 2007. RG162 guidelines were intended to facilitate the exchange of information, advice and opinions about securities among non-professional investors. It also restricts a licensed person or professional advisor (e.g., an analyst) from providing opinions. The policy rationale under Section RG162.9 provides a balance between three public policy concerns to ensure that: (a) investors are able to communicate freely with one another; (b) investors have an inexpensive and easy method of access to better inform themselves about securities and the developments in securities markets; and (c) there is better investors protection and market integrity by minimising the risk that IDSs may be used for market manipulation, insider trading and other abuse, or to allow people to take advantage of naïve investors. Further, non-compliance with RG162 guidelines potentially breaches the law of the Australian Corporations Act 2001 and may face enforcement actions.

Despite the RG162, in 2012-2013, the David Jones and Whitehaven Coal incidents worried regulators about the rumour mill effects of social media in Australia, whereby these firms suffered a significant drop in their stock prices due to market rumours spread over social media channels. In response to these cases, ASX stipulated social media monitoring requirements for potential rumours and misinformation in their revised GN8 for all ASX-listed firms. For guidance to be

effective, ASIC emphasises that firms should monitor social media sites that are important to a material portion of the investing community, particularly Twitter and popular stock message boards. However, in recent years, ASIC has noted a concerning trend of market manipulation. Following the social media-driven market frenzy for GameStop's shares in 2021, ASIC has significantly increased the scrutiny of social media posts. This includes directly engaging on the platform to identify people involved in the blatant 'pump-and-dump' activity and crack down on any investment advice shared by unlicensed entities (e.g., nonprofessional analysts).[12]

2.4 Current regulatory issues of the CDR and the role of social media

The Australian regulators have emphasised the timeliness, completeness and accuracy of corporate disclosures in GN8 of Listing Rule 3.1, as evidenced by 51 regulatory actions from 2005 to 2019 (shown in Table 2.1), including 8 court actions, 4 enforceable undertakings and 39 infringement notices. Regarding disclosure type, there were 37 regulatory actions related to nonperiodic disclosures: 6 court actions, 2 enforceable undertakings and 29 infringement notices. In comparison, there were 14 regulatory actions for periodic disclosures: 2 court actions, 2 enforceable undertakings and 10 infringement notices. Besides public enforcement by ASIC, Figure 2.3 shows the escalating number of class actions over the past few years for misleading and deceptive conduct, particularly for nonearnings-specific disclosures. The common claim in these lawsuits of misleading and deceptive conduct is that the announcements made by the listed company were not complete, clear and accurate, resulting in losses for the investors (North, 2013). According to data presented in

[12] For example, on 11 October 2021, an ASIC staff member disguised themselves as a member of a private chat group named "pump and dump" on the messaging app Telegram and took the unprecedented step of warning day traders that they could face serious legal actions for illegal trading schemes.

Figure 2.4, the total settlements for securities class actions amounted to approximately $1.8 billion from 2003 to 2018. Out of 64 shareholder class actions settlement between 1999 and 2018, 35 were related to nonperiodic event-specific breaches of the CDR.

This observation begs the question of why nonperiodic disclosures attract more public and private enforcement within the CDR than periodic disclosures, particularly for misleading and deceptive conduct. Part of the blame for firms facing more lawsuits in respect of misleading and deceptive conduct is attributable to market confusion about what 'immediate' disclosure means. Due to the stringent timing requirement, companies may face challenging and intricate decisions in a limited timeframe when an unanticipated event occurs. In such situations, the company must decide whether to disclose the event via nonperiodic disclosures immediately (which could lead to incomplete or rushed disclosures that may mislead the market) or take the time to ensure accuracy (which could lead to regulators accusing the company of taking too long).

Moreover, in recent years, ASIC expressed concern that the growing textual complexity of financial reports and other corporate disclosures can impede stock price efficiency (Price, 2015). The formation of the financial reporting complexity task force[13] and ASIC's ever-increasing emphasis on lessening the textual complexity of corporate disclosures further reflect ongoing regulatory concerns. Given the importance of textual format regarding whether firms face lawsuits for misleading and deceptive conduct, investigating the textual characteristics of nonperiodic disclosures and the potential factors that influence them is important, particularly

[13] The FRC appointed a task force to review the growing complexities in the financial reporting post-IFRS adaptation from Australia's perspective. For details, see https://frc.gov.au/sites/frc.gov.au/files/2013/10/FRC-MR-02-2012.pdf

with the growing concerns about textual complexity. This is because factors such as litigation concerns, firm-specific factors, and managers' incentives may not necessarily affect the textual complexity of nonperiodic disclosures in similar ways to periodic disclosures. Specifically, the growing number of class actions led to the question of whether firms' strategic alteration of textual information (i.e., increased thoroughness, and use of legal and complex words) to reduce the risk of lawsuits influences the textual complexity of nonperiodic disclosures comparatively more than periodic disclosures.

Furthermore, ASIC recognises the growing importance of social media in financial markets in assisting investors' decision-making and the complexity that it brings. However, RG162 and the monitoring requirements put in place by the GN8 revision make Australian stock message boards distinct from the rest of the world, which ensures greater investor protection. Therefore, Australian stock message boards provide an interesting setting in which to examine whether investors view them as a credible information processing source, particularly when they face textually complex disclosures.

2.5 Research framework

Drawing insights from the institutional setting, I rely on the incomplete revelation hypothesis (IRH) and first empirically test the textual complexity of nonperiodic disclosures and how it may differ from periodic disclosures in terms of determinants **(*RQ1*)** in Chapter 3. Extant literature on periodic disclosures primarily relies on the IRH to explain how firms with poor earnings can influence textual complexity to delay the incorporation of information into stock prices (Guay et al., 2016; Lee et al., 2012; Li, 2008). However, IRH provides little guidance on the textual complexity of nonperiodic disclosures. I make two additional points

regarding the theoretical assumptions of IRH. First, nonperiodic disclosures do not directly indicate performance, but investors view them as useful information in assessing and forecasting firms' operational performance, as evidenced by significant immediate price and volume responses around these disclosures (Lerman & Livnat, 2010; Noh et al., 2019). This indicates that managers can strategically use textual complexity to obfuscate nonperiodic disclosures that contain bad news to get positive market outcomes. Second, managers' strategic use of textual complexity could reflect their attempt to convey the impact of unanticipated material events on firms' value. For example, complex businesses are expected to incur more material events, but the bad news is simply difficult to describe and thus may necessitate using more complex sentences to tie those events to performance (Cazier & Pfeiffer, 2016; Li, 2008). Therefore, the textual complexity of nonperiodic disclosure could be driven more by firm-specific factors.

Chapter 4 extends the analysis of nonperiodic disclosures by examining whether managers' strategic reporting to meet regulatory pressure within a highly litigious environment could affect the textual complexity. Motivated by the litigation costs hypothesis, I then argue that litigation for misleading and deceptive conduct may influence managers to strategically improve thoroughness to reduce the risk of lawsuits. But the unintentional consequence of added boilerplate and complex language for a strategic approach to improve thoroughness could have worsened the disclosure readability post-GN8 revision (***RQ2***). Consistent with the theoretical work of Bloomfield (2002) and Grossman and Stiglitz (1980), firms with more boilerplate nonperiodic disclosures post-GN8 may increase investors' information processing costs due to lower readability, leading to negative market reactions (***RQ3***).

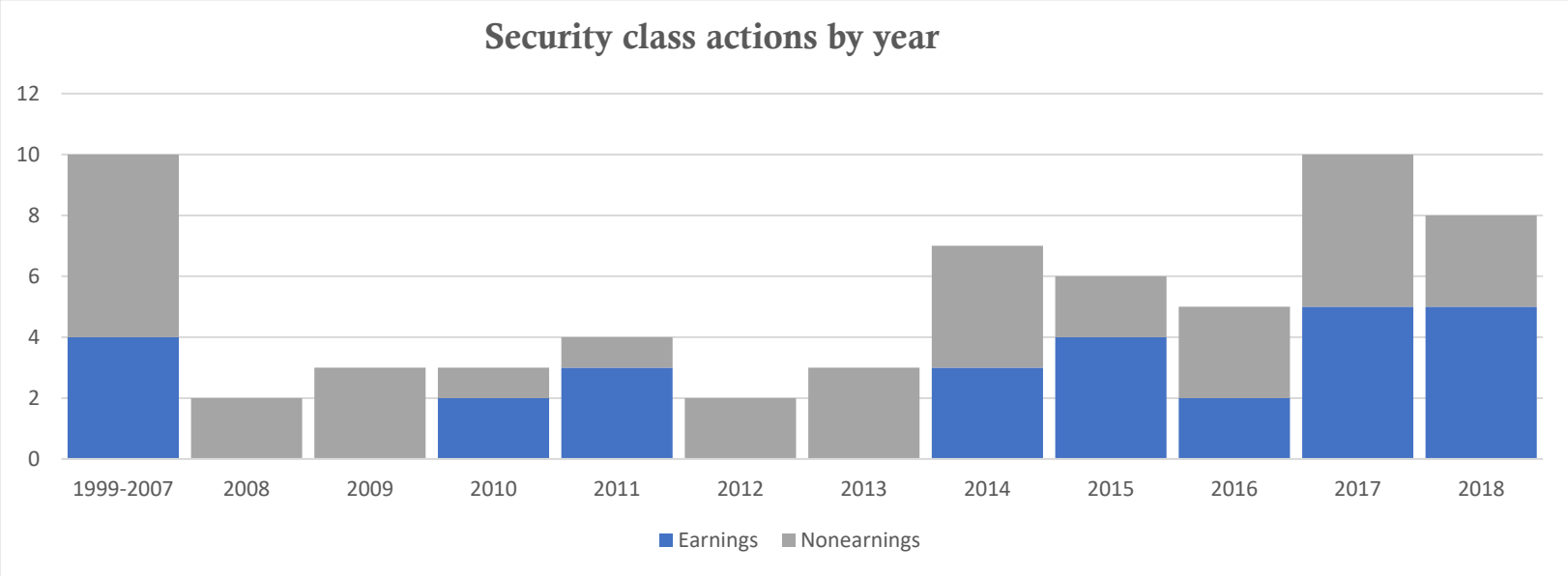
Drawing from the growing body of help-seeking and learning literature (Ding et al., 2020; Lawrence, Ryans, Sun, & Soni, 2017), Chapter 5 contends that investors

may extend their information demand from alternative channels to process textually complex disclosures, particularly from popular interactive platforms like stock message boards (***RQ4***). Next, I utilise a regulated stock message board where expert opinion sharing is restricted by RG162 and GN8 to regulate misinformation in order to address its information processing role. Given social media's documented negative effects, regulators seek to understand the role of regulation before implementing strict social media regulations. The theoretical work of Golub and Jackson (2010) shows that collective efforts by naïve investors to solve an issue could be more effective when there are no influential agents. Consistent with Golub and Jackson (2010), I predict that if RG162 diminishes experts' biases and GN8 regulates misinformation, higher numbers of stock message board discussions may lower stock price synchronicity by facilitating more credible information at lower costs for the processing of textually complex disclosures (***RQ5***). The theoretical perspectives used to identify the research problems are summarised in Figure 2.5.

Table 2.1: Statistics of regulatory enforcement relating to CDR Listing Rule 3.1 contraventions by years and by disclosure types

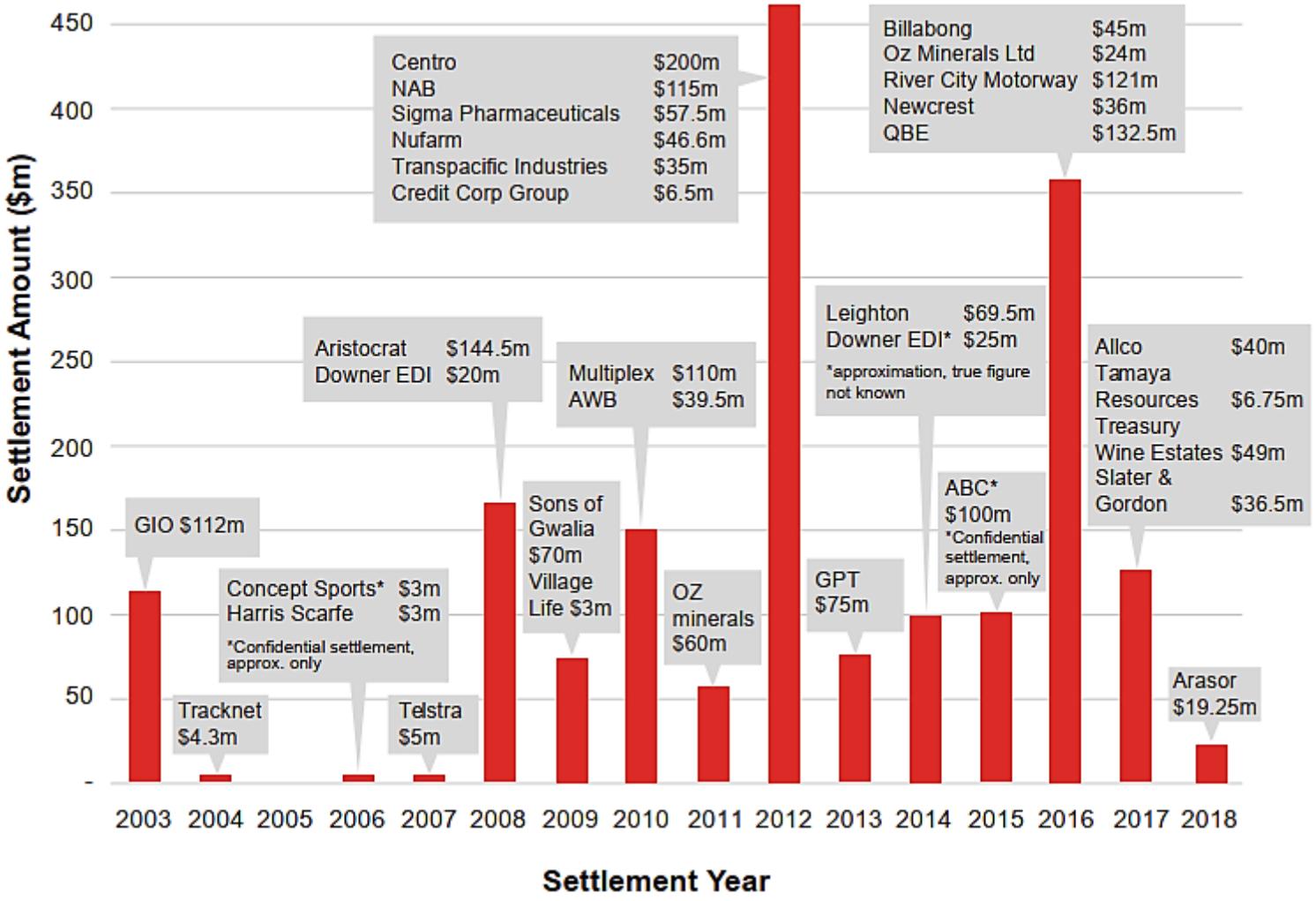
Area of enforcement	2005-2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Court Actions												
Periodic disclosure	0	0	0	0	0	0	0	0	1	1	0	0
Nonperiodic disclosure	3	0	0	0	0	0	1	1	0	0	1	0
Enforceable undertakings												
Periodic disclosure	2	0	0	0	0	0	0	0	0	0	0	0
Nonperiodic disclosure	0	0	0	0	0	0	1	0	1	0	0	0
Infringement Notice												
Periodic disclosure	1	0	1	0	0	0	0	0	3	4	1	0
Nonperiodic disclosure	10	1	1	1	7	3	2	4	0	0	0	0
Total	**16**	**1**	**2**	**1**	**7**	**3**	**4**	**5**	**5**	**5**	**2**	**0**

Figure 2.3: Security class actions for breaching CDR by year



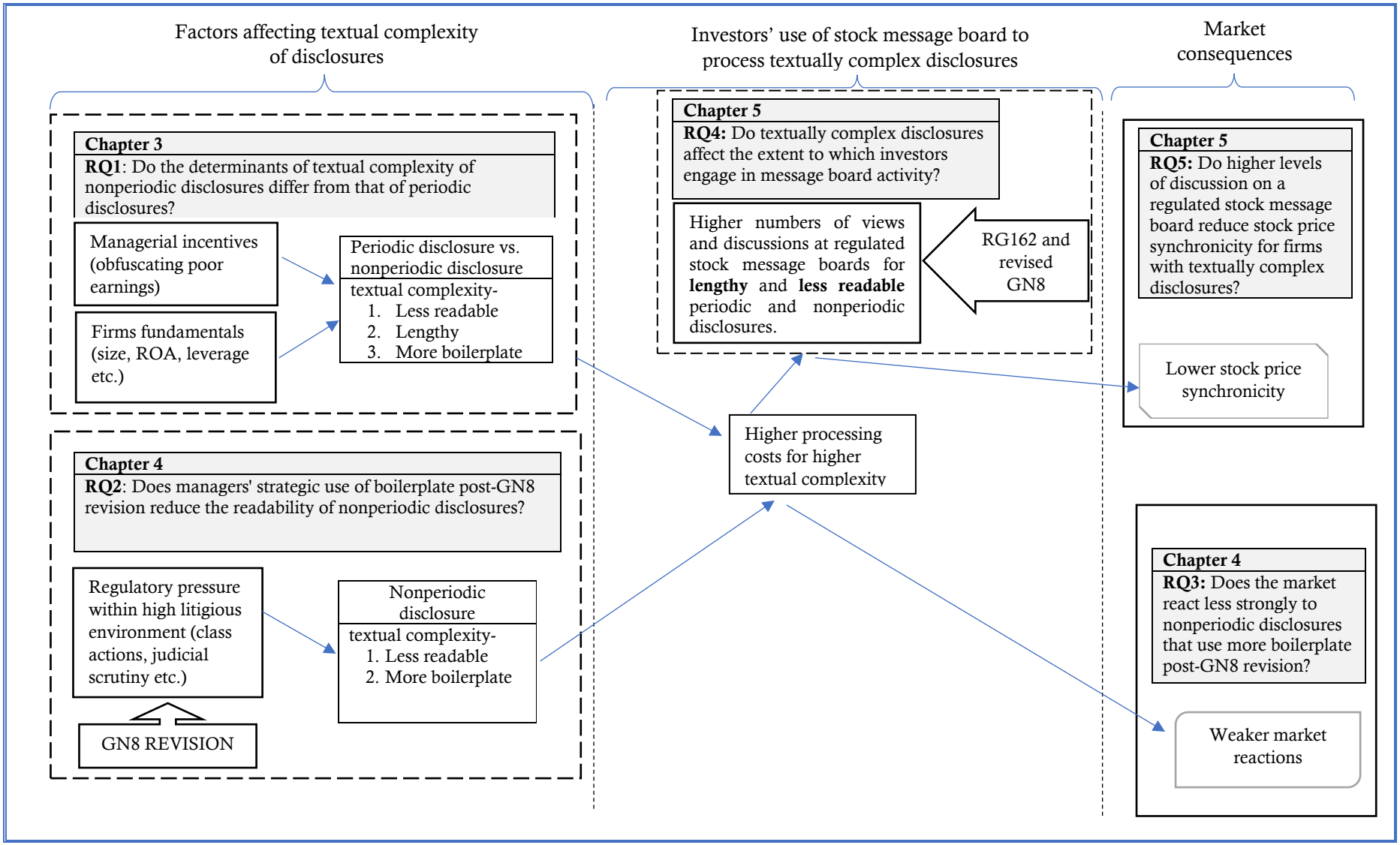
Note. Data from ASIC websites

Figure 2.4: Security class action settlements for breaching CDR (in $ millions)



Note. Data from Norton Rose Fulbright (2019).

Figure 2.5 A framework for textually complex disclosures and investors' use of regulated stock message boards to process complex textual corporate information



Chapter Three:
Textual Complexity of Periodic and Nonperiodic Disclosures and Their Determinants

3.1 Introduction

Textual complexity may impede investors' ability to process information (Blankespoor et al., 2020). This concern is reinforced by the growing body of research that has established a link between the textual complexity of periodic disclosures and negative market outcomes (Lawrence, 2013; Li, 2008; Miller, 2010). However, textual complexity may matter to investors when they process a broad set of non-earning/nonperiodic disclosures (Li & Tan, 2022; Rubin et al., 2017). But do investors perceive similar textual complexity across periodic and nonperiodic disclosures? This question is pertinent because nonperiodic disclosures are sporadic and event-based communications (Li & Tan, 2022; Watkins, 2022) that investors find value-relevant (Brown et al., 1999; Carter & Soo, 1999; Debreceny & Rahman, 2005; Lerman & Livnat, 2010).[14] As nonperiodic disclosures are unanticipated, their textual complexity may not be associated with firm-specific factors, regulations and managerial incentives similar to those identified in previous studies of periodic disclosures (Cazier & Pfeiffer, 2016; Dyer et al., 2017; Li, 2008). Therefore, understanding textual complexity across periodic and nonperiodic disclosures in terms of determinants is important, particularly considering investors' information processing dynamics.

[14] For example, prior studies found that more frequent and timelier 8-K filings for nonperiodic material events are associated with significant market reactions (Lerman & Livnat, 2010) improved price formation (McMullin et al., 2019) and act as a more informative substitute for voluntary guidance by broadening the flow of material information (Noh et al., 2019).

This study conducts textual analysis in several dimensions of textual disclosures in corporate announcements to investigate whether the textual complexity of nonperiodic disclosures differs from that of periodic disclosures and whether their determinants vary as well. Since nonperiodic disclosures are unanticipated and depend on the occurrence of material events, there are several reasons to expect that the textual complexity of nonperiodic disclosures will vary from those of periodic disclosures. Firstly, in contrast to periodic disclosures, nonperiodic disclosures are immediately issued following the triggering material events (Watkins, 2022). Since firms with growing business complexity are expected to incur increased numbers of transactions and material events over the years (Cazier & Pfeiffer, 2016; Li, 2008), the textual complexity of nonperiodic disclosures could be driven more by firm-specific factors and time trends than managers' incentives. Secondly, prior evidence suggests that managers strategically report bad news on *ATH*, *LTD* and *ATHonLTD* to offset negative market reactions (Chapple et al., 2020; Segal & Segal, 2016). Being unanticipated, nonperiodic disclosures aggravate investors' processing difficulty because they cannot gather additional information in advance as they can for periodic disclosures (Li & Tan, 2022; Rubin et al., 2017). Thus, the textual complexity in nonperiodic disclosures can hinder investors' ability to detect potential managerial biases when these disclosures contain bad news and are strategically released on *ATH*, *LTD* and *ATHonLTD* when investors pay less attention. As such, the textual complexity of nonperiodic disclosures may be more influenced by managerial incentives due to the greater flexibility in the format, content and language choice than periodic disclosures.

I use the Australian CDR setting to conduct my study for two reasons. Firstly. ASX and ASIC equally emphasise the need for periodic and nonperiodic

announcements to be timely, complete and written in plain English,[15] as evidenced by GN8 of ASX Listing Rules 3.1. Secondly, despite ASIC's strong stance on timeliness (Jackson et al., 2015), managers are less likely to face regulatory oversight for the level of detail and language choice in their disclosures (Price, 2015) unless the disclosures are proved to be misleading. Thus, the CDR provides an ideal setting to capture the impact of managers' incentives on textual complexity as they have the freedom to release nonperiodic disclosures on *ATH*, *LTD* and *ATHonLTD* when they contain bad news. I use a sample of 17,364 firm announcements from 2010 to 2018. In my analysis, I focus on a broad set of textual complexity measures: readability (Bonsall et al., 2017), length and use of boilerplate (Cazier et al., 2021; Dyer et al., 2017; Lang & Stice-Lawrence, 2015) because no single measure can conceptually or empirically capture all aspects of the textual complexity that are relevant to users.

From a descriptive perspective, I first document that firms report comparatively more nonperiodic than periodic announcements. Out of the total announcement sample, 28.51% accounted for periodic and quarterly activity reports and 55.76% for progress reports, issued capital, takeover, asset acquisition, and disposal announcements. Regarding textual complexity, I partition announcements by their types and find that annual and half-yearly reports appear to be longer and more boilerplate. In contrast, quarterly activity reports prepared by mining, oil and gas companies are less readable. For nonperiodic announcements, I find takeover, issued capital, and other announcements appear to be longer, more boilerplate, and less readable, whereas announcements on company administration and ASX Query are more readable despite the presence of a larger amount of boilerplate. My trend analysis reveals that both announcements became less readable and substantially

[15] For details, see section 4.15- Guidelines on the contents of announcements under Listing Rule 3.1.

longer and boilerplate over the sample period 2010-2018. But such textual complexity has become more pronounced for nonperiodic announcements following the GN8 revision in 2013. The industry analysis further reveals that industries that report more textually complex disclosures are more concentrated on resource, financial and regulated industries because of their complex structures and business models and differential disclosure practices. My bivariate analysis shows a significant mean difference in readability, length, and boilerplate between nonperiodic and periodic announcements, suggesting that both announcements differ in terms of textual complexity. Overall, on average, nonperiodic announcements are less textually complex as they are more readable, shorter, and contain fewer boilerplate words than periodic announcements.

Generally, periodic and nonperiodic announcements' textual complexity appears to be impacted by time trends, firm characteristics, and business complexity. To compare textual complexity across disclosures, I create a dummy variable for nonperiodic announcements and interact it with time trends and firm-specific factors. The results suggest that nonperiodic announcements are more influenced by time trends, market-to-book, and firms with higher gearing and special items, but not by poor performance. The impact of special items and market-to-book indicates that firms with growth prospects may adopt complex business models, leading to more complex language in explaining extraordinary events. Next, I interact the nonperiodic announcement dummy with managers' strategic reporting variables in my regression analysis and find that nonperiodic announcements containing bad news released on *ATH*, *LTD,* and *ATHonLTD* might influence managers to release more complex nonperiodic announcements strategically. Further, I rerun managers' strategic reporting analysis, excluding nonperiodic announcements with extremely negative news, to rule out the concern that managers' use of complex language might

be influenced by the unanticipated triggering events themselves rather than intended to obfuscate them. Finally, my robustness test confirms that omitted correlated variables do not drive my results on determinants and managers' strategic reporting analysis. For parsimony, I also aggregate my textual complexity measures using factor analysis for all specifications to assess whether the determinants also explain the change in the aggregated measures, and I find support for that proposition.

The contribution of this chapter is threefold. Firstly, I show that nonperiodic disclosures differ from periodic disclosures in terms of textual complexity, and they are more readable, less lengthy, and less boilerplate. This adds to the existing literature that primarily examines the textual complexity of periodic disclosures (Cazier & Pfeiffer, 2016; Cazier et al., 2021; Dyer et al., 2017; Guay et al., 2016; Lang & Stice-Lawrence, 2015; Lee, 2012; F. Li, 2008; Merkley, 2013; Yekini et al., 2016), which lacks evidence on the textual complexity of nonperiodic disclosures to gauge the understanding of investors' processing costs within a disclosure framework. This is significant because the growing substitution of nonperiodic disclosures for periodic disclosures reflects investors' increasing reliance on these disclosures to evaluate firms' performance (Guay et al., 2016 Noh et al., 2019). Secondly, the existing literature primarily links nonperiodic disclosures' timeliness and frequency to factors such as firm-specific issues and regulatory change (Brown et al., 1999; Carter & Soo, 1999; Debreceny & Rahman, 2005; Lerman & Livnat, 2010; McMullin et al., 2019) but lacks in the context of textual complexity. My study adds to this literature by showing that nonperiodic disclosures became textually more complex over time and were more strongly influenced by factors such as market-to-book, higher gearing and special items than periodic disclosures.

Thirdly, this study documents how the release of bad news during *ATH, LTD,* and *ATHonLTD* to meet timeliness requirements may influence managers to provide textually complex nonperiodic disclosures. This finding contributes to the literature on the managerial strategic reporting of nonperiodic disclosures (Li & Tan, 2022; Rubin et al., 2017; Segal & Segal, 2016) and enhances the understanding of managerial strategic textual reporting, particularly within an environment of strict timeliness requirements for nonperiodic disclosures.

The remainder of this chapter is structured as follows. Section 3.3 discusses the regulatory setting and summarises prior literature. Section 3.4 details data and sample selection. Section 3.5 presents the results, followed by robustness tests in Section 3.6, and Section 3.7 concludes the chapter.

3.2 Prior literature and hypothesis development

Investors process a wide range of periodic and nonperiodic disclosures within a disclosure framework (Carter & Soo, 1999; Lerman & Livnat, 2010). Despite the broader empirical research on the textual complexity of periodic disclosures, the factors that influence the textual characteristics of nonperiodic disclosures have received less attention. Therefore, it is crucial to understand how nonperiodic disclosures' textual complexity may differ from periodic disclosures, particularly to comprehend the variations in the cost of processing the information for investors. Prior studies have identified several textual complexity measures that could influence the informative value of disclosures. These measures include length (Loughran & McDonald, 2014a), readability (Miller, 2010), amount of boilerplate (Lang & Stice-Lawrence, 2015), redundancy (Cazier & Pfeiffer, 2016), and stickiness (Brown & Tucker, 2011).

I primarily concentrate on three primary textual complexity measures- readability, length and boilerplate that I believe are likely to be of interest to regulators and investors and are more relevant measures to compare textual content between periodic and nonperiodic disclosures[16]. To overcome the limitations of relying on a single measure of textual complexity, I use length, readability and amount of boilerplate in the Australian context to comprehensively assess the textual complexity of nonperiodic disclosures (Dyer et al., 2017).

There are several reasons to expect the textual complexity of nonperiodic disclosures may differ from that of periodic disclosures. Firstly, being scheduled, periodic disclosures can be edited and refined until their release date. As opposed to periodic disclosures, nonperiodic disclosures must be released immediately according to ASX Listing Rule 3.1 following material events, which can limit managers' ability to communicate the impact of these events on the firm's value in a clear, concise and effective manner (Watkins, 2022). However, ASIC believes that listed firms are often familiar with most nonperiodic material events and thus may not be as constrained by strict timeframes. If firms invest in developing internal systems for identifying and responding to unanticipated material events (Price, 2012), they may be able to promptly draft complete and clear disclosures using plain language.

Further, nonperiodic disclosures are subject to greater regulatory scrutiny than periodic disclosures when they are not written in a complete, clear, concise and

[16] Redundancy measures capture the additional information requirements that regulators permit firms to voluntarily disclose, such as notes to financial statements (Cazier & Pfeiffer, 2016). In comparison, the stickiness measure captures the level of change in narrative over the year to year between annual report documents, such as Management Discussion and Analysis (MD&A) disclosures (Brown & Tucker, 2011). However, such additional information is not required for nonperiodic disclosures. Also, given the wide range of unanticipated events, changes in the narrative between each of these event-specific disclosures year to year are less likely to be significant. Therefore, I do not incorporate redundancy and stickiness measures in my thesis.

effective manner, as per Section 4.15 of Listing Rule 3.1 (North, 2013). Given the increased risk of litigation for nonperiodic disclosures, I anticipate firms draft these disclosures as more readable, shorter and less boilerplate than periodic disclosures to ease future lawsuits. Based on this expectation, I seek to investigate whether nonperiodic disclosures differ from periodic disclosures in terms of textual complexity, and I hypothesise as follows:

$H_{3.1}$: *Nonperiodic disclosures are less textually complex than periodic disclosures.*

Secondly, extant literature suggests that periodic disclosures have become longer, more redundant, less readable, less specific, and more boilerplate over time (Dyer et al., 2017). The underlying explanation for why textual complexity has been changing over time includes firm/economic and regulatory factors (Lang & Stice-Lawrence, 2015) and managerial incentives (Li, 2008). While the existing literature on nonperiodic disclosures primarily focuses on factors that affect the timeliness and frequency of these disclosures (Brown et al., 1999; Carter & Soo, 1999; Debreceny & Rahman, 2005; Jackson et al., 2015; Lerman & Livnat, 2010; McMullin et al., 2019), this study broadens the literature by considering textual complexity. Consistent with prior literature on textual complexity, I contend that time trends and firm-specific factors can also affect nonperiodic disclosure text. Since firms with greater operational complexity are expected to report more unanticipated transactions, subsidiaries and events, a reasonable inference is that nonperiodic disclosure texts are comparatively more associated with firm-specific factors than periodic disclosures (Cazier & Pfeiffer, 2016; Dyer et al., 2017; Li, 2008). This is because, unlike anticipated periodic disclosures, nonperiodic disclosures are relatively unpredictable and may require more words and complex definitions to convey the impact of triggering events. Further, evidence suggests that the economic fundamentals of firms, such as business complexity, leverage, size, auditor, and profitability, have

changed over time (Dyer et al., 2017) due to technological, environmental and economic changes. Thus, I intend to study this by contrasting nonperiodic and periodic disclosures and proposing that, as unanticipated operational complexity increases, the language in nonperiodic disclosures will comparatively become increasingly complex than periodic over time. I hypothesise that as follows:

$H_{3.2a}$: *Textual complexity of nonperiodic disclosures is more influenced by time trends than periodic disclosures.*

$H_{3.2b}$: *Textual complexity of nonperiodic disclosures is more influenced by firm-specific factors than periodic disclosures.*

Thirdly, Bloomfield's (2002) incomplete revelation hypothesis (IRH) suggests that managers may try to conceal negative information by making it costlier to process to delay its impact on stock prices. Based on the IRH, the prevalent view in the literature on periodic disclosures is that, beyond firm-specific factors, managers' incentive to conceal poor performance can affect the use of complexity in the language (Asay et al., 2018; Bushee et al., 2018; Davis & Tama-Sweet, 2012; Li, 2008; Lo et al., 2017). Prior evidence suggests that managers can report nonperiodic disclosures on *ATH*, *LTD* and *ATHonLTD* to reduce negative market reactions because of investors' less attention and unavailability of supplementary information, thus making it hard for investors to identify biases in disclosures made by managers (Chapple et al., 2020; Li & Tan, 2022; Segal & Segal, 2016). My study extends this literature by examining whether managers' strategic language choices affect the textual complexity of nonperiodic disclosures, particularly when managers are required to release them on *ATH*, *LTD* and *ATHonLTD*. In Australia, managers have discretion in the level of detail and language used in nonperiodic disclosures despite the ASIC's strict application of timeliness (Jackson et al., 2015). Therefore, consistent with the IRH, I expect managers to comparatively use more complex language for

nonperiodic disclosures with bad news, particularly when meeting the strict timeliness requirements for *ATH, LTD* and *ATHonLTD* disclosures. I hypothesise that as follows:

$H_{3.3}$: *Nonperiodic disclosures with bad news are more textually complex than periodic disclosures when they are released after trading hours, on the week's last trading day, and after trading hours on the last trading day of the week.*

3.3 Data, sample selection and definitions of textual complexity measures

3.3.1 Data and sample selection

My initial sample comprises S&P/ASX 200 firms from January 2010 to December 2018. I download all price-sensitive announcements[17] in PDF format from the ASX website (https://www2.asx.com.au/) and categorise them into periodic and nonperiodic announcements using the Morningstar DataAnalysis database. I follow Li (2008), Loughran and McDonald (2014b), and Bonsall et al. (2017) to parse all the price-sensitive announcements. I first employ Microsoft VBA code to convert all the PDF files into docx files and then use a Python program to convert all docx files into plain text files and exclude all the tables, headers/titles, markup tags (e.g., HTML), bullet point signs and special characters (e.g., ?, #, $, etc.).[18] Given the difference in the document structure for nonperiodic announcements, a separate Python code is used to delete the text heading and the firm's contact/company information at the bottom (tagged with "contact or further information" or "about….). Since my focus

[17] I exclude non-price-sensitive announcements because they attract less attention from investors and regulators than price-sensitive announcements due to their less materiality. A more detail discussion can be found in Hsu (2009).

[18] This process also eliminates all the blank spaces and single non-alphabetic paragraphs to ensure that all tabulated text is excluded. For details on the parsing process, see Bonsall et al. (2017).

is on measuring textual attributes, announcements that only contain presentation slides, tables, graphs and pictures are excluded. I exclude announcements related only to appendix tables (e.g., 3B, 3C, 3D, 4D and 4E) and admission to official quotation. Announcements containing periodic and nonperiodic information in single and nonreadable PDF documents are also dropped. Finally, the sample is restricted to announcements containing 300 words or more.[19] Periodic and nonperiodic announcements' textual complexity measures (readability, length, boilerplate) are estimated based on the remaining text. My final sample contains 17,364 observations. Table 3.1 shows the sample selection procedure.

[Insert Table 3.1 about here]

3.3.2 Measures of textual complexity

To conduct textual analysis for periodic and nonperiodic announcements, this study focuses on length, readability and boilerplate to capture textual complexity. Firstly, I use *TOTAL_WORDS* and *File_Size* as proxy measures for length to capture the quantity of the textual component of the announcement (e.g., overwriting). I define *TOTAL_WORDS* as the number of words contained in the entire announcement. Based on Loughran and McDonald (2014a), *File_Size* is an alternative disclosure quantity measure calculated as the number of kilobytes used by the entire announcement. For regression analysis, the raw number of words and file size are transformed into natural logarithms, *Ln(TOTAL_WORDS)* and *Ln(File_Size),* due to the skewness in the number of words and file size across firms and the presence of some extreme values. These quantity-based measures have theoretical support as

[19] The sample announcement with more than 300 words represents 70% of the total announcement sample.

too-detailed and lengthy information can adversely affect investors' information processing capacity (Lang & Stice-Lawrence, 2015; Li, 2008).

Secondly, I use the Bog Index (*BOG*) (Bonsall et al., 2017) to capture the notion of 'understandability', representing how clearly and concisely textual information is classified, characterised, and presented within an announcement. Despite the popularity of the Fog Index (Lang & Stice-Lawrence, 2015; Li, 2008), I use *BOG* as my primary readability measure because *BOG*'s use of a proprietary 200,000-word dictionary allows it to overcome the Fog Index's limitation of using the multisyllable count, which has been extensively criticised in the literature.[20] I use the *StyleWriter* computer software to derive *BOG;* a higher value equates to a less readable document.

Thirdly, beyond the length and readability of disclosure, regulators and standard setters have further identified the use of "boilerplate" in disclosure as problematic. Consistent with Lang & Stice-Lawrence (2015), the basis of my measure is also built upon the assumption that the use of extremely common phrases is a sign of boilerplate disclosures because when the disclosure is duplicated across numerous firms, it is unlikely to contain important firm-specific information. To measure boilerplate, I first identify extremely common three-word phrases, known as trigrams[21], for periodic and nonperiodic announcements separately for all firms in the same six-digit GICS industry. Next, I construct a list of commonly used trigrams based on announcement-specific thresholds. The rationality of using a threshold is to exclude common innocuous phrases (such as "as a result" or "the end of"), regulatory phrases and phrases from the auditor's letter to capture the uninformative and formulaic portion of text that firms include in their announcements. However,

[20] For details, see Bonsall et al. (2017).

[21] Examples of common three-word phrases (trigram) within announcements include "the end of", "one of the", "member of the", "of the most", and "part of our".

nonperiodic announcements are more concise[22] and require less exercise of accounting standards, suggesting that the volume of innocuous phrases and regulatory phrases would be lower than periodic announcements. Therefore, I use thresholds between 10% and 90% for nonperiodic announcements and between 30% and 75% for periodic announcements[23]. The rationale for using a more aggressive threshold for periodic announcements is to exclude these innocuous common phrases and regulatory phrases from the auditor's letter (Lang & Stice-Lawrence, 2015). Next, I flagged those sentences containing at least one commonly used trigram, identified based on thresholds between 30% and 75% (between 10% and 90%), as the standardised sentences in the periodic (nonperiodic) announcement. Then I required the R program to count the number of words in these standardized sentences in the periodic (nonperiodic) announcement and labelled it as *BOILER_WORDS.* Then I construct *BOILER* by dividing the total boilerplate words by the total number of words in an announcement, representing the percentage of words in standardised sentences in the periodic (nonperiodic) announcement.

In addition, since these textual complexity measures are not independent, I further use factor analysis to combine these variables into factors (Lang & Stice-Lawrence, 2015). Table 3.2 reports the result of the factor analysis. In terms of components, Factor 1 (*FACTOR1*) is higher for announcements with the higher *BOG* and *Ln(TOTAL_WORDS)*, capturing the less informative announcements. Factor 2 is also higher for announcements with higher *BOG* and *Ln(TOTAL_WORDS)*, suggesting that it captures less informative reporting. I only retain *FACTOR1* because

[22] Comparative descriptive statistics from Table 3.6 show that nonperiodic announcements are shorter than periodic announcements.

[23] In the robustness test, a +/- 5% change in upper and lower thresholds for trigram does not change the main results. In addition, I also construct *BOILER_WORDS* using four-word phrases (known as tetragrams) and my main result further remains unchanged using this measure.

Horn's Parallel Analysis and reported eigenvalue are greater than 1, indicating the appropriateness for inclusion.

[Insert Table 3.2 about here]

3.3.3 Determinants of textual complexity

There is a variety of factors that may affect textual complexity, so it is crucial to identify these factors. I control for several firm-specific factors, which prior studies have documented as important cross-sectional determinants of textual complexity (Dyer et al., 2017; Lang & Stice-Lawrence, 2015; Li, 2008). To control for the firm's operational and business complexity, I include firm size (*SIZE*), market-to-book ratio (*MTB*), special items (*SPECIAL*), business (*LNBSEG*) and geographic segments (*LNBSEG*). I expect that firms that are larger, have growth potential, have multiple business and geographic segments, and experience more special events will necessitate a more intricate language to convey their operational complexity. Loss firms (*LOSS*) are included to control for the earnings information because the management obfuscation hypothesis argues that managers have incentives to obfuscate poor performance. Thus, I expect firms that incur losses within a fiscal year are expected to produce more textually complex disclosures. I add the firms' age (*AGE*) and expect the disclosures of older firms will be less complex in terms of their text because investors incur less information asymmetry and uncertainty for older firms (Li, 2008). I include the leverage ratio (*LEVERAGE*) and expect firms with higher leverage to produce less complex disclosures to lower their debt costs, as research has shown that less transparent disclosures are linked to a worse credit rating and higher debt costs (Bonsall & Miller, 2017). I also control for the big four audit firms (*BIG4*) to capture the effect of audit firms on textual complexity. I expect that large audit firms can devote more effort and skill to help firms to comply with the CDR, hence leading to less complex disclosures.

3.4 Results

3.4.1 Distribution of price-sensitive announcement frequency by announcement types

Table 3.3 lists the 18 price-sensitive announcement types and ranks them based on (1) the number of times each type appears during the sample period (frequency), and (2) the portion of the total types this represents (% of the announcement type). Periodic announcements comprise annual reports, half-yearly reports, earnings guidance, quarterly activity reports, quarterly cashflow reports, dividend announcements, notice of call and chairman's address. The nonperiodic announcements comprise takeovers, shareholders' detail, issued capital, asset acquisition and disposal, stock exchange announcement, progress reports, company administration, a notice of call, other, letters to shareholders, ASX Query and warrants. During the sample period between 2010 and 2018, firms reported 24,809 price-sensitive announcements, among which 8,290 were periodic, and 16,519 were nonperiodic. Periodic and quarterly activity reports are the most frequently filed periodic announcements (5,881 and 1,192, respectively), accounting for 28.51% of total announcement observations. Four types of nonperiodic announcement – progress reports, issued capital, asset acquisition and disposal, and takeover announcements – are the most frequently filed (7,388, 2,621, 2,394 and 1,431, respectively) and constitute over half of the total announcement observations (55.76%). Finally, the results show that most of the announcements made by listed firms during the sample period were nonperiodic, indicating a high number of extraordinary and unexpected events. Four out of the five most common types of announcements were nonperiodic. For the main analysis, I exclude quarterly cash flow reports, notice of meetings, the chairman's address, notice of call and warrants because of the lack of textual content in those documents.

[Insert Table 3.3 about here]

3.4.2 Distribution of textual complexity measures by announcement types and year

Table 3.4 presents the descriptive data for textual complexity by announcement types. Periodic reports (e.g., annual and half-yearly reports) are longer, more boilerplate, whereas quarterly activity reports are less readable because they are prepared by the mining oil and gas-producing entities that cover a detailed technical summary of exploration activities and incurred expenditures.[24] For nonperiodic announcements, takeover and issued capital announcements appear to be the longest, most boilerplate and least readable, followed by announcements labelled as 'other'. Since unanticipated litigation and regulatory issues are released via the 'other' announcement type, the lower readability, greater length, larger file size and increased use of boilerplate might reflect firms' incentive to optimise legal language for matters that are more clearly related to judicial and regulatory assessments (Cazier et al., 2021). In comparison, announcements related to company administration and ASX Query are the most readable, but these announcements contain more boilerplate text.

[Insert Table 3.4 about here]

Figure 3.1 provides initial descriptive evidence on the trends in the textual complexity of periodic and nonperiodic announcements over the sample period, including for *TOTAL_WORDS, File_Size, BOG* and *BOILER_WORDS*. In general, there has been an upward trend in the textual complexity for both announcement types, perhaps leading to ASIC's concerns over the increased textual complexity of corporate disclosures (Price, 2015). However, while there is evidence of growing textual complexity for both announcement types following the release of the revised

[24] For details, see Guidance Note 23 of ASX listing rules.

GN8 in March 2013, the increase is more pronounced for nonperiodic announcements. Specifically, nonperiodic announcements comparatively became more textually complex than periodic announcements, as evidenced by an average increase in *TOTAL_WORDS* (7.748% vs 0.066%), *BOG*(1.092% vs 0.869%) and *BOILER_WORDS* (8.727% vs 0.066%) between 2013 and 2018. While I observed the upward trend in textual complexity til 2015 for periodic and nonperiodic announcements following the GN8 revision in 2013, the *TOTAL_WORDS* and *BOILER_WORDS* of both announcements have decreased in more recent years (2016-2018), but not for *BOG*.

[Insert Figure 3.1 about here]

3.4.3 Industry analysis

Table 3.5 documents the wide variability of the textual complexity between periodic and nonperiodic announcements across industries, which are identified by their Global Industrial Classification System (GICS) codes. The Energy, Material, Industrial and Financial industries appear to release more periodic and nonperiodic material announcements. Energy, Real Estate, Materials and Utilities appear to have poor readability (e.g., higher *BOG*) for periodic announcements, whereas Communication Services, Financial, Utilities, and Materials produce lengthy (e.g., higher *No. of Words* and *File_Size*) and boilerplate announcements. Similarly, I document that the Financial, Communication Services, Material and Utilities industries have greater length and more boilerplate for nonperiodic announcements, and Utilities, Health Care, Material and Real Estate industries have lower readability. The potential explanations for the resource and regulated industries having poorer textual information may be their complex structures and business

models, and their differential disclosure practices[25] that are difficult to communicate, because these industries require more complex textual language in their periodic announcements to account for future uncertainties. To account for this observation, I include industry-fixed effects in my regression analysis and control for these specific industries.

[Insert Table 3.5 about here]

3.4.4 Descriptive statistics and correlation matrix

Table 3.6 reports the descriptive statistics on textual complexity measures and firm fundamentals across periodic and nonperiodic announcements. For the full sample in Panel A, the mean (median) value of *TOTAL_WORDS* is 4109 (797), and the mean (median) *File_Size* is 689.226 (236) kilobytes. The mean (median) *BOG* Index is 75.757 (76), which *StyleWriter* software interprets as 'poor' readability.[26] The mean (median) announcement has 529.97(49) words in sentences containing boilerplate phrases (*BOILER_WORDS*), which represents 7.8% (6.6%) of the announcement. Thus, nonperiodic disclosures are comparatively more readable, less lengthy and less boilerplate than periodic disclosures, initially supporting the $\mathbf{H}_{3.1}$.

[Insert Table 3.6 about here]

In the bivariate analysis in Panel B, the mean value of *TOTAL_WORDS* (*File_Size*) for the periodic announcement is 7629.71(1125.51 kilobytes) and

[25] For example, in Australia, listed resources firms are exempt from the ASX's requirements to release half-yearly and preliminary final reports, but they are required to file quarterly reports detailing mining production, development and exploration activities.

[26] For a better perspective, Bonsall et al. (2017) further note that the BOG index can range from a score of zero to well over 1000 and the breakdown of scores can be interpreted as follows: 0 to 20 = excellent; 21 to 40 = good; 41 to 70 = average; 71 to 100 = poor; 101 to 130 = bad; 131 to 1000 = dreadful; 1000+ = gobbledygook.

2274.87(461.81 kilobytes) for nonperiodic announcements. This suggests that periodic announcements come with more information content, whereas nonperiodic announcements are more concise for the reader. Furthermore, nonperiodic announcements have a lower *BOG* Index and fewer boilerplate words (*BOILER_WORDS*) than periodic announcements (mean nonperiodic *BOG* score = 73.316 compared to mean periodic *BOG* score = 80.44; and mean nonperiodic *BOILER_WORDS* = 289.1 compared to mean periodic *BOILER_WORDS* = 992.05). In all cases, the differences in means are statistically significant, suggesting that periodic and nonperiodic announcements differ in terms of textual complexity. Thus, on average, nonperiodic announcements are less textually complex as they are more readable, shorter, and contain fewer boilerplate words than periodic announcements. The underlying higher textual complexity in periodic disclosures compared to nonperiodic disclosures is due to the mandatory disclosure requirements related to material information in various parts of annual reports. For instance, firms often face accounting issues when making complex decisions about their operations, financing, and investments within a fiscal year. These issues may require more extensive disclosures, particularly for choices involving derivatives, complex tax arrangements, share-based compensation plans, pensions and post-retirement benefits, and other financial instruments. On the contrary, nonperiodic disclosures mostly arise from a particular material event and thus only require event-specific disclosure.

[Insert Table 3.7 about here]

Table 3.7 presents the correlation. Here I discuss several sets of comparisons that are relevant. First, the correlation among the textual complexity measures is not particularly high, with most correlations below 30%, except between length and boilerplate (58.6%). Because the boilerplate measure is calculated as a percentage of

total word count, it can be mechanically affected by length (Lang & Stice-Lawrence, 2015). Therefore, the positive association indicates that longer announcements also tend to have more boilerplate words. Second, the positive correlation between time trends and *Ln(TOTAL_WORDS)* (9.6%), *Ln(File_Size)* (18.8%), *BOG* (15%), and *BOILER* (3.7%) give initial evidence of textual attributes changing over time, albeit without controls. Third, the correlations between textual complexity measures and firm-specific variables offer further reassurance that they are correlated mostly in a predictable way. However, these correlations need to be interpreted cautiously, as regression results would include determinants and industry fixed effects. Finally, the correlation statistics do not raise concerns regarding multicollinearity, as most correlations are below 50%.

3.4.5 Determinants of textual complexity

To explore the determinants of *BOG, Ln(TOTAL_WORDS)*, *Ln(File_Size), BOILERPLATE* and *FACTOR1* of periodic and nonperiodic announcements in a multivariate regression setting, I use the following regression model:

$$TEXTUAL\ COMPLEXITY = \beta_0 + \beta_1 TREND + SIZE + \beta_2 LEVERAGE + \beta_3 MTB + \beta_4 AGE + \beta_5 LOSS + \beta_6 SPECIAL + \beta_7 LNBSEG + \beta_8 LNGSEG + \beta_9 BIG4 + \sum \alpha_i INDUSTRY + \epsilon_{i,d} \quad (3.1)$$

$$TEXTUAL\ COMPLEXITY = \beta_0 + \beta_0 NONPRD + \beta_1 TREND * NONPRD + \beta_2 SIZE * NONPRD + \beta_3 LEVERAGE * NONPRD + \beta_4 MTB * NONPRD + \beta_5 AGE * NONPRD + \beta_6 LOSS * NONPRD + \beta_7 SPECIAL * NONPRD + \beta_8 LNBSEG * NONPRD + \beta_9 LNGSEG * NONPRD + \beta_{10} BIG4 * NONPRD + \sum \alpha_i INDUSTRY + \epsilon_{i,d} \quad (3.2)$$

where the dependent variable *TEXTUAL COMPLEXITY* represents *BOG, Ln(TOTAL_WORDS)*, *Ln(File_Size), BOILER,* and *FACTOR1,* and higher values of these measures represents greater textual complexity within disclosures. *NONPRD* is

a binary variable set to 1 if the price-sensitive announcement is nonperiodic. To provide a comparative understanding of the impact of time trends and economic factors on the textual complexity across periodic and nonperiodic announcements, all the variables interact with *NONPRD*. My variables of interest are particularly those that interact with *NONPRD,* as these provide a comparative understanding across periodic and nonperiodic announcement complexity. *TREND* is a variable that increments by 1 each year starting from 2010 to capture the time-series trend in textual attributes (Dyer et al., 2017).

In terms of determinants, I control for firm-specific factors identified in Section 3.3.3. All firm-specific data from the annual reports is from the most recent fiscal year at the time of the announcement. *SIZE* is the natural logarithm of market capitalisation. *LEVERAGE* is total debt divided by total assets. *MTB* is the market value of equity divided by the book value of equity. *AGE* is the natural log of the number of years as a firm first appears in the Morningstar database. *LOSS* is an indicator variable that takes the value of 1 if a firm's net income is below 0, otherwise it is set to 1. *SPECIAL* is the amount of special items divided by total assets. *LNBSEG* is the natural log of the number of business segments. *LNGSEG* is the natural log of the number of geographic segments. *BIG4* is a binary variable set to 1 if the audit firm is one of the big four and 0 otherwise. Finally, I winsorise all continuous variables at the first and 99th percentile and cluster standard errors by the firm. I also include industry fixed effects to control the variation across industries over the sample period. I define all variables and data sources in Appendix C.

[Insert Table 3.8 about here]

Table 3.8 reports the results of regressing the *BOG, Ln(TOTAL_WORDS)*, *Ln(File_Size), BOILER,* and *FACTOR1* on their potential determinants and time

trends. I first present results for both announcement types without interaction in Panel A. Textual measures are positively associated with *TREND*, suggesting that both periodic and nonperiodic announcements have become less readable and longer (measured as total words and file size) with more boilerplate words. In general, both announcement length and amount of boilerplate tend to be higher for firms that are younger, highly geared, incur losses and report more special items. At the same time, announcement readability is higher for younger and less profitable firms, consistent with Li (2008). In panel B, I interact all variables with *NONPRD,* allowing me to comparatively investigate the determinants and time trends between periodic and nonperiodic announcements. *NONPRD* is negatively significant for all textual complexity measures, suggesting that nonperiodic announcements are comparatively more readable, shorter and less boilerplate than periodic disclosures, which is consistent with $\mathbf{H}_{3.1}$. The positive and significant interaction term of *TREND*NONPRD* confirms that the textual complexity of nonperiodic announcements is significantly influenced by time trends, suggesting that there is an upward trend in textual complexity. Thus, supporting $\mathbf{H}_{3.2a}$.

Nonperiodic announcements' *Ln(TOTAL_WORDS), Ln(File_Size)* and *BOG* are negatively associated with interaction terms for *AGE* and *LNGSEG* and positively associated with *MTB* and *SPECIAL*. The notion is that firms with growth prospects, firms that incur more special items, and younger firms with fewer geographically diverse segments provide less readable and longer announcements. The amount of boilerplate tends to be higher for geared firms, firms that incur more special items, and firms with growth prospects and fewer geographically diverse segments, as evidenced by the positive association with *LEVERAGE, MTB, SPECIAL* and negative association with *LNGSEG*. In terms of component analysis, the stronger influence of *MTB, SPECIAL and LNGSEG* on *FACTOR1* suggests that the composited *BOG* and

Ln(TOTAL_WORDS) capture the variation across economic factors. The positive association between *MTB, SPECIAL,* and all textual complexity measures is likely driven by greater underlying operational complexity because firms with growth prospects tend to operate in industries with a complex business model and thus, they incur more extraordinary unanticipated events (Cazier & Pfeiffer, 2016; Li, 2008). Further, the positive association between *LOSS* and textual complexity in Panel A appears to be mainly and significantly driven by the periodic announcements, as I do not find any such link for nonperiodic announcements. The counterintuitive negative association between *LNGSEG* and all textual complexity measures suggests that more geographically diverse firms provide less textually complex nonperiodic announcements, consistent with Li (2008).[27] Overall, I find initial evidence that the textual complexity of nonperiodic announcements is affected by firm-specific factors and time trends, thus supporting $\mathbf{H_{3.2a}}$ and $\mathbf{H_{3.2b}}$.[28]

3.4.6 Managers' strategic use of textual attributes

3.4.6.1 Summary statistics

This section examines managers' strategic use of textual complexity across periodic and nonperiodic announcements based on news type (good vs bad) and differential timing. Though I only found evidence that managers who incur losses tend to provide textually complex periodic announcements in the previous section

[27] For details, see Li (2008).

[28] One potential concern that can arise from not including time trends and firm factors along with all the interacted terms in the regression is that their effects could be absorbed in the constant time and can be assumed to be non-variant for periodic disclosures. To mitigate the concern, I rerun model 3.2 by adding time trends, firm factors, and all the interaction terms. The untabulated results for variables *NON*, *NON*TREND* remain significant. Interestingly, the *TREND* variable is significant for all specifications, supporting the $H_{3.2a}$ that nonperiodic announcements indeed became textually complex over time.

3.4.5, it is unclear how managers' intentional choices may vary with other triggering events where bad news is concerned. Despite managers' strategic timing and bundling of news in nonperiodic 8-K filings documented by Segal and Segal (2016), recent evidence on improved timeliness and frequency following mandated regulation indicates that managers' strategic choices in timing have become more confined (McMullin et al., 2019). Likewise, given the reduced amount of room for strategically timing a nonperiodic announcement with the growth in ASIC's interventions and actions (Jackson et al., 2015), it is important to know whether managers manage textual attributes in announcements of bad news and when investors pay less attention, namely at the weekend or after trading hours (Segal & Segal, 2016).

[Insert Table 3.9 about here]

First, I partition the textual attributes of both announcements by good and bad news. Using the market model, I calculate each announcement's three-day cumulative abnormal return (*RET*) as immediate returns from one trading day before the event date to one trading day after the announcement date. I choose the return-based measure over the textual sentiment to classify news because textual sentiment has low explanatory power of abnormal return for public disclosures (Loughran & McDonald, 2011; Segal & Segal, 2016). If *RET* is positive (negative), I classify the corresponding announcement as conveying good (bad) news.[29]

[29] One possible concern when conducting event studies is the presence of non-synchronous or thin trading, which can potentially impact the accuracy of the results. We adopt a pro-rate allocation approach to address this issue and ensure that non-synchronous trading does not unduly influence the main findings. This method involves distributing daily returns proportionally to any preceding non-trading days to enhance result reliability. Further, to validate RET, I regress the bad news dummy of each announcement on three-day cumulative abnormal returns. The regression controls for the number of firm-specific factors, year and announcement type fixed effects. The negative and

Panel A of Table 3.9 tabulates the frequency, textual complexity and mean *RET* for each type of announcement separately for good and bad news. Overall, my results suggest that managers tend to provide longer, more boilerplate and less readable announcements with bad news except for dividend, progress and company administration announcements. The announcements with all types of news significantly differ from 0 based on their t-tests on *RET*, indicating a linear relationship between the magnitude of news and market reactions. Further, the fairly balanced distribution of the good and bad news for each announcement mitigates the concerns that my results are not driven by one specific news side. Panel B reports that the sign of *RET* is consistent with the news sign and highly significant, and the difference in mean *RET* for bad and good news is statistically significant.

Next, in Panel C I partition the announcements with good and bad news by *ATH*, *LTD* and *ATHonLTD*. Regular market trading hours for ASX are 9:30 a.m. to 4:00 p.m. and *ATH* is set to 1 if any announcement is released between 4:01 p.m. and 12:00 p.m., otherwise 0.[30] *LTD* is set to 1 if the announcement is released on Friday during trading hours, otherwise 0. Finally, *ATHonLTD* is set to 1 if the announcement is released on Friday after trading hours, otherwise 0. For parsimony, I only discuss the sample of bad news in the table. The reported results show that

significant coefficient on the bad news dummy in each regression indicates that there is linear relation between the magnitudes of the news and market reaction. For robustness, I use textual sentiment to classify announcements with good (bad) news. I rerun the regression for the bad news dummy of each announcement on the three-day cumulative abnormal returns, and the results remain unchanged for the linear relation between the magnitudes of the news and market reaction.

[30] About 71% of *ATH* cases were released between 4:00 p.m and 6:00 p.m, and about 56% of these announcements came with bad news. About 9.5% of the observations were filed before the market opened (*BMO*), and I treat these announcements as released during trading hours. To rule out concerns about whether *BMO* is associated with the strategic use of textual attributes, I conduct a sensitivity analysis and find no such association.

managers provide longer, more boilerplate and less readable nonperiodic announcements with bad news released on *ATH*, *LTD* and *ATHonLTD*. The differences in means are statistically significant, suggesting that managers manage the textual complexity of nonperiodic announcements comparatively more than they do for periodic announcements when investors pay less attention. This initially supports my final hypothesis, $\mathbf{H}_{3.3}$.

3.4.6.2 Regression analysis

To examine managers' strategic use of textual complexity, I use the following multivariate regression:

$$\begin{aligned} TEXTUAL\ COMPLEXITY = {} & \beta_0 + \beta_1 NONPRD + \beta_2 BAD + \beta_3 NONPRD{*}BAD + \\ & \beta_4 TREND{*}NONPRD + \beta_5 SIZE{*}NONPRD + \beta_6 LEVERAGE{*}NONPRD + \\ & \beta_7 MTB{*}NONPRD + \beta_8 AGE{*}NONPRD + \beta_9 LOSS{*}NONPRD + \\ & \beta_{10} SPECIAL{*}NONPRD + \beta_{11} LNBSEG{*}NONPRD + \beta_{12} LNGSEG{*}NONPRD \\ & + \beta_{13} BIG4{*}NONPRD + \sum \alpha_i INDUSTRY + \epsilon_{i,d} \end{aligned} \quad (3.3)$$

I partition the sample by *ATH*, *LTD* and *ATHonLTD* and run regression models 3.3 separately. To capture the impact of the news types, I introduce the interaction term of *NONPRD*BAD*. My variables of primary interest are the sign and significance of the coefficient for *NONPRD*BAD*. Consistent with $\mathbf{H}_{3.3}$, if managers strategically use textual complexity in nonperiodic announcements, I expect the coefficient β_3 to be positive and statistically significant. *BAD* is set to 1(0) if announcements contain bad (good) news based on the negative (positive) three-day cumulative abnormal return (*RET*). Similar to the model (3.2), I control for firm size (*SIZE*), leverage (*LEVERAGE*), growth (*MTB*), age (*AGE*), loss firms (*LOSS*), special items (*SPECIAL*), business complexity (*LNBSEG* and *LNGSEG*) and big four audit firms (*BIG4*). I also include industry fixed effects to control the variation across industries over the sample period. I define all variables and data sources in Appendix C.

[Insert Table 3.10 about here]

Table 3.10 reports the regression results. The coefficient on the *NONPRD*BAD* variables is positive and significant for all textual complexity measures for the *ATH* sample, whereas the coefficient on the *NONPRD*BAD* variables is positive and significant for all textual complexity measures except *Ln(File_Size)* for the *LTD* sample. This suggests that the likelihood of strategic use of textual complexity increases when nonperiodic disclosures are released on *ATH* and *LTD*. However, I find the coefficient on the *NONPRD*BAD* variables is only positive and significant for *Ln(TOTAL_WORDS)* and *BOILER*, when I run *ATHonLTD* sample.

These findings imply that nonperiodic announcements with bad news released on *ATH*, *LTD* and *ATHonLTD* appear to influence managers to draft less readable, longer, and boilerplate announcements strategically. This may be because providing more textually complex nonperiodic announcements during non-trading hours and/or on Friday may benefit managers in delaying the incorporation of bad news into the stock price, particularly within a regulatory environment where managers have no discretion on timing announcements under Listing Rule 3.1. Overall, the results in Table 3.10 support firms' strategic use of textual complexity when nonperiodic announcements come with negative news and it is more pronounced when they are released on *ATH*, *LTD* and *ATHonLTD*. Hence, the results are consistent with the incomplete revelation hypothesis and support my hypothesis $\mathbf{H}_{3.3}$.

One can argue that the above-reported results for the strategic textual complexity of nonperiodic announcements released on *ATH, LTD* and *ATHonLTD* are unrelated to managers' incentives to obfuscate the bad news. Rather, managers may require more words and complex definitions to provide more detail to the

investors to explain the implications of the unanticipated triggering events (Bloomfield, 2008; Bushee et al., 2018; Cazier & Pfeiffer, 2016). Recall that in Section 3.4.3 I document that resource and regulated industries tend to make textually complex disclosures. Because of their complex structures and business models, the findings that textually more complex nonperiodic announcements are released on *ATH, LTD* and *ATHonLTD* are perhaps driven by managers' use of complex language in explaining the unanticipated triggering events rather than in obfuscating them. To rule out this explanation, I identify firms that belong to resource and regulated industries and rank the sample forms into quartiles based on the sign and size of the *RET* of negative events. I exclude the upper quartile (797 observations) of the *RET* of negative events in the subsample because they represent extremely negative news which may require managers to use more complex language to explain it. I rerun Table 3.10, and the untabulated results show that my findings are robust and are not driven by alternative explanations.

3.5 Robustness tests

The firm-specific determinants and managers' strategic reporting in Tables 3.8 and 3.10 are truncated to add only a subset of the control variables that could affect the textual complexity across periodic and nonperiodic announcements. The variables added to my models are based primarily on prior literature. This could raise the concerns that I have omitted important variables from the models that may explain significant variation in textual complexity. This would lead to overestimating the amount of variation in textual complexity across the periodic and nonperiodic announcements that should be considered residual disclosure. To test the sensitivity of my inferences in regard to this concern, I add three additional variables suggested by prior studies, namely the pre-announcement volatility ($SRV_{i,d\text{-}90}$) for operating risk

(Segal & Segal, 2016), and unusual merger-and-acquisition (*MA*) and seasoned equity offering events (*SEO*) (Li, 2008). I rerun Tables 3.8 and 3.10 and found the change in regression R^2 and coefficient estimate for *NONPRD* and *TREND*NONPRD* for Table 3.8 and *NONPRD*BAD* for Table 3.10 remain significantly unchanged in the untabulated results. I conclude that my allocation of textual attributes across periodic and nonperiodic announcements to the portion explained by firm-specific factors, bad news and report timing are largely robust with respect to the concerns about the omitted variable bias.

3.6 Conclusion

I find that nonperiodic disclosures are textually less complex than periodic disclosures as they are more readable, shorter and less boilerplate. However, when analysing trends, it can be seen that both nonperiodic and periodic disclosures have become more textually complex in terms of language over the sample period. However, these changes were more significant for nonperiodic disclosures after the GN8 revision in 2013. Also, firms in the resource, financial, and regulated industries tend to report more textually complex periodic and nonperiodic disclosures due to their complex structures, business models, and differential disclosure practices. Additionally, the significant mean differences for readability, length, and boilerplate in the bivariate analysis confirm that the two types of disclosures differ in terms of textual complexity. The results of the multivariate analysis indicate that nonperiodic disclosures are more affected by factors such as time trends, market-to-book ratio, gearing, and special items rather than poor performance, which contradicts previous research. Additionally, the analysis of managers' strategic reporting suggests that when managers have negative news to report, they are more likely to use complex

language in nonperiodic disclosures, particularly when they are released on *ATH, LTD*, and *ATHonLTD*.

Figure 3.1: Distribution of textual attributes of price-sensitive announcements by year

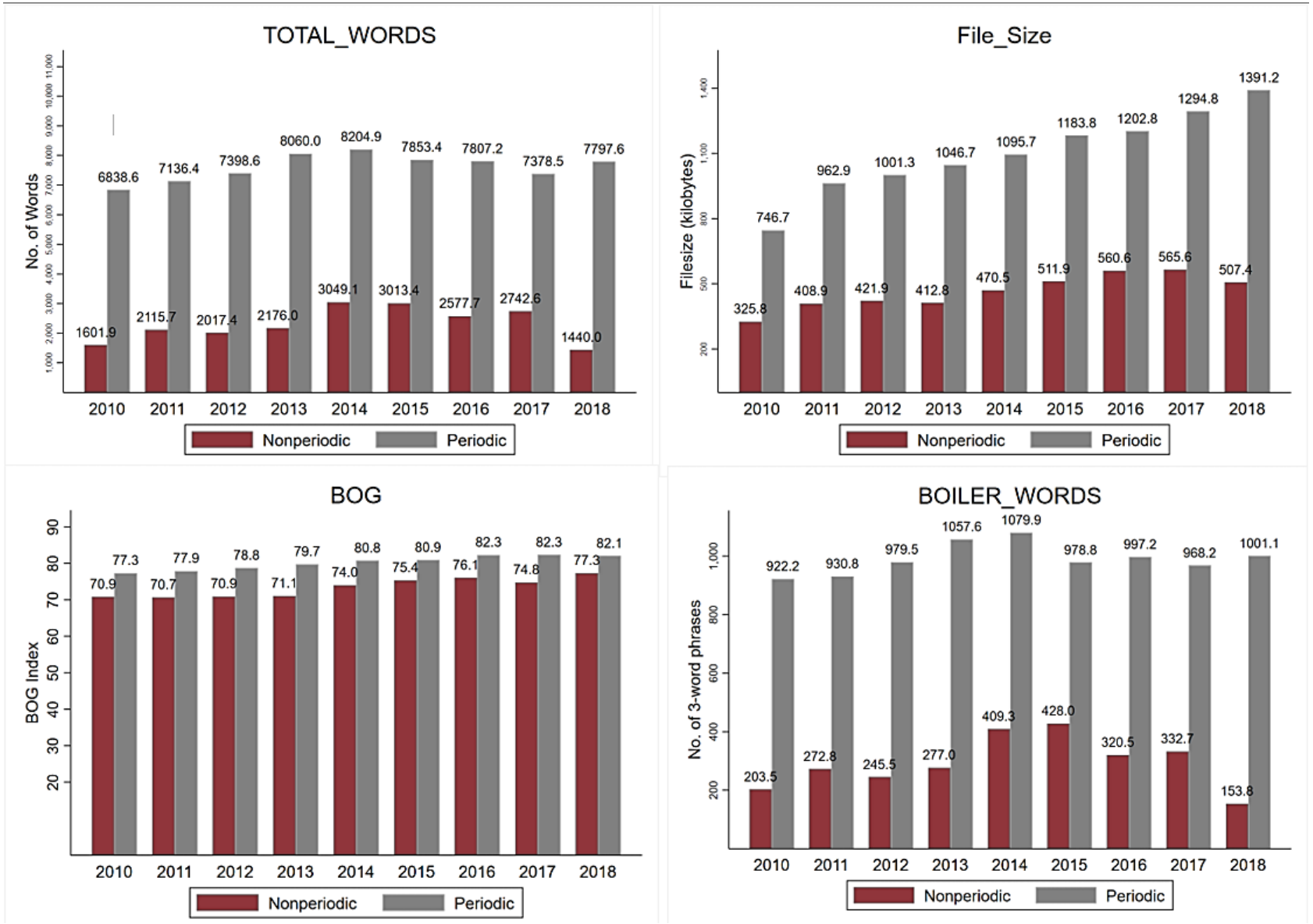


Table 3.1: Sample creation

Sample source/screen	
Total downloaded price-sensitive announcements	**24,809**
Minus	
Announcement only contains presentation slides, tables, graphs and pictures	1,052
Announcement only contains appendix tables (e.g., 3B, 3C, 3D, 4D and 4E) and is related to admission to official quotation	194
Announcement contains both nonperiodic and periodic information in a single document	102
Drop if the announcement document is not file readable	83
Drop if the number of words < 300 words	6,014
Total restricted sample (2)	**7,445**
The final sample of price-sensitive announcements	**17,364**

Table 3.2: Factor analysis of textual attributes

	Factor Pattern		Factor Pattern: Varimax rotation	
	Factor 1	Factor 2	Factor 1	Factor 2
BOG	0.7188	0.1714	0.26029	0.17575
Ln(TOTAL_WORDS)	0.8369	-0.0221	0.52342	-0.01431
Ln(File_Size)	0.3243	0.0889	0.06745	0.18810
BOILER	0.6103	-0.1647	0.19734	-0.21244
Eigenvalue	1.6992	0.06491	1.04054	0.03116
Eigenvalue (Horn's parallel analysis)	1.8028221 (Retain adjusted components > 1)			

Note. This table reports the results of a principal factor analysis of the four textual complexity measures.

Table 3.3: Announcement types by frequency and constitution

Panel A: Distribution of price-sensitive announcements issued by type				
ASX Primary Category Code	Announcement Type	Frequency	% of announcement	Rank
	Periodic Announcements			
3	Periodic reports (including earnings guidance, annual and half-yearly reports)	5,881	23.71	2
4	Quarterly activities report	1,192	4.80	6
5	Quarterly cash flow reports	273	1.10	11
8	Notice of meeting	49	0.20	15
10	Dividend announcement	625	2.52	9
15	Chairman's address	270	1.09	12
	Total periodic announcements	**8,290**		
	Nonperiodic Announcements			
1	Takeover announcements	1,431	5.77	5
2	Shareholder details	284	1.14	10
6	Issued capital	2,621	10.56	3
7	Asset acquisition and disposal	2,394	9.65	4
9	Stock exchange announcement	860	3.47	8
11	Progress report	7,388	29.78	1
12	Company administration	1,110	4.47	7
13	Notice of call	12	0.05	17
14	Other	237	0.96	13
16	Letter to shareholders	16	0.06	16
17	ASX Query	158	0.64	14
18	Warrants	8	0.03	18
	Total nonperiodic announcements	**16,519**		
	Total price-sensitive announcements (1)	**24,809**		

Note. This table reports the distribution of price-sensitive announcements by ASX primary category code. ASX's primary categories are based on Signal G, which organises the price-sensitive announcement based on 18 primary codes. The total sample includes 24,809 price-sensitive announcements of S&P/ASX200 firms from January 2010 to December 2018.

Table 3.4: Mean textual complexity measures by announcement type

ASX Primary Category Code	Announcement Type	Textual Complexity				
		Obs.	*TOTAL_ WORDS*	*File_Size (kilobytes)*	*BOG*	*BOILER_ WORDS*
	Periodic Announcements					
3	Periodic reports	4,616	8905.43	1172.51	79.35	1174.22
4	Quarterly activities report	1,056	3814.54	1170.86	84.58	433.48
10	Dividend announcement	278	939.25	172.62	82.83	89.02
	Nonperiodic Announcements					
1	Takeover announcements	1,061	5815.02	717.15	75.73	923.36
2	Shareholder details	174	1485.75	276.12	70.69	184.78
6	Issued capital	1,795	5473.08	650.67	76.69	768.91
7	Asset acquisition and disposal	1,693	1021.27	265.25	72.93	101.54
9	Stock exchange announcement	245	1110.65	246.74	73.96	112.82
11	Progress report	5,479	1145.54	457.19	70.65	102.62
12	Company administration	727	1471.31	242.18	68.41	145.17
14	Other	116	1886.74	556.72	74.07	162.52
17	ASX Query	124	1184.79	313.88	56.16	173.55

Note. This table provides the distribution of sample announcement textual complexity by announcement type. The price-sensitive announcements are categorised based on Morningstar Database Premium. The total sample includes 17,364 price-sensitive announcements of S&P/ASX200 from January 2010 to December 2018.

Table 3.5: Mean textual complexity measures by industry

GICS Codes	Sector	Periodic Announcements					Nonperiodic Announcements				
		Obs.	*BOG*	*No. of Words*	*File_Size (kilobytes)*	*BOILER_ WORDS*	Obs.	*BOG*	*No. of Words*	*File_Size (kilobytes)*	*BOILER_ WORDS*
1000-1499	Energy	940	83.6	4246.6	887.4	499.1	1,789	72.7	1278.2	398.6	143.5
1500-1999	Materials	1,442	82.6	10135.9	1345.3	972.3	3,211	75.4	3114.9	653.2	424.6
2000-2499	Industrials	810	76.3	5836.5	831.848	723	1,769	69	1582.3	299.2	191.5
2500-2999	Consumer Discretionary	470	79.1	7915.6	1305.5	984.8	598	69.7	1936.6	487.1	221.5
3000-3499	Consumer Staples	239	73.9	7602.4	1435.1	1227.1	379	64.5	2122.6	375.1	254.7
3500-3999	Health Care	320	78.2	7896.5	872.9	1033.1	423	78.6	1180.9	224.2	110.5
4000-4499	Financial	653	79.4	11712.2	1302.7	1527.9	1,069	73.2	5272.1	507.7	726.8
4500-4999	Information Technology	201	76.7	6390.9	1163.8	717.1	323	73.9	1417.2	277.5	135.8
5000-5499	Communication Services	251	81.4	12483.1	1349.9	1753.9	469	74.2	4179.1	472.3	596.9
5500-5999	Utilities	119	81.5	11247.92	1420.1	1923.7	353	79.7	2903.7	337.2	438.1
6000-6499	Real Estate	505	82.8	7208.7	832.4	1085.3	1,031	75.3	2342.6	416.7	329.7

Note. This table provides the distribution of sample price-sensitive announcement' textual complexity by industry. Industry categories are based on the GICS codes of related companies. The total sample includes 17,364 price-sensitive announcements of S&P/ASX200 from January 2010 to December 2018.

Table 3.6: Descriptive statistics

Variable	N	Mean	SD	Min	Percentiles			Max
					P25	P50	P75	
Panel A: Full Sample								
BOG	17,364	75.757	15.76	26	65	76	87	133
TOTAL_WORDS	17,364	4,109	10,127	300	493	797	2,451	204,763
Ln(TOTAL_WORDS)	17,364	7.313	1.336	5.905	6.216	6.782	8.097	12.304
File_Size (kilobytes)	17,364	689.226	1,388.89	7.2	96	236	640	2,0000
Ln(File_Size)	17,364	5.552	1.363	1.974	4.564	5.463	6.461	9.903
BOILER_WORDS	17,364	529.972	1,570.86	0.000	20	49	235.5	37,942
BOILER	17,364	0.078	0.053	0.000	0.039	0.066	0.111	0.63
SIZE	17,364	21.811	1.812	16.553	20.731	21.792	22.961	26.237
LOSS	17,364	0.176	0.381	0.000	0.000	0.000	0.000	1.000
LEVERAGE	17,364	0.205	0.165	0.000	0.067	0.191	0.300	1.636
MTB	17,364	3.025	3.544	0.224	1.162	1.828	3.192	21.731
AGE	17,364	2.682	0.934	0.000	2.197	2.772	3.401	4.19
LNBSEG	17,364	1.003	0.743	0.000	0.000	0.693	1.386	2.565
LNGSEG	17,364	0.742	0.742	0.000	0.000	0.693	1.386	2.773
SPECIAL	17,364	0.019	0.077	-0.695	0.000	0.001	0.012	1.143
BIG4	17,364	0.868	0.339	0.000	1.000	1.000	1.000	1.000

Panel B: Bivariate analysis

Variable	Periodic announcements				Nonperiodic announcements				Mean Differences
	N	Mean	SD	P50	N	Mean	SD	P50	
TOTAL_WORDS	5,950	7,629	11,265	3,197	11,414	2,274	8,947	587	5,354***
Ln(TOTAL_WORDS)	5,950	8.242	1.418	8.317	11,414	6.828	0.992	6.452	1.413***
File_Size (kilobytes)	5,950	1125.51	1765.472	515	11,414	461.81	1076.61	169	663.701***
Ln(File_Size)	5,950	6.165	1.399	6.244	11,414	5.231	1.226	5.129	0.933***
BOG	5,950	80.44	12.895	80	11,414	73.316	16.565	73	7.124***
BOILER_WORDS	5,950	992.05	1,673.885	311	11,414	289.096	1457.482	31	702.953***
BOILER	5,950	0.101	0.049	0.105	11,414	0.066	0.05	0.052	0.036***

Note. This table reports the descriptive statistics of textual complexity measures across periodic and nonperiodic announcements. Panel A provides descriptive statistics for the full sample containing 17,364 firm-announcement observations for all the price-sensitive announcements from 2010 to 2018. Panel B reports the bivariate analysis where the announcements sample is partitioned into subsamples based on periodic and nonperiodic announcements. The subsample of periodic announcements includes 5,950 firm-announcement observations, and the subsample of nonperiodic announcements includes 11,414 firm-announcement observations over the sample period. P25(P75) is the 25th (75th) percentile of the variable's distribution. All continuous variables are winsorised at the 1st and 99th percentiles. Superscripts ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively, for two-tailed tests. See Appendix C for the variable definitions.

Table 3.7: Correlation matrices

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Ln(TOTAL_WORDS)	1.000													
(2) Ln(File_Size)	0.274*	1.000												
(3) BOG	0.281*	0.269*	1.000											
(4) BOILER	0.586*	0.204*	0.136*	1.000										
(5) TREND	0.096*	0.188*	0.150*	0.037*	1.000									
(6) SIZE	0.021*	-0.120*	-0.084*	0.018*	0.057*	1.000								
(7) LOSS	-0.028*	0.040*	0.076*	-0.017*	0.007	-0.272*	1.000							
(8) LEVERAGE	-0.027*	-0.094*	-0.034*	0.022*	0.025*	0.200*	-0.034*	1.000						
(9) MTB	0.002	0.000	-0.008	0.000	0.000	0.001	0.011	-0.010	1.000					
(10) AGE	-0.033*	-0.033*	-0.084*	-0.012	0.031*	0.405*	-0.061*	-0.046*	0.009	1.000				
(11) LNBSEG	0.035*	-0.072*	-0.084*	0.035*	0.028*	0.409*	-0.123*	0.018*	-0.022*	0.238*	1.000			
(12) LNGSEG	0.015*	-0.053*	-0.060*	-0.007	-0.053*	0.343*	-0.030*	0.000	0.002	0.178*	0.154*	1.000		
(13) SPECIAL	0.007	0.063*	0.027*	0.018*	0.024*	-0.139*	0.416*	0.012	-0.004	0.037*	0.003	0.005	1.000	
(14) BIG4	0.017*	-0.130*	-0.043*	0.009	0.111*	0.297*	-0.099*	0.170*	-0.020*	0.011	0.195*	0.241*	-0.082*	1.000

Note. This table reports Pearson correlations between the independent variables used in the Table 3.8 tests. All variables are defined in Appendix C.
* significant at the 5% level (two-tailed).

Table 3.8: Determinants of the textual complexity

Panel A						Panel B					
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)	(10)
Variable	*BOG*	*Ln(TOTAL_ WORDS)*	*Ln(File_Size)*	*BOILER*	*FACTOR1*	Variable	*BOG*	*Ln(TOTAL _WORDS)*	*Ln(File_Size)*	*BOILER*	*FACTOR1*
Constant	88.413***	8.520***	8.404***	0.097***	0.646***	Constant	78.372***	8.694***	6.650***	0.112***	0.735***
	(9.829)	(19.686)	(15.446)	(6.760)	(2.611)		(13.192)	(185.575)	(140.517)	(32.732)	(9.037)
						NONPRD	-1.292**	-1.549***	-0.710***	-0.055***	-0.923***
							(-2.165)	(-4.278)	(-3.111)	(-4.029)	(-4.379)
TREND	1.002***	0.045***	0.110***	0.001**	0.027***	*TREND* NONPRD*	0.955***	0.027***	0.103***	0.000**	0.019***
	(7.637)	(6.836)	(12.651)	(2.175)	(6.621)		(5.632)	(4.056)	(11.557)	(2.199)	(4.353)
SIZE	-0.634	-0.018	-0.099	0.000	-0.011	*SIZE* NONPRD*	-0.253	0.012	-0.067	0.001	0.008
	(-1.627)	(-0.803)	(-0.363)	(0.074)	(-0.798)		(-0.639)	(0.633)	(-0.072)	(1.290)	(0.755)
LEVERAGE	-3.084	0.024**	-0.041	0.013**	0.077	*LEVERAGE* NONPRD*	-3.577	-0.082	-0.238	0.011*	0.026
	(-1.215)	(2.177)	(-0.245)	(1.985)	(0.851)		(-1.172)	(-0.547)	(-1.179)	(1.693)	(0.276)
MTB	0.090	0.007	0.008	0.000	0.004	*MTB* NONPRD*	0.208*	0.013***	0.005**	0.000**	0.005*
	(0.908)	(1.064)	(1.108)	(1.107)	(1.071)		(1.740)	(2.745)	(2.289)	(2.023)	(1.780)
AGE	-1.020*	-0.049*	-0.066*	-0.000**	-0.026	*AGE* NONPRD*	-1.012*	-0.040*	-0.079*	0.000	-0.019
	(-1.887)	(-1.794)	(-1.732)	(-2.313)	(-1.458)		(-1.746)	(-1.738)	(-1.758)	(0.213)	(-1.132)
LOSS	1.557*	0.153***	0.190***	0.003*	0.065***	*LOSS* NONPRD*	1.675	0.056	-0.152	0.003	0.033
	(1.883)	(4.560)	(3.319)	(1.666)	(2.906)		(1.369)	(1.482)	(-0.045)	(1.490)	(-1.233)
SPECIAL	2.404	0.439***	0.722***	0.021***	0.284***	*SPECIAL* NONPRD*	5.774*	0.248***	0.003**	0.019**	0.177*
	(0.622)	(2.604)	(2.817)	(2.671)	(2.853)		(1.786)	(2.850)	(2.222)	(2.014)	(1.682)
LNBSEG	-0.822	0.036	-0.022	0.001	0.017	*LNBSEG* NONPRD*	-0.870	0.011	-0.125	0.001	0.005
	(-1.213)	(1.104)	(-0.444)	(0.857)	(0.793)		(-1.103)	(0.272)	(-1.281)	(0.407)	(0.186)
LNGSEG	-0.124	0.012	-0.029	-0.001	-0.007	*LNGSEG* NONPRD*	-0.990*	-0.098***	-0.621*	-0.005***	-0.074***
	(-0.191)	(0.355)	(-0.600)	(-1.008)	(-0.350)		(-1.714)	(-3.188)	(-1.885)	(-3.594)	(-4.095)
BIG4	0.835	0.103	-0.252***	0.002	0.056	*BIG4* NONPRD*	-0.159	-0.025	-0.313***	-0.002	-0.028
	(0.649)	(1.323)	(-2.805)	(0.457)	(0.960)		(-0.101)	(-0.416)	(-3.209)	(-0.553)	(-0.545)
N	17,364	17,364	17,364	17,364	17,364	N	17,364	17,364	17,364	17,364	17,364
Adj. R^2	0.085	0.059	0.122	0.026	0.052	Adj. R^2	0.123	0.302	0.216	0.144	0.272
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Industry fixed effects	Yes	Yes	Yes	Yes	Yes

Note. This table reports the determinants of textual complexity, including cross-section determinants and a time-series trend (*TREND*). *NONPRD* is a binary variable that takes 1 when the announcement is nonperiodic. All continuous variables are winsorised at the 1st and 99th percentiles, except for the factors, which were formed from truncated variables. Standard errors are adjusted for heteroskedasticity and clustered by firm. Superscripts ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively, for two-tailed tests.

Table 3.9: Managers' strategic use of textual complexity

Panel A: Good vs Bad News

ASX Category Code	Announcement Type	Good News							Bad News						
		Obs.	*BOG*	*TOTAL_WORDS*	*File_Size (kilobytes)*	*BOILER_WORDS*	*RET (%)*	t-Stat.	Obs.	*BOG*	*TOTAL_WORDS*	*File_Size (kilobytes)*	*BOILER_WORDS*	*RET (%)*	t-Stat.
	Periodic Announcements														
3	Periodic reports	2,613	79.2	8870.1	1114.1	1178	4.8%	44.59	2,003	79.5	8980.1	1250.06	1186	-4.3%	-20.67
4	Quarterly activities report	493	84.2	3795	1156.8	434.3	3.8%	20.66	563	84.8	3831.6	1187.1	438.6	-3.9%	-22.55
10	Dividend announcement	143	83.1	1148.2	192.4	117.4	2.5%	9.91	135	82.5	717	151.6	151.6	-1.9%	-10.61
	Nonperiodic Announcements														
1	Takeover announcements	570	73.5	5204.5	646.7	829.2	3.2%	17.01	491	73.9	6523	758.9	1032.5	-3.5%	-4.165
2	Shareholder details	97	72.7	837.6	200.4	81.7	2.9%	8.22	77	68.14	2302.2	375.2	314.5	-2.3%	-9.725
6	Issued capital	911	75.9	5413.2	626.4	743.5	3.6%	23.6	884	77.5	5534.8	678.3	795.1	-3.1%	-24.77
7	Asset acquisition and disposal	930	74.5	1140.7	255.8	130.8	3.1%	26.78	763	75.5	1225	272.2	65.8	-2.7%	-20.86
9	Stock exchange announcement	112	75.3	854.2	234.4	49.1	6.1%	5.069	133	76.4	1326.6	258.7	166.5	-3.1%	-10.71
11	Progress report	2,902	72.7	1190.4	457.5	110.3	3.5%	42.15	2,577	72.6	1096	468.5	93.9	-3.4%	-35.89
12	Company administration	343	69.9	1527.2	229.1	160.1	3.4%	16.93	384	67.1	1421.2	257.5	131.8	-4.8%	-13.79
14	Other	53	71.9	1987.8	374.3	165.8	3.7%	4.51	63	72.2	2801.6	773.5	159.7	-4.5%	-5.33
17	ASX Query	71	54.5	1120.1	325.4	165.4	11.2%	5.229	53	58.34	1271.4	298.3	184.3	-6.7%	-7.06

Panel B: Mean *RET* for bad and good news

	Periodic Announcements	Nonperiodic Announcements
Good News	0.045***	0.035***
Bad News	-0.041***	-0.034***
Mean Diff.	0.0859***	0.0694***

Panel C: Textual complexity on *ATH*, *LTD* and *ATHonLTD*

Sample on Good News	Periodic Announcement					Nonperiodic Announcement				
	Obs.	*BOG*	*TOTAL_ WORDS*	*File_Size (kilobytes)*	*BOILER_ WORDS*	*Obs.*	*BOG*	*TOTAL_W ORDS*	*File_Size (kilobytes)*	*BOILER_ WORDS*
During trading hours (*NonATH*)	2,797	80.4	7,520.6	1067.2	991.8	5,148	73.3	2,123.1	453.1	264.1
After trading hours (*ATH*)	452	78.6	8,968.8	1192.9	1184.3	841	73.2	2,816.9	458.5	382.4
Mean Diff.		1.725**	-1,403.2	-125	-192.4*		0.487	-693.7**	-5.44	-118.3*
Other trading days *(NonLTD)*	2,798	80.3	7,939.1	1102.9	1,039	4,937	73.2	2,228.1	464.4	280.9
Last trading day (*LTD*)	451	79.	6,654.4	971.8	892.2	1,052	73	2,185.1	404.4	279.4
Mean Diff.		**1.28***	**1284.7****	**-131.1**	**146.8***		**0.227**	**43.03**	**59.9**	**1.466**
Regular announcements *(NonATHonLTD)*	3,175	80.3	7,810.4	1094.3	1,025.3	5,849	73.2	2,207.2	454.9	278
After trading hours on the last trading day (*ATHonLTD*)	74	74.5	5,630.6	669.8	731.9	140	73.5	2,775.8	408.7	390.7
Mean Diff.		**5.75*****	**2,179.7***	**-424.5***	**293.4**		**-0.272**	**-568.5**	**46.2**	**-112.6**
Sample on BAD News	*Obs.*	*BOG*	*TOTAL_ WORDS*	*File_Size (kilobytes)*	*BOILER_ WORDS*	*Obs.*	*BOG*	*TOTAL_W ORDS*	*File_Size (kilobytes)*	*BOILER_ WORDS*
During trading hours (*NonATH*)	2,336	80.8	7,366.8	1170.4	938.8	4,667	73.9	2,272.1	461.2	285.4
After trading hours (*ATH*)	346	80.1	8,274.8	1205.8	1096.5	724	72.4	2,372.6	509.1	321.3
Mean Diff.		**0.717**	**-907.9**	**-35.3**	**-157.6**		**-0.456****	**-100.5****	**-47.7****	**-35.89****
Other trading days *(NonLTD)*	2,338	81	7,636.4	1190.8	981.8	4,487	73.3	2,264.1	427.3	285
Last trading day (*LTD*)	344	79.4	6,447.8	1067.4	885.1	904	73.3	2,391.8	475.8	316.3
Mean Diff.		**1.559***	**1188.6***	**123.4**	**176.7***		**-0.065****	**-127.7****	**-48.4***	**-31.33****
Regular announcements *(NonATHonLTD)*	2,634	80.8	7,493.5	1179.7	959.1	5,266	73.3	2,253	466.3	285.8
After trading hours on the last trading day (*ATHonLTD*)	48	79.3	6,959	918.5	962.1	125	74.4	3,655.1	526.4	479.3
Mean Diff.		**1.452**	**534.4***	**261.2**	**-2.914**		**-1.118****	**-1,402.1****	**-60.1****	**-193.5****

Note. This table reports the summary statistics on managers' strategic use of textual complexity. Panel A reports the summary statistics of the main sample on all announcement types separately for good and bad news observations. Panel B shows mean three-day cumulative abnormal returns for good and bad news across periodic and nonperiodic disclosures as well as their mean differences. Panel C separates the good and bad news to report the mean differences for *ATH-NonATH*, *LTD-NonLTD* and *ATHonLTD-NonATHonLTD* across periodic and nonperiodic announcements. Superscripts ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively, for two-tailed tests.

Table 3.10: Strategic reporting

	ATH					*LTD*					*ATHonLTD*				
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	BOG	*Ln(TOTAL_ WORDS)*	*Ln(File_Size)*	*BOILER*	*FACTOR1*	*BOG*	*Ln(TOTAL_ WORDS)*	*Ln(File_Size)*	*BOILER*	*FACTOR1*	*BOG*	*Ln(TOTAL_ WORDS)*	*Ln(File_Size)*	*BOILER*	*FACTOR1*
Constant	78.260***	8.716***	9.462***	0.113***	0.753***	96.779***	9.782***	9.023***	0.092***	1.121***	78.161***	8.725***	6.366***	0.113***	0.756***
	(13.087)	(109.685)	(13.781)	(25.960)	(7.644)	(5.714)	(19.876)	(14.267)	(3.889)	(2.998)	(13.024)	(111.299)	(6.000)	(25.718)	(7.658)
NONPRD	-1.042**	-1.559***	-1.027***	-0.055***	-0.869***	-6.983***	-1.342***	-0.913***	-0.034***	-0.753***	-0.992**	-1.565***	-0.620***	-0.055***	-0.869***
	(-2.134)	(-4.330)	(-10.771)	(-4.009)	(-3.888)	(-5.896)	(-11.396)	(-7.764)	(-7.593)	(-10.646)	(-2.127)	(-4.360)	(-3.001)	(-4.001)	(-3.900)
BAD	1.220**	0.142***	-0.085	0.000	0.062**	0.205	-0.030	0.016	-0.006*	-0.056	1.405	0.129	0.144	0.004	0.066
	(2.472)	(3.039)	(-0.998)	(0.279)	(2.399)	(0.259)	(-0.349)	(0.170)	(-1.761)	(-1.235)	(1.403)	(1.477)	(0.609)	(1.321)	(1.400)
NONPRD*BAD	**1.188***	**0.099***	**0.129***	**0.001***	**0.050***	**1.147***	**0.047****	**-0.074**	**0.001****	**0.025***	**1.251**	**0.059***	**0.016**	**0.001***	**0.033**
	(1.845)	**(1.828)**	**(1.708)**	**(1.707)**	**(1.723)**	**(1.882)**	**(2.042)**	**(-0.704)**	**(2.302)**	**(1.837)**	**(1.115)**	**(1.695)**	**(0.063)**	**(1.721)**	**(1.124)**
Observations	2,759	2,759	2,759	2,759	2,759	2,371	2,371	2,371	2,371	2,371	387	387	387	387	387
Adjusted R-squared	0.084	0.258	0.193	0.096	0.215	0.127	0.300	0.189	0.152	0.275	0.085	0.206	0.113	0.115	0.203
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note. This table reports the impact of managers' strategic reporting on textual complexity. Dependent variables are *BOG*, *Ln(TOTAL_WORDS)*, *Ln(File_Size), BOILER*, *FACTOR1*. *NONPRD* is a binary variable that takes 1 when the announcement is nonperiodic. All continuous variables are winsorised at the 1st and 99th percentiles, except for the factors, which were formed from truncated variables. Standard errors are adjusted for heteroskedasticity and clustered by firm. *** p < 0.01, ** p < 0.05, * p < 0.1.

Chapter Four:
Does Managers' Strategic Use of Textual Content to Meet Regulatory Pressure Make Nonperiodic Disclosures Less Readable?

"When continuous disclosure is discussed in Australia, it is often based on the image of directors being caught by surprise by a difficult disclosure decision." - John Price, ASIC Commissioner at Chartered Secretaries Australia (CSA) 2012 Annual Conference.

4.1 Introduction

This chapter expands the analysis of the effect of managers' strategic reporting on the textual complexity of nonperiodic disclosures and how the higher processing costs of these disclosures may affect market reactions. The costs and benefits of regulating disclosure timeliness, completeness, and textual complexity are important but still developing research areas. In recent years, regulators have been increasingly emphasising disclosure readability by using plain English to enhance understandability for all market participants (Bonsall et al., 2017; Lawrence, 2013; Miller, 2010). Unlike periodic disclosures, greater time pressure for reporting nonperiodic disclosures can lead to incomplete and inaccurate disclosure, and managers can face a greater litigation risk for misleading and deceptive conduct (Jackson et al., 2015; Watkins, 2022). However, firms that are sufficiently concerned about litigation tend to strategically make disclosure more thorough, nuanced, and boilerplate to reduce the risk of regulatory actions and lawsuits (Cazier et al., 2021; Hope et al., 2016; Humphery-Jenner et al., 2019). Therefore, this begs the question of whether managers' strategic reporting of textual content to meet regulatory pressure reduces nonperiodic disclosure readability.

My study is motivated to explore this issue by Australian GN8 of Listing Rules 3.1, which requires listed firms to report timely, complete and accurate nonperiodic disclosure covering a wide range of unanticipated material events while emphasising such disclosures must be drafted in plain English.[31] Breaching GN8 of Listing Rules 3.1 can cause serious litigation, as evidenced by ASIC's infringement notices, civil penalty proceedings, and shareholder class actions.[32] However, I specifically utilise the GN8 revision in 2013 by ASX, which clarifies what constitutes an 'immediate', complete and accurate nonperiodic disclosure in response to market confusion being compounded by several of ASIC's[33] controversial regulatory actions. The GN8 revision was intended to lessen market confusion by clarifying the definition of 'immediate' disclosure to allow firms to draft complete and accurate nonperiodic disclosures[34] to ease the litigation risk. Despite these clarifications, ASIC's strict application of the 'immediacy' rule with no stated filing deadline (Price, 2014) and the citation of pre-GN8 revision infringement notices for timeliness as the standard for promptness worried directors. With the sizable increase in the number of shareholder class actions for CDR breaches,[35] directors were concerned that ASIC's strict view on timeliness might exert more pressure to meet complete and accurate

[31] Section 4.15 of GN8 (version 2013) states that written announcements must be couched in language that is factual, relevant and expressed clearly and objectively. For details, see https://www.asx.com.au/documents/rules/Guidance_Note_8.pdf.

[32] Among 78 shareholder class actions, around 38 have been filed in the Federal Court for nonperiodic events since misleading or deceptive conduct provisions were introduced in the Corporations Act in 2002. For details, see Panel C of Table 4.1.

[33] These include infringement notices for delaying announcements and civil penalty proceedings for misleading the market.

[34] The GN8 revision included some worked examples that discussed scenarios based on nonperiodic material events to assist and guide listed firms to draft complete announcements. This topic is covered in further detail in Section 2.1.

[35] See Appendix B for details.

disclosure, leading to greater litigation risk for misleading and deceptive conduct post-GN8 revision (Bryans, 2012; Chew & Scott, 2013; Digby et al., 2018).

I contend that managers' strategic reporting to minimise litigation for misleading and deceptive conduct within ASIC's strict timeliness application could affect the textual complexity of nonperiodic disclosure in two ways. Firstly, in practice, the penalty under an infringement notice is less likely to outweigh the litigation costs for incomplete and inaccurate disclosure, even if firm successfully defended (Featherstone, 2012).[36] But shareholder class actions are far more costly for firms than ASIC's civil penalty proceedings (e.g., Australia's biggest-ever settlement in a class action was $200 million paid by Centro Properties Group).[37] The existing research on risk factor disclosures suggests that companies facing a higher risk of litigation tend to rely more on standardised language or boilerplate disclosure, which is less costly and time-consuming to prepare (Brown & Tucker, 2011). This is because firms that use boilerplate to increase the length of their disclosures, and use it as a measure of completeness, are less likely to be flagged as misleading by regulators and courts (Cazier & Pfeiffer, 2017; Cazier et al., 2021). However, the downside of boilerplate disclosure is that it can make the information provided less clear and harder to understand (Humphery-Jenner et al., 2019; Lang & Stice-Lawrence, 2015; McClane, 2019). Therefore, I posit that firms that are sufficiently concerned about regulatory actions and shareholder class actions would make greater use of boilerplate disclosure to meet time pressure post-GN8 revision, though the downside

[36] According to Section 1317E (civil penalty provisions) and Section 1317G (pecuniary penalty orders), the maximum penalty (per person) is $200,000 and a maximum of $1 million for a body of corporate. For infringement notices, the penalty would be $100,000 for companies whose market capitalisation exceeds $1,000 million, $66,000 for companies whose market capitalisation exceeds $100 million, and $33,000 for companies whose market capitalisation is below $100 million.

[37] For more details, see https://www.smh.com.au/business/court-approves-centros-200m-class-action-settlement-20120619-20m2m.html.

is that nonperiodic disclosure may become less readable (Humphery-Jenner et al., 2019; Lang & Stice-Lawrence, 2015; McClane, 2019). However, nonperiodic disclosures are unanticipated events outside the normal reporting cycle (Lerman & Livnat, 2010; Li & Tan, 2022) and put higher costs on managers to provide sufficient disclosure detail with time pressure (Watkins, 2022). Thus, ASIC's strict timeliness application may limit managers' ability to make disclosures more thorough, in order to meet the requirement for complete disclosure.

Furthermore, investors may incur higher processing costs to obtain relevant information from companies that use more boilerplate language in their disclosures (Blankespoor et al., 2020), which may result in weaker market reactions. However, the view of ASIC is that most nonperiodic events are well-defined and familiar to Australian-listed companies (Price, 2012). Therefore, if firms anticipate such events and strategically invest in their internal systems to respond to the GN8 revision (McGrath, 2013; Nicholson, 2011), managers may not need to make significant changes to their disclosures, and there may be no reduction in the readability of nonperiodic disclosures or market reactions after the revision.

To test the research questions, I use a sample of 9,995 nonperiodic announcements downloaded from the ASX website from 2010 to 2017. I use boilerplate disclosure to capture the managers' strategic textual reporting because longer and more boilerplate disclosure appears to provide better protection against a highly litigious environment (Cazier & Pfeiffer, 2017; Cazier et al., 2021). Next, I use the Bog Index (*BOG*) as my primary measure of announcement readability to capture the ease of understanding written text post-GN8 revision, with a higher level indicating lower readability. I first provide evidence that nonperiodic announcements became less readable post-GN8 revision. My DiD design further confirms that treated firms (as proxied by a greater increase in the use of boilerplate) were more

impacted by the GN8 revision than other firms (control group) and have the largest reduction in readability. I use propensity score matching in my analyses to ensure these two samples are similar across observable covariates. These findings imply that managers may use boilerplate disclosure to allow them to make an 'immediate' disclosure that is also sufficiently 'complete' and accurate to minimise regulatory risk. Thus, boilerplate disclosure is likely to be particularly useful in the nonperiodic announcements setting, considering that many are unanticipated events outside the normal reporting cycle.

Next, I examine the impact on the usefulness of these announcements and find a higher level of negative market reactions for announcements with lower readability produced by firms more impacted by the GN8 revision. This suggests that greater costs are associated with extracting relevant information from nonperiodic announcements with lower readability and greater use of boilerplate disclosure. This relation is only significant for firms with lower institutional ownership, and there is no consistent evidence of an association between analyst revisions and reduced nonperiodic announcement readability. I infer that the costs of lower readability for firms with greater use of boilerplate disclosure are predominantly borne by retail investors. My results are robust to several sensitivity tests, including alternative readability measures, placebo tests, and alternative regression specifications using restricted samples excluding loss firms.

This study makes three main contributions. Firstly, this study provides insights into the international policy debate surrounding enhanced regulation for disclosure timeliness, completeness, and textual complexity. Existing literature has primarily focused on the positive impact of regulation on improving nonperiodic disclosure timeliness and frequency (Brown et al., 1999; Lerman & Livnat, 2010; McMullin et al., 2019). My findings add to prior research by showing the unintended

consequences of GN8 revision by exploring how managers' use of boilerplate disclosure to decrease legal risk affects readability and leads to negative market results. I contribute to this literature by identifying an unintended negative consequence of regulatory pressure through lower readability and related negative market consequences. Specifically, I extend the work of Watkins (2022) by showing that because managers face high costs and litigation risks for reporting nonperiodic disclosures, lower readability is a consequence of firms attempting to disclose more thoroughly to ease regulatory burden within a strict timeframe.

Secondly, I contribute to the body of literature that examines managers' incentives to use boilerplate language (Cazier & Pfeiffer, 2017; Cazier et al., 2021; Li, 2019) and its associated impact on disclosure readability and capital market outcomes (Dyer et al., 2017; Lang & Stice-Lawrence, 2015; McClane, 2019). While prior research focuses primarily on periodic reports, my findings highlight managers' strategic use of lengthy boilerplate disclosure as 'complete' disclosure to relieve the time pressure for nonperiodic announcements that may result from minimising the risk of regulatory actions and shareholder class actions. In addition, I also show that the negative market reactions surrounding less readable nonperiodic announcements post-GN8 are more pronounced for firms with more boilerplate disclosure. The evidence suggests that, despite the negative market outcomes, firms probably release boilerplate and lengthy nonperiodic announcements post-GN8 because regulatory and legal outcomes generally do not reward more readable disclosures.

Lastly, the Australian Federal Government recently passed the Treasury Laws Amendment (2021 Measures No. 1) Bill 2021, which is expected to give directors more confidence in disclosing information to the market without fear of being sued for misleading or deceptive conduct in speculative class actions. The amendment could lead to lower litigation risk for firms that provide complete disclosure, which

may lead to less use of boilerplate language to meet timeliness requirements. As a result, nonperiodic announcements may decrease in size and become less complex. The findings of this study may be useful for Australian regulators to understand the implications of the amendment and determine whether it would decrease the regulatory burden for listed firms and reduce the risk of litigation.

The remainder of this study is organised as follows. Section 4.2 discusses the revised GN8, prior literature and hypothesis development. Section 4.3 describes the data and variable construction. Section 4.4 describes the research design and reports the results of the main regressions, while Section 4.5 reports the results of robustness checks. The final section concludes the study.

4.2 Background and prior literature

4.2.1 Revised Guidance Note 8

Despite the guidance of GN8 of Listing Rule 3.1, there had been significant confusion before 2013 about what constitutes a breach of 'immediacy' and disclosure completeness and accuracy for nonperiodic material events (Bryans, 2012; Chew & Scott, 2013; Featherstone, 2012).[38] This confusion arose from two types of GN8-related breaches, putting directors in a significant dilemma in complying with GN8. Firstly, when managers delayed announcements to allow them to be complete and accurate, ASIC fined firms for breaching the 'immediacy' rule as they did not come to the market quickly enough with material information. This confusion was compounded by a series of controversial 'infringement notices' (known as 'speeding fines') against Rio Tinto in June 2008 by delaying an acquisition announcement for

[38] Following these cases, ASIC Commissioner John Price (2012) also acknowledged the existence of significant conflict between the timely disclosure of material information and preventing premature disclosure of incomplete or indefinite matters in his address to Chartered Secretaries Australia (CSA) 2012 Annual Conference.

90 minutes and the CBA in 2009 by delaying 60 minutes for an expected loan impairment announcement.[39]

Secondly, ASIC alleged that firms made misleading, deceptive and incomplete announcements without taking enough time to investigate the material event's substance and thus releasing the announcement too quickly. This led to a series of civil penalty proceedings against Fortescue Metals Group Ltd[40] and James Hardie Industries Ltd for engaging in misleading and deceptive conduct. In combination, ASIC's interpretation dismayed directors and gave the impression that firms had to disclose information immediately that might not yet have been fully quantified, even if it proved to be misleading later, paving the way for more shareholder class actions (Featherstone, 2012). However, Fortescue's win against ASIC and Federal Court's decision in 2012 revealed the importance of the context of detailed statements for the perspective of recipients when assessing if the conduct is misleading. During the consultation on the GN8 revision, directors expected that Fortescue's outcome would have huge ramifications for the interpretation of continuous disclosure rules for companies (Bryans, 2012).

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[39] The *Sydney Morning Herald* reported that Rio Tinto was fined $100,000 for delaying disclosure about an acquisition of Alcan Inc until approximately 4 p.m., information that ASIC believed they were aware of from 2:30 p.m. Similarly, *ABC News* reported that the CBA faced an infringement notice for not releasing disclosure about the company's expected loan impairment expense until 7:14 p.m. ASIC believed they were aware of this issue from 3 p.m. and withheld that information for 60 minutes, letting the market for that day close at 4 p.m.

[40] ASIC commenced proceedings against Fortescue in March 2006, alleging announcements Fortescue made to the market in 2004 and 2005 concerning certain framework agreements with three major state-owned Chinese companies were overstated in ASX announcements, media releases and investor presentations. In response to the allegation over misleading conduct under Section 1041H of the Corporations Act 2001 (Cth), the Full Court rejected the case under the consideration that the investing public would have regarded Fortescue's statements as sufficiently complete to understand the ramification of the projects.

ASX revised GN8 in May 2013 to respond to several concerns articulated during the consultation process, including clarifying 'immediately' as 'promptly and without delay'. It further clarified that an adequate response time for compliance would be determined by the circumstances rather than how much time has elapsed, to allow companies to capture unanticipated material events more fully in drafting complete announcements. Besides emphasising announcements need to be factual, relevant, and written in plain English (ASX, 2013), more examples were added in Section 4.15 of the revised GN8 to guide company officers in drafting announcements with sufficient detail.[41] However, despite these clarifications, ASIC commissioner John Price cited previous infringement notices as examples of the standard of promptness and enforcement action. ASX's apparent suggestion in the GN8 revision was that trading halts could be used more frequently as a tool to meet the timeliness, completeness, and accuracy of announcements.[42] However, boards of directors appear reluctant to use halts because they are perceived negatively by market participants and because of the risk of a substantive information gap being revealed (Chew & Scott, 2013). Therefore, despite clarification, ASIC's strict view on timeliness makes it unclear whether the GN8 revision would have led to a different result, particularly for drafting complete and accurate disclosure.

[41] In the initial 2013 version, ASX included a scenario of signing a contract relating to a significant acquisition or disposal in which a list of information was added as an example of what listed entities must add to provide a better perspective on the circumstances arising from the complex and uncertain event. Later, ASX added another scenario of signing a market-sensitive contract with a customer in their 2018 revised version of GN8. For details, see GN8 of ASX Listing Rules 3.1.

[42] According to ASX Listing Rule 3.1B, the term 'false market' refers to a situation where there is material misinformation or materially incomplete information in the market which is compromising proper price discovery. Under such a situation, if ASX believes that there is a possibility of a false market in the entity's security due to market speculation or media comment, then the company must make an 'immediate' announcement to the market to dispel or clarify the rumour.

4.2.2 The effects of GN8 revision on nonperiodic announcement readability

Extant literature suggests that strict regulatory actions for failing to provide timely disclosures (e.g., 8-K filings and the Australian CDR) can help discipline firms. For example, an earlier study from Brown et al. (1999) found improved frequency for nonperiodic disclosures post-civil and criminal sanctions in Australia for firms with little analyst following and those likely to report 'bad' news. Similarly, the Securities and Exchange Commission (SEC) in the US prescribed the filing deadline to be four business days, and a failure to file 8-Ks within the deadline may result in SEC actions. In response, empirical studies find that improved timeliness (Lerman & Livnat, 2010) and frequency (McMullin et al., 2019) of 8-K filings have been associated with positive market outcomes since SEC's 2004 changes. In contrast, Watkins (2022) examines the unintended negative consequences of the prescribed filing deadline of the 2004 regulation and finds that firms that are more constrained by the prescribed filing deadline exhibit more information asymmetry and investor disagreement due to the decline in the 8-K filing detail. However, managers can strategically time 8-Ks to mitigate regulatory actions (Segal & Segal, 2016). But it is unclear whether managers intentionally report textual content strategically to ensure accuracy and completeness for regulatory purposes while complying with the strict timeliness requirements.

In general, the reporting of nonperiodic disclosures is a comprehensive process under the Australian CDR setting, including 1) detecting and investigating the triggering events, 2) getting approval from the board of directors, and 3) preparing, formatting and reviewing with ASX. The unanticipated nature of the triggering events makes it difficult for firms to provide complete and accurate, thus managers could be more strategic under such circumstances. There are several reasons to expect managers' strategic reporting to meet the GN8 revision could impact firms'

nonperiodic announcement readability in unintended ways. First, as managers require time to analyse the impact of unanticipated events, reporting complete and accurate disclosures against ASIC's strict timeliness application would be costly (Watkins, 2022).[43] Second, rather than emphasising readability, companies may emphasise longer disclosure with more boilerplate as a proxy for complete disclosure to offset litigation risk, because lengthy boilerplate disclosure requires lower preparation costs and time (Brown & Tucker, 2011; McClane, 2019) and is less likely to be flagged as misleading under judicial and regulatory assessment (Cazier et al., 2021). Thus, I expect firms that are more concerned about regulatory actions post-GN8 revision are more likely to use lengthy boilerplate nonperiodic announcements to meet increased timeliness requirements (Chew & Scott, 2013). However, increased boilerplate reflects lower information content in disclosure and is associated with lower readability (Cazier & Pfeiffer, 2017; Dyer et al., 2017; Humphery-Jenner et al., 2019; Lang & Stice-Lawrence, 2015; McClane, 2019).

However, the revised GN8 is based on the principle of 'immediate' disclosure but does not have a stated deadline like the US Form 8-K (four business days) in which to release the material information, even though this has been previously interpreted strictly by ASIC. Given they are subject to regulatory interpretation, if firms have invested in internal systems accordingly, then the GN8 revision might not constrain managers' ability (McGrath, 2013; Nicholson, 2011; Price, 2014). As a result, it would allow managers to provide detailed announcements more clearly without using boilerplate text to meet time pressure, and thus they would be less

[43] The underlying argument is that improving internal processes and complying with post-regulatory changes is costly. For example, Kajüter et al. (2019) note that compliance costs post-regulatory change includes one-off costs, such as IT investments, the reshaping of reporting processes, the recruiting of staff, and additional training and potential advisory costs. Moreover, there are also recurring costs that relate mostly to additional staff.

likely to produce less readable announcements. On balance, I state my first two hypotheses as follows:

$H_{4.1}$: *The decrease in nonperiodic disclosures' readability post-GN8 revision is more pronounced for firms with greater use of boilerplate text in the document.*

4.2.3 *Market reaction to reduced nonperiodic announcement readability post-GN8 revision*

Although boilerplate most likely adds additional length to nonperiodic announcements, evidence suggests that phrases commonly used across the industry can help market participants process the information more easily (Cazier & Pfeiffer, 2017; Li, 2019). However, Grossman and Stiglitz (1980) and Bloomfield (2002) argue that information that is more costly to extract is less likely to be completely reflected in market prices. Consistent with this notion, greater use of boilerplate in IPO disclosures is associated with lower readability and a higher cost of equity arising from a decrease in investors' ability to process information (McClane, 2019). Lang and Stice-Lawrence (2015) find that increased boilerplate and lower readability of annual reports post-IFRS adoption is associated with decreased liquidity, analyst following, and institutional ownership for an international sample. Thus, I hypothesise that the cumulative abnormal stock return (*CAR*) is negatively associated with firms which make greater use of boilerplate text post-GN8 revision. This occurs because boilerplate may decrease readability as an unintentional consequence of firms attempting to improve disclosure thoroughness and hedge their language, making it more costly for users to process the disclosed information (Blankespoor et al., 2020), and this behaviour will reduce the *CARs* around the firm's announcement. However, compared to periodic reports, nonperiodic announcements tend to receive less media attention (Lerman & Livnat, 2010; Li & Tan, 2022; McMullin et al., 2019), thus investors may pay less attention to these unanticipated material events.

Therefore, I may not observe any reduction in market reactions post-GN8 revision. On the balance of probabilities, I state my second hypothesis as:

$H_{4.2}$: *There is a negative association between CAR and greater use of boilerplate text in disclosures post-GN8 revision.*

4.3 Data and variable construction

4.3.1 Sample selection

The sample comprises all companies in the S&P/ASX200 from 2010 to 2017.[44] The S&P/ASX200 is recognised as the institutional benchmark in Australia, representing approximately 80% of Australian equity market capitalisation. I initially downloaded 15,543 price-sensitive nonperiodic announcement documents as PDF files over the sample period from the ASX website. I first employ Microsoft VBA code to convert all the PDF files into docx files and convert all docx files into plain text files using a Python program by employing a parsing procedure. Following the parsing procedure in Bonsall et al. (2017), I exclude all tables, header/title/bottom contact info (tagged with 'contact or further information' or 'about …'), markup tags (e.g., HTML), bullet point signs and special characters (e.g., ?, #, $, etc.).[45] Since the focus is on measuring textual content, announcements are dropped if they (1) only contain presentation slides, tables, graphs, or pictures, (2) only contain appendix tables (e.g., 3B, 3C) and are related to admission to official quotation, (3) contain both nonperiodic and periodic information in a single document,[46] (4) are

[44] To construct the sample, I verify the listed companies for each year over the sample period to ensure that the sample firms remain in the top S&P/ASX200 list during the study period for consistency. This process reduces the sample size from 200 to 184 firms.

[45] The program also eliminates all the blank spaces and single non-alphabetic paragraphs within this procedure to ensure that all the tables and tabulated text are excluded. For detail, see Bonsall et al. (2017).

[46] I can draw one such example from the announcement made by Ausdrill Ltd on 15/08/2018 titled "FY18 Outstanding Results and Strategic Barminco Acquisition."

nonreadable by *StyleWriter* software (e.g., when the file is corrupted or is a scanned PDF), or (5) contain less than 300 words.[47] My final sample contains 9,995 firm-announcement observations from 184 companies, and the sample selection process is reported in Table 4.1. I also report announcements classified into different categories based on Morningstar DataAnalysis Premium event types (excluding nonapplicable categories).[48] Data related to firm fundamentals, stock returns and analyst coverage are collected from Thomson Reuters Eikon, and daily news coverage data is hand-collected from the Factiva database. All continuous variables are winsorised at the 1% and 99% levels.

[Insert Table 4.1 about here]

4.3.2 Measures of textual complexity

Following Bonsall et al. (2017), I use *BOG* as the primary measure to capture the writing clarity component of readability. My choice of *BOG* is motivated by the benefits of using its proprietary 200,000-word list dictionary over the Fog Index, which relies on the multisyllabic count that has been extensively criticised.[49] I use *StyleWriter*, a commercial software program, to derive *BOG* for all nonperiodic announcements, with a higher score reflecting lower document readability.

[47] Sample announcements with more than 300 words represent the upper 70% of the total announcement sample. However, the results remain consistent with the 5% variation in the cut-off point.

[48] Morningstar DataAnalysis database uses the Signal G database to classify all announcements by date and time of release, according to announcement type and whether ASX highlighted such announcements as price sensitive.

[49] For example, Loughran and McDonald (2014) raised this concern by showing that all words with three or more syllables that the Fog Index identified as 'complex' (e.g., company) should be well understood by the least sophisticated investors. However, in additional tests, I show the results are robust to using alternative readability measures, including Fog Index, Flesch-Kincaid Index and file size.

To capture the use of boilerplate disclosure, I first identify common three-word phrases in announcements, which are termed 'trigrams'. I set a cut-off in which these trigrams appear in at least 10% but no more than 90% of all nonperiodic announcements produced by firms in the same six-digit GICS industry. Next, I identify standardised sentences as those that contain at least one of these identified trigrams in the sentence. I then counted the number of boilerplate words in these standardised sentences and labelled this variable as *BOILER_WORDS*. My approach to this variable is similar to the approach used by Cazier et al. (2021) and Lang and Stice-Lawrence (2015) to capture the extent of standardised language in disclosures that are unlikely to be informative. See Section 3.3.2 for a more detailed discussion of estimating this variable.

4.3.3 Market reaction analysis

To empirically test the market reaction to nonperiodic announcement readability post-GN8 revision, I follow prior studies that employ an event study methodology with a market model to observe changes in stock returns (Lerman & Livnat, 2010; Yekini et al., 2016). Unlike the cost of equity model that captures the transaction costs for given disclosure quality, the market reaction model allows capturing of investors' information processing capacity in the price discovery process. Therefore, I chose the market reaction model to capture the investors' information processing costs in relation to the nonperiodic announcement readability post-GN8 revision. I calculate the abnormal return for firm *i* on day *t* (where the announcement date is day *t*) as:

$$AR_{i,t} = R_{i,t} - (\hat{a}_i + \hat{\beta}_i R_{m,t}) \quad (4.1)$$

where $AR_{i,t}$ is the abnormal return of firm *i* on day *t*. $R_{i,t}$ and $R_{m,t}$ are, respectively, actual realised return of firm *i* on day *t* and S&P/ASX200 equally weighted index for day *t*. α and β_i are estimated parameters from a market model where the realised

return of firm *i* on day *t* is regressed on the return of the S&P/ASX200 equally weighted index for day *t* over an estimation window.[50] I use a 75-day window to estimate event-specific parameters that begin 90 trading days before the event and end 16 days before the nonperiodic announcement release date (day *t*). Consistent with prior studies, I choose to focus on two short periods, namely three-day *(-1,1)* and five-day *(-1,3)* windows, to calculate cumulative abnormal returns (*CARs*) for firm *i* on day *t* over a window period by simply summing up abnormal returns. *CARs* over the period (*m,n*) are calculated as:

$$CAR_{i,t}(m,n) = \sum_{j=m}^{n} AR_{i,t} \tag{4.2}$$

where the parameter *m* denotes the beginning of the event window, *-1* in this case, while *n* can take a value of either *+1* or *+3* depending on the specification.

4.3.4 Control variables

I include several control variables for the event, and firm characteristics that prior literature argues may influence disclosure readability (Bonsall et al., 2017; Li, 2008). All annual report data is from the most recent fiscal year at the time of the announcement. *SIZE* is the natural logarithm of the firm's market capitalisation. *LEVERAGE* is total debt scaled by total assets. *ROA* is income before extraordinary items scaled by total assets. *MTB* is the ratio of the market value of equity to the book

[50] All prices are adjusted for changes in the basis of quotation, such as dividends on the ex-dividend day. To provide confidence that non-synchronous trading drives or biases the main results, I pro-rate allocate daily returns to any immediately preceding non-trading days (Jackson et al., 2015). I estimate a market model, where stock returns are regressed against a stock market index R_m, as follows: $R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$. I estimate $R_{i,t} = In\left[\frac{P_{i,t}}{P_{i,t-1}}\right]$ and $R_{m,t} = In\left[\frac{P_{m,t}}{P_{m,t-1}}\right]$, where $P_{i,t}$ is the share price of firm *i* on day *t* and $P_{m,t}$ is the aggregate market index on day *t*.

value of equity. *AGE* is the natural logarithm of the number of years as the firm first appears in the Morningstar database. *LNBSEG* is the natural logarithm of the number of business segments, and *LNGSEG* is the natural logarithm of the number of geographic segments. *SPECIAL* is the total amount of special items scaled by total assets. *M&A* is a binary variable set to 1 if the firm engaged in a merger and acquisition transaction in a fiscal year, and 0 otherwise. *SEO* is set to 1 if the firm had a common equity offering in the secondary market during the fiscal year, and 0 otherwise. To control the firm's information environment, I add *VOLATILITY* as the standard deviation of the average daily stock returns during the (0, -90) day pre-event window, where day 0 is the day the nonperiodic announcement is released. *BIG4* is a binary variable set to 1 if the audit firm is one of the big four, and 0 otherwise. *ANALYSTS* is the natural logarithm of 1 plus the number of unique analysts providing annual earnings forecasts from the I/B/E/S for the 12 months ending on the day the nonperiodic announcement is filed. To differentiate the impact of macroeconomic events on the financial market, I add *NEWS* measured as the natural logarithm of 1 plus the number of news articles recorded by Factiva (using the company name as the search criterion) for the 12 months ending on the day the nonperiodic announcement is released.

4.3.5 Matching

I identify the most impacted firms and least impacted firms by calculating the percentage change in the boilerplate words (*BOILER_WORDS_CHANGE*) for three years immediately before the GN8 revision to the four years post-GN8 revision, after eliminating the firm-year that contains the regulation date (1 May 2013). Next, I split all firms into quartiles based on their percentage change in the boilerplate words (*BOILER_WORDS_CHANGE*). I define firms as treatment (control) firms if the firm is in the highest (lowest) quartile of *BOILER_WORDS_CHANGE* and missing

otherwise.[51] Thus, *TREAT* is set to 1 (0) for treatment (control) firms that experience a greater (lesser) increase in the use of boilerplate post-GN8 revision. Furthermore, Figure 4.1 shows that *BOG* is less likely to be affected mechanically by *BOILER_WORDS_CHANGE*,[52] thus providing more confidence in the DiD research design. Finally, I also define *POST* as equal to 1 for observations after the effective date of the GN8 revision (1 May 2013) in the DiD analysis.

[*Insert Fig. 4.1 about here*]

Next, for each treatment firm, I select a matched control firm based on a propensity score after a logit model is estimated. *TREAT* is the dependent variable in the logit model, and I include *SIZE, LEVERAGE, ROA, MTB, AGE, LNBSEG, LNGSEG, SPECIAL, M&A, SEO, HIGHTECH, REGULATED, RESOURCES, VOLATILITY* as well as all other covariates to control any pre-GN8 revision differences in readability between treatment and control firms. I also control for the

[51] I use the highest and lowest quartiles to ensure that the regulation had distinct impacts on high- and low-impact firms. However, using multiple observations in the pre-and post-GN8 revision period may raise a potential concern that serial correlation may affect the standard errors (McMullin et al., 2019). To address this concern, I averaged together the four years of data before and four years after the GN8 revision for each firm to create a single variable for each pre- and post-period. I conduct a robustness test (untabulated) using this sample and find that the reported results in Table 4.3 and 4.5 are unaffected.

[52] Since the boilerplate measure is calculated as a percentage of total word count, Lang and Stice-Lawrence (2015) and Brown and Tucker (2011) raised concerns about the use of document length and boilerplate measures in the research design as they may affect each other mechanically. However, the length component of the *BOG* index in this study, 'Sentence Bog', is calculated based on the average sentence length across the entire document instead of the total word count. Therefore, using the *BOG* index in the research design is less likely to be influenced more directly mechanically by the boilerplate measure. Figure 4.1 shows that while the number of words and *BOILER_WORDS* move in a similar direction over the sample period, the *BOG* and *BOILER_WORDS* only show this trend post-GN8 revision until 2016, thus lessening such concerns. In an untabulated calculation, I use four-word phrases (known as 'Fourgrams') to calculate *BOILER_WORDS_CHANGE* and the results remain unchanged.

firm, year and announcement type fixed effects. I match pre-GN8 revision firms with post-GN8 revision firms based on the observations' estimated propensity scores.[53] After matching, the pre-GN8 revision observations take the same value of *TREAT* as its post-GN8 revision match. I use this matched sample in all of the following analyses.

[Insert Table 4.2 about here]

4.4 Research design and empirical results

4.4.1 Summary statistics

Panel A of Table 4.2 shows that the mean (median) *BOG* for the sample of nonperiodic announcements is 72.713(73), where the mean (median) *BOILER_WORDS* is 300(31). There is an increase in *BOG* and the use of boilerplate disclosure post-GN8 revision (i e., *BOG* = 70.887 to 74.817; *BOILER_WORDS* = 253 to 353), and the mean differences are statistically significant. Furthermore, Panel B provides univariate DiD analyses using the propensity score-matched sample for the variables of interest. By construction, the firm for which *TREAT = 1* (firms with a greater increase in the use of boilerplate) have a significantly greater increase in *BOG* and *BOILER_WORDS* compared to those for which *TREAT = 0,* as well as a decrease in *CAR(-1,+1)* and *CAR(-1,+3)* surrounding the nonperiodic announcement where the

[53] I use nearest neighbour matching without replacement, using a caliper of 0.001. In an untabulated analysis, I run logit regressions using sample firms before matching with standard errors clustered by firm. Before I conduct nearest-neighbour propensity score matching without replacement, I find that the logit model explains the choice variable well, with a p-value from the χ^2 test of below 0.001. Further, the coefficients for SIZE and M&A are positively significant at better than the 5% and the 1% level, respectively, implying that larger firms and firms that engage in mergers and acquisitions tend to experience greater increases in boilerplate disclosures. However, there are significant differences in the distributions of the covariates between the pre-and post-regulatory change samples.

differences in means are statistically significant. Overall, the results provide univariate support for $\mathbf{H_{4.1}}$ and $\mathbf{H_{4.2}}$.

4.4.2 Nonperiodic announcement readability

I first investigate whether nonperiodic announcements became less readable post-GN8 revision for firms with higher use of boilerplate. I utilise the propensity score-matched sample to provide evidence that any potential differences in firm characteristics are not influencing the results. I implement a DiD approach to examine the change from the pre-GN8 revision period to the post-GN8 revision period in the readability of nonperiodic announcements for the most impacted firms ($TREAT = 1$) relative to least impacted firms ($TREAT = 0$). Specifically, I estimate the following OLS regression to test $\mathbf{H_{4.1}}$ clustering standard errors by firms and including firm, year and announcement type fixed effects:

$$\begin{aligned} BOG_{i,t} = {} & \beta_0 + \beta_1 POST_t + \beta_2 TREAT_i + \beta_3 POST_t{*}TREAT_i + \beta_4 SIZE_{i,t} + \\ & \beta_5 LEVERAGE_{i,t} + \beta_6 ROA_{i,t} + \beta_7 MTB_{i,t} + \beta_8 AGE_{i,t} + \beta_9 LNBSEG_{i,t} \\ & + \beta_{10} LNGSEG_{i,t} + \beta_{11} SPECIAL_{i,t} + \beta_{12} M\&A_{i,t} + \beta_{13} SEO_{i,t} + \beta_{14} HIGHTECH_{i,t} \\ & + \beta_{15} REGULATED_{i,t} + \beta_{16} RESOURCE_{i,t} + \beta_{17} VOLATILITY_{i,t\text{-}90} + FIRM\_FE \\ & + YEAR\_FE + ANNOUNCMENT\_FE + \epsilon_{i,d} \end{aligned} \quad (4.3)$$

where I include binary variables for the high-impact sample ($TREAT_i$) and post-GN8 revision observations ($POST$). The coefficient for $POST{*}TREAT$ is the DiD estimator. A positive and significant coefficient for $POST{*}TREAT$ is consistent with my prediction in $\mathbf{H_{4.1}}$ that the GN8 revision leads to a greater decline in the announcement readability for firms with a greater increase in the use of boilerplate disclosure. Table 4.3 reports results using the matched sample with this variable of interest, $POST{*}TREAT$, is significant and positive in columns 1 and 2 (3.603, t = 2.188; 4.683, t = 3.311). I interpret this as suggesting that the reduction in announcement readability post-GN8 revision is more pronounced for firms with a

greater increase in the use of boilerplate disclosure, and the result is robust when controlling for firm, year and announcement type fixed effects in column (2). Furthermore, I note that *POST* is not significant in both specifications, indicating that the overall reduction in the announcement readability post-GN8 revision is more pronounced for most impacted firms. Overall, the findings in Table 4.3 support $\mathbf{H_{4.1}}$ and suggest that firms that had a greater increase in the use of boilerplate disclosure post-GN8 revision had a greater reduction in nonperiodic announcement readability.

[Insert Table 4.3 about here]

4.4.3 Market reaction analysis

To test $\mathbf{H_{4.2}}$, I estimate the following OLS regression model, clustering standard errors by firms and including firm, year and announcement type fixed effects:

$$\begin{aligned}|CARs_{i,t}(m,n)| = {} & \beta_0 + \beta_1 POST_t + \beta_2 TREAT_i + \beta_3 POST_t{*}TREAT_i + \beta_4 SIZE_{i,t} \\ & + \beta_5 LEVERAGE_{i,t} + \beta_6 ROA_{i,t} + \beta_7 MTB_{i,t} + \beta_8 AGE_{i,t} + \beta_9 LNBSEG_{i,t} \\ & + \beta_{10} LNGSEG_{i,t} + \beta_{11} SPECIAL_{i,t} + \beta_{12} M\&A_{i,t} + \beta_{13} SEO_{i,t} + \beta_{14} HIGHTECH_{i,t} \\ & + \beta_{15} REGULATED_{i,t} + \beta_{16} RESOURCE_{i,t} + \beta_{17} VOLATILITY_{i,t-90} + \beta_{18} BIG4_{i,t} \\ & + \beta_{19} ANALYSTS_{i,t} + \beta_{20} NEWS_{i,t} + \beta_{21} NONPERD_{i,t} + \beta_{22} PERD_{i,t} \\ & + \beta_{23} TONE_{i,t} + FIRM\_FE + YEAR\_FE + ANNOUNCMENT\_FE + \epsilon_{i,d} \quad (4.4)\end{aligned}$$

where $|CARs(m,n)|$ is the absolute cumulative abnormal return for firm *i* over three day (*-1,+1*) and five day (*-1,+3*) windows. Consistent with $\mathbf{H_{4.2}}$, if *POST*TREAT* is significantly negative, it suggests a stronger negative market reaction to nonperiodic announcements for firms with a greater increase in the use of boilerplate post-GN8 revision. I include a set of control variables that prior research has shown to influence the market reaction (Lerman & Livnat, 2010; Yekini et al., 2016). I also add two dummy variables: *NONPERD* set to 1 if another nonperiodic announcement is released by the firm on days *t*-1 to *t*, and 0 otherwise; *PERD* set to 1 if the nonperiodic announcement is followed by the release of a periodic announcement on days *t*-1 to

t, and 0 otherwise. It is important to control for these events as daily market reactions might jointly capture nonperiodic announcements and other price-sensitive announcements. To control for the announcement tone (Yekini et al., 2016), I also include *TONE*, measured as the difference between positive and negative words in a nonperiodic announcement scaled by the total number of words in that announcement.[54] I define all variables in Appendix C.

Table 4.4 reports the univariate results of Models (4.1) and (4.2) in calculating abnormal returns and *CARs* surrounding nonperiodic announcements. The reported results for the full sample in Panel A depict a significant positive return on event day *t* (announcement day) of 0.185%. In addition, the three-day and five-day *CAR* windows are significantly positive, indicating that the nonperiodic announcements in the sample represent significant information events for firm value. Further, the lack of consistent negative returns over the event days -5 to 5 suggests that the positive reaction to nonperiodic announcements is not quickly reversed. Together, these results show that nonperiodic announcements are meaningful and informative to investors. Panel B compares the difference between matched samples. I find consistent evidence that the least impacted firms ($TREAT = 0$) only have a significant positive reaction post-GN8. However, there is no consistent evidence of a significant market reaction for the most impacted firms.

[Insert Table 4.4 about here]

[Insert Table 4.5 about here]

[54] I use word dictionaries developed explicitly for financial context by Loughran and McDonald (2011) to estimate announcement tone. I thank Tim Loughran and Bill McDonald for making sentiment word lists and Python code publicly available at https://sraf.nd.edu/textual-analysis/code/.

Table 4.5 reports the results of regressions examining the relationship between *BOG* and *CARs* post-GN8 revision. Using a propensity score-matched sample, I find that *POST*TREAT* is significantly negative for both three-day (-0.008, t = -2.113) and five-day (-0.011, t = -2.633) *CARs*. Thus, the negative market reactions around nonperiodic announcements are more pronounced for firms with a greater increase in boilerplate disclosure post-GN8 revision. These negative market reactions are economically significant in relation to the reaction to nonperiodic announcements as they represent 13.8% and 15.94% of the standard deviation of *CAR(-1,+1)* and *CAR(-1,+3),* respectively.[55] Overall, my findings support **$H_{4.2}$** and are consistent with prior theoretical studies (Bloomfield, 2002) that indicate impairing investors' ability to extract relevant information from boilerplate and less readable announcements imposes greater processing costs.[56]

4.4.4 Readability post-GN8 revision and sophisticated investors

This section extended previous analyses focusing on the impact of nonperiodic announcements' readability on different users' processing capacity post-GN8 revision. First, to test the impact of GN8 revision on the information processing differences between retail and institutional investors, I partition the matched sample based on whether the firm's institutional ownership is below or above the median and rerun the market reaction analysis. I obtain ownership data from Thomson

[55] The calculations are as follows: -0.137931=-0.008/0.059 and -0.159421=-0.011/0.069, where -0.008 and -0.011 are the DiD estimators presented in Table 4.5, and 0.059 and 0.069 are the standard deviations of *CAR(-1,+1)* and *CAR(-1,+3)* respectively, presented in Table 4.2.

[56] However, one potential explanation for the negative association between firms' use of boilerplate disclosure and CARs could be that managers have incentives to hide bad news. To omit the alternative explanation, I estimate the cumulative abnormal return of each announcement and rank them based on higher negative values because these represent announcements with significant bad news. We exclude the upper quartile of the announcements with bad news (1,479 observations) and rerun the market reaction regression. However, my coefficients for *CAR(-1,+1)* and *CAR(-1,+3)* remain statistically significant but at a 10 percent significance level.

Reuters Eikon and measure institutional ownership as firms' averaged institutional holdings during the fiscal year (Li, 2019). Table 4.6 shows that *POST*TREAT* is only significantly negatively associated with the market reaction for firms with lower institutional ownership. As the results are insignificant for the higher institutional group, I infer any impact of the GN8 revision on information processing reported in Table 4.6 is driven by retail investors. This is consistent with prior studies that highlight the associated processing difficulties of retail investors for less readable disclosures (Lawrence, 2013; Miller, 2010).

[Insert Table 4.6 about here]

Next, I examine the impact of the GN8 revision on sell-side analysts as they incorporate nonperiodic material information into their reports of forecasts and recommendations (Livnat & Zhang, 2012; Rubin et al., 2017). Analyst forecast data is collected from the I/B/E/S database available at Thomson Reuters Eikon. My dependent variable is $|Revision|$, measured as the absolute value of the difference between the mean analyst forecast issued in the 90-day window before the release of the nonperiodic announcement and the mean forecasts issued in the 30-day window after the release, scaled by the end-of-month stock price. Table 4.7 reports results obtained when I re-estimate Equation (4.3) with either $|Revision|$ or $ln|Revision|$ as a dependent variable. I find no consistent evidence of a relationship between analyst forecast revisions and reduced nonperiodic announcement readability. However, given my limited analysis, I hesitate to conclude how detrimental the lower announcement readability is to analysts' forecast post-GN8. Because analysts' forecast revision in response to the nonperiodic 8-Ks depends on their interpretation skills (Rubin et al., 2017), thus it may vary post-GN8 revision based on their skills. Together, these findings suggest that the increased processing costs of lower

readability for firms with greater use of boilerplate disclosure post-GN8 revision were predominantly borne by retail investors.

[Insert Table 4.7 about here]

4.5. Robustness tests

4.5.1 Alternative measures of readability

I also rerun the analysis using alternative readability measures from prior studies in Table 4.8. I use the Fog Index (*FOG*), Flesch–Kincaid (*FLESCH*), and file size *Ln(File_Size)*, measured as the natural log of the file size in kilobytes for nonperiodic announcements. A higher value of the *FOG, FLESCH* and *Ln(File_Size)* reflects lower readability. When I rerun Table 4.4, the results show that all alternative measures are positive and significant in columns 1, 2, and 3. Furthermore, in columns 4, 5 and 6, *POST*TREAT* is also positive for all measures using the matched sample, suggesting that the main results are robust to alternative readability measures.

[Insert Table 4.8 about here]

4.5.2 Placebo tests

In Table 4.9, I conduct a series of placebo tests to mitigate any potential concerns that my primary results are not driven by the GN8 revision. I reconstruct the TREAT by redefining the regulation date as pseudo dates precisely one and two years before the actual date (1 May 2013) and 1 July 2015, when ASX made a minor revision to GN8. When I rerun Table 4.4, I find that *POST*TREAT* is insignificant for all specifications. These results increase my confidence that the documented decline in the nonperiodic announcement readability for the firms with a greater increase in the use of boilerplate disclosure around the actual regulation is driven by the GN8 revision rather than a result of firm characteristics or a general time trend.

[Insert Table 4.9 about here]

4.5.3 Poor performance and managers' strategic disclosure

Li and Tan (2022) argued that managers may use nonperiodic 8-Ks to achieve positive market outcomes. Therefore, one potential explanation for the findings in Table 4.4 is that less readable nonperiodic announcements released in a period of poor earnings performance post-GN8 revision could be driven by managers' intention to obfuscate bad news to delay the incorporation of this news into the stock price. I identify loss firms in the matched sample and re-estimate Tables 4.3 and 4.5 by excluding those firms to explore this alternative explanation. In untabulated results, I find that *POST*TREAT* is positively (negatively) significantly associated with *BOG* (*CARs*) using restricted samples excluding loss firms. I infer that the reduced nonperiodic announcement readability post-GN8 revision is not driven by information uncertainty arising from poor firm performance. Further, I rerun Model (4.3), excluding regulated and resource firms because of their strong observed association with *BOG* in Table 4.3. My untabulated results remain consistent.

4.6 Conclusion

This study is motivated by concerns that managers' efforts to lessen litigation risk for timeliness and complete disclosure requirements by GN8 revision can impact the readability of nonperiodic announcements. I find a reduced readability post-GN8 revision pronounced for those firms that use boilerplate disclosure. The greater use of boilerplate allows managers to meet strict timeliness requirements while also increasing the length of disclosure to offset the concerns around completeness. Additionally, I show that firms that are more impacted by the GN8 revision through the greater use of boilerplate disclosure receive a stronger negative market reaction to their nonperiodic announcements. Collectively, my findings respond to Australian

directors' concerns about the pressure to balance 'immediate' and 'complete' disclosure requirements without breaching the revised GN8 and how managers' strategic use of boilerplate to alleviate such pressure may reduce announcement readability and increase processing costs for retail investors.

Figure 4.1: Trends in nonperiodic announcement readability, length, and boilerplate words

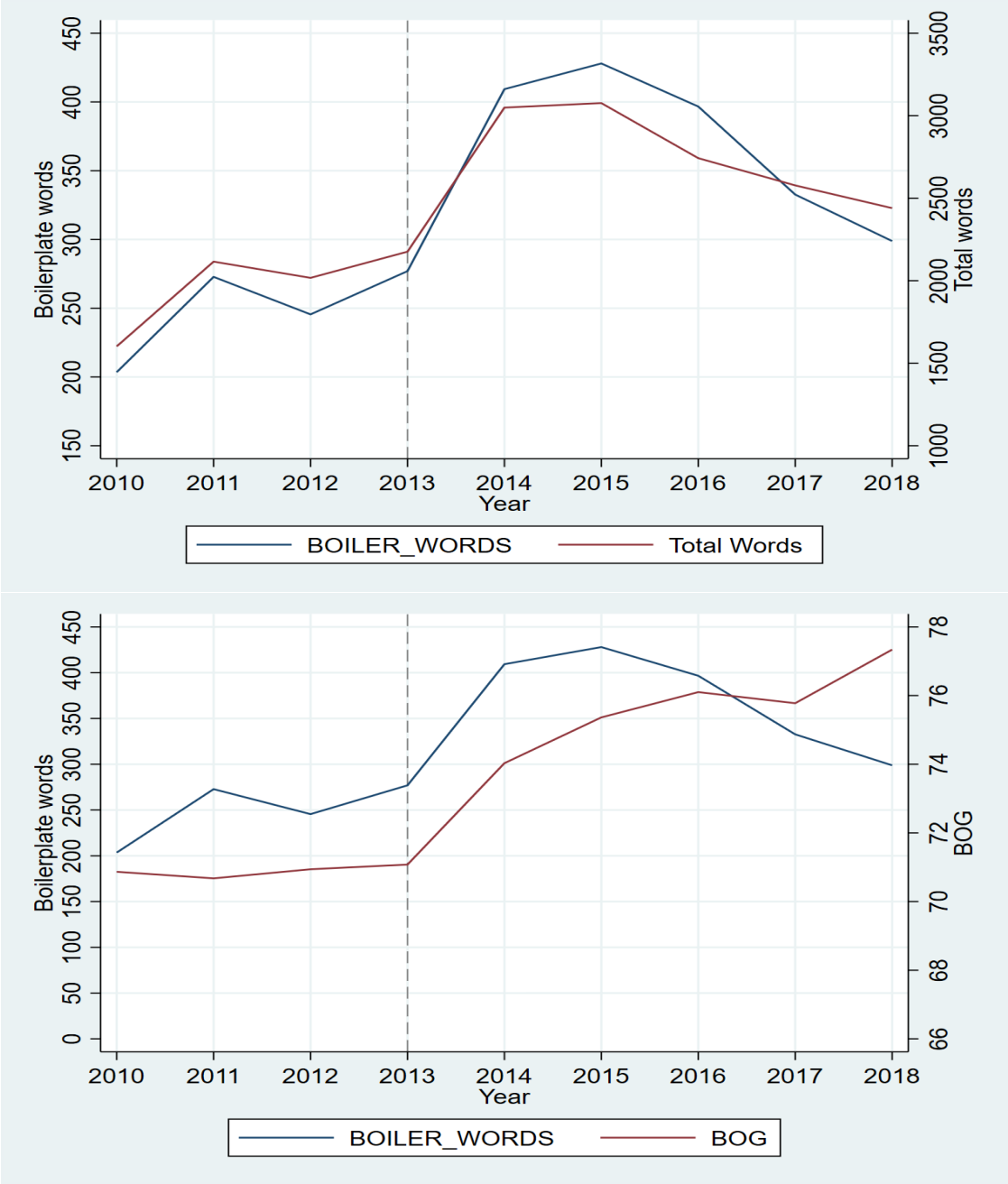

Table 4.1: Sample selection

ASX Primary Category Code	Nonperiodic announcement type	N	% of sample
1	Takeover announcements	1,269	8.16
2	Shareholder details	267	1.72
6	Issued capital	2,282	14.68
7	Asset acquisition and disposal	2,368	15.24
9	Stock exchange announcement	853	5.49
11	Progress report	7,042	45.31
12	Company administration	930	5.98
14	Other	382	2.46
17	ASX Query	144	0.93
18	Warrants	6	0.04
Total nonperiodic announcements (1)		**15,543**	**100%**
Restrictions on sample selection			
Drop if an announcement only contains presentation slides, tables, graphs and pictures		487	
Drop if an announcement only contains appendix tables (e.g., 3B, 3C) and is related to admission to the official quotation		176	
Drop if an announcement contains both nonperiodic and periodic information in a single document		61	
Drop if an announcement is not file readable		68	
Drop if an announcement contains less than 300 words		4,756	
Total restricted sample (2)		**5548**	
The final sample of nonperiodic announcements (1)-(2)		***9,995***	

Note. This table reports nonperiodic announcements of the constituent stocks of the S&P/ASX 200 Index, released by ASX, from 2010 to 2017. Nonapplicable periodic announcements are excluded from the analysis.

Table 4.2: Summary statistics

Panel A: Full sample

Variable	N	Mean	Std.Dev	Min	P50	Max	Mean Pre	Mean Post	Mean Diff.
BOG	9,995	72.713	16.007	36	73	111	70.887	74.817	3.931***
BOILER_WORDS	9,995	300	1,467	0.000	31	37,942[57]	253	353	100***
CAR (-1,+1)	9,995	0.003	0.059	-0.752	0.001	0.254	0.001	0.004	0.003***
CAR (-1,+3)	9,995	0.002	0.069	-0.752	0.001	0.922	0.000	0.005	0.005***
SIZE	9,995	21.801	1.781	17.473	21.813	25.887	21.788	21.815	-0.027
LEVERAGE	9,995	0.201	0.156	0.000	0.190	0.627	0.196	0.204	0.008***
ROA	9,995	0.044	0.139	-0.539	0.051	0.411	0.045	0.043	-0.002
MTB	9,995	2.813	3.196	0.257	1.770	19.732	2.687	2.957	0.264***
AGE	9,995	2.716	0.907	0.000	2.772	4.061	2.705	2.727	0.021
LNBSEG	9,995	1.389	0.539	0.000	1.386	2.398	1.378	1.401	0.023**
LNGSEG	9,995	1.148	0.554	0.000	1.098	2.398	1.190	1.098	-0.091***
SPECIAL	9,995	0.021	0.065	-0.075	0.001	0.429	0.173	0.023	0.005***
M&A	9,995	0.299	0.458	0.000	0.000	1.000	0.449	0.134	-0.314***
SEO	9,995	0.589	0.491	0.000	1.000	1.000	0.053	0.657	0.126***
HIGHTECH	9,995	0.038	0.192	0.000	0.000	1.000	0.026	0.052	0.026***
REGULATED	9,995	0.297	0.457	0.000	0.000	1.000	0.322	0.268	-0.054***
RESOURCE	9,995	0.273	0.446	0.000	0.000	1.000	0.278	0.266	-0.012
VOLATILITY	9,995	0.022	0.011	0.008	0.018	0.062	0.021	0.021	0.000***
BIG4	9,995	0.854	0.353	0.000	1.000	1.000	0.820	0.892	0.071***
ANALYST	9,995	2.223	0.818	0.000	2.564	3.091	2.133	2.325	0.191***
NEWS	9,995	1.148	0.899	0.000	1.098	3.332	1.386	0.872	-0.513***
TONE	9,995	0.004	0.012	-0.035	0.004	0.034	0.003	0.004	0.001***

Panel B: Univariate DiD (using matched sample)

Variable	*TREAT = 1 (Most impacted firms)*			*TREAT* = 0 (*Least impacted firms*)			Diff-in-Diff
	Pre Mean	Post Mean	Diff. Post-Pre	Pre Mean	Post Mean	Diff. Post-Pre	
BOG	69.457	75.106	5.648***	71.387	73.955	2.568***	3.080***
BOILER_WORDS	181.403	634.276	452.873***	281.862	216.987	-64.874	517.749***
CAR (-1, +1)	0.001	0.001	-0.000**	-0.000	0.006	0.006***	-0.007**
CAR (-1, +3)	0.002	0.001	-0.001***	-0.001	0.007	0.009***	-0.011***

Note. Panel A of this table reports the descriptive statistics for key variables for the full sample of 9,995 firm-announcement observations for all S&P/ASX200 firms. Panel B provides the univariate DiD results related to the variables of interest, including *BOG, BOILER_WORDS, CAR (-1, +1) and CAR (-1, +3). TREAT = 1* (*TREAT = 0*) indicates most (least) impacted firms that experience a greater (lesser) increase in the use of boilerplate disclosure post-GN8 revision. All continuous variables are winsorised at the first and ninety-ninth percentiles. Superscripts ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively, for two-tailed tests. In Panel B, *t*-statistics are presented in parentheses. See Appendix C for variable definitions.

[57] National Australia Bank Ltd released this announcement titled "Clydesdale Bank business update" on 7 July 2015 under the "Asset Acquisition & Disposal" announcement type. The total number of words for this announcement is 158,312.

Table 4.3: Matched sample analysis

Variable	Hyp. Sign.	*BOG*	*BOG*
	?	(1)	(2)
Constant	+	107.974***	76.251***
		(10.862)	(4.997)
POST	+	2.425	3.653
		(0.970)	(0.183)
TREAT	+	-2.124	-2.722
		(-1.387)	(-1.103)
POST*TREAT	+	**3.603****	**4.683*****
		(2.188)	**(3.311)**
SIZE	+	-1.430***	-1.446*
		(-2.935)	(-1.870)
LEVERAGE	+	1.399	-4.521
		(0.303)	(-1.066)
ROA	+	-5.004	-3.158
		(-1.017)	(-0.883)
MTB	+	-0.065	-0.090
		(-0.389)	(-0.592)
AGE	+	-1.457**	-3.712**
		(-2.250)	(-2.206)
LNBSEG	+	-0.549	0.186
		(-0.547)	(0.153)
LNGSEG	+	0.063	1.748
		(0.063)	(1.198)
SPECIAL	+	-6.787	-1.889
		(-0.982)	(-0.356)
M&A	+	-0.856	-0.770
		(-0.843)	(-0.995)
SEO	+	0.731	-0.414
		(0.731)	(-0.469)
HIGHTECH	+	2.176	-2.970**
		(0.516)	(-2.356)
REGULATED	+	4.040***	27.076***
		(2.751)	(5.180)
RESOURCE	+	5.792***	21.573***
		(3.959)	(5.378)
VOLATILITY	+	-143.602**	-64.094
		(-2.579)	(-1.348)
N		6,070	6,070
Adj. R^2		0.056	0.221
Firm/Year/ Announcement-type fixed effects		NO	YES

Note. This table reports the results of the Model 4.3 estimated over the propensity score-matched sample. The dependent variable is *BOG*. *POST* is set to 1 for observations since 2013. *TREAT = 1* (*TREAT = 0*) indicates most (least) impacted firms that experience a greater (lesser) increase in the use of boilerplate in disclosures post-GN8 revision. All continuous variables are winsorised at the 1st and 99th percentiles. Firm, year, and announcement-type fixed effects are included in column (2). The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for both columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 4.4: Univariate analysis of differences in the market reaction to the nonperiodic announcement

Event day	*Panel A: Full sample (N = 9,995)*		*Panel B: Matched sample*							
			TREAT = 1 (Most impacted firms) (N = 2,964)				*TREAT = 0 (Less impacted firms) (N = 3,106)*			
			POST = 0		*POST* = 1		*POST* = 0		*POST* = 1	
	Mean (%)	*t*-stat	Mean (%)	*t*-stat	Mean (%)	*t*-stat	Mean (%)	*t*-stat	Mean (%)	*t*-stat
t-5	0.036%	1.6395	0.083%	1.6714 *	0.043%	0.7183	0.052%	1.0999	-0.066%	-1.1757
t-4	-0.008%	-0.3738	0.026%	0.5585	-0.029%	-0.4936	-0.056%	-1.0806	-0.004%	-0.0653
t-3	0.005%	0.2357	-0.002%	-0.0506	-0.072%	-1.1672	0.052%	0.8785	0.104%	1.5117
t-2	-0.004%	-0.2168	-0.061%	-1.2634	-0.011%	-0.1828	0.041%	0.7969	-0.052%	-0.9149
t-1	0.021%	0.8982	0.047%	1.5491	-0.054%	-0.9265	0.037%	0.6467	0.034%	0.5436
t-0	0.185%	4.4635 ***	0.102%	1.1784	0.134%	1.3650	0.151%	1.8329 *	0.305%	2.4472 **
t+1	0.097%	2.8628 ***	-0.033%	-0.5320	0.052%	0.6862	-0.128%	-1.7190 *	0.311%	2.3918 **
t+2	0.015%	0.5994	0.083%	1.5894	-0.029%	-0.4667	-0.122%	-1.8182 *	0.181%	2.3564 **
t+3	-0.038%	-1.5416	0.068%	1.2306	0.015%	0.2487	-0.041%	-0.6622	-0.103%	-1.4527
t+4	0.011%	0.4511	0.052%	1.0295	-0.011%	-0.1633	-0.022%	-0.4292	-0.007%	-0.1266
t+5	-0.008%	-0.3915	-0.055%	-1.1724	-0.103%	-1.7013 *	0.001%	0.0297	0.121%	2.1148 *
CAR(-1,+1)	0.304%	5.1773 ***	0.143%	1.1817	0.132%	0.9928	-0.031%	-0.2322	0.651%	3.2472 ***
CAR(-1,+3)	0.281%	4.0406 ***	0.295%	2.0199 *	0.118%	0.7310	-0.193%	-1.1805	0.727%	3.1619 ***

Note. This table reports univariate event study results surrounding the release of nonperiodic announcements as calculated in Models 4.1 & 4.2. Results are presented using various return specifications. *CAR* is calculated for abnormal returns measured against the market return on the S&P/ASX200 equally weighted index. Panel A presents event study results for the full sample, whereas Panel B presents comparative event study results for matched sample for most impacted firms (*TREAT = 1*) and least impacted firms (*TREAT = 0*) and tests if they are significantly different from zero using Student *t*-tests. Superscripts ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively, for two-tailed tests.

Table 4.5: Market reaction post-GN8 revision

Variable	*CAR(-1,+1)*	*CAR(-1,+3)*
	(1)	(2)
Constant	0.108	0.259***
	(1.336)	(2.945)
POST	0.004	0.009**
	(1.238)	(2.206)
TREAT	0.057	0.085*
	(1.149)	(1.910)
POST*TREAT	**-0.008****	**-0.011*****
	(-2.113)	**(-2.633)**
SIZE	-0.006*	-0.014***
	(-1.835)	(-3.587)
LEVERAGE	0.017	0.031**
	(1.341)	(2.006)
ROA	-0.029	-0.024
	(-1.573)	(-1.083)
MTB	0.000	0.000
	(0.683)	(0.191)
M&A	0.002	0.001
	(1.109)	(0.594)
SEO	-0.003	-0.004
	(-1.107)	(-1.258)
HIGHTECH	0.003	-0.011
	(0.084)	(-0.440)
REGULATED	0.004	-0.001
	(0.070)	(-0.018)
RESOURCE	0.019	0.015
	(1.243)	(0.855)
VOLATILITY	0.313	0.275
	(1.292)	(1.064)
BIG4	-0.003	0.004
	(-0.422)	(0.560)
ANALYSTS	0.006	0.010**
	(1.465)	(2.154)
NEWS	-0.001	-0.001
	(-1.362)	(-1.183)
NONPERD	-0.001	0.000
	(-0.622)	(0.084)
PERD	0.010**	0.013***
	(2.133)	(2.604)
TONE	0.305***	0.385***
	(3.879)	(4.237)
N	6,070	6,070
Adj. R^2	0.074	0.080
Firm/Year/ Announcement-type fixed effects	YES	YES

Note. This table reports the results of the Model 4.4 estimated over the matched sample. The dependent variable is either *CAR(-1,1)* or *CAR(-1,3)*. All continuous variables are winsorised at the 1st and 99th percentiles. *POST* is set to 1 for observations since 2013. *TREAT = 1* (*TREAT = 0*) indicates the most (least) impacted firms that experience a greater (less) increase in the use of boilerplate disclosure post-GN8 revision. Regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for both columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 4.6: Retail vs institutional investors

Variable	High institutional ownership		Low institutional ownership	
	CAR(-1,+1)	*CAR(-1,+3)*	*CAR(-1,+1)*	*CAR(-1,+3)*
	(1)	(2)	(3)	(4)
Constant	0.019	0.007	0.184	0.173**
	(0.576)	(0.220)	(1.595)	(2.111)
POST	-0.004	-0.005	0.014**	0.016***
	(-1.003)	(-1.170)	(2.196)	(2.679)
TREAT	-0.001	0.005**	0.002	0.007
	(-0.389)	(1.970)	(0.438)	(1.517)
POST*TREAT	**-0.001**	**-0.007**	**-0.012****	**-0.019*****
	(-0.316)	**(-1.581)**	**(-2.128)**	**(-2.987)**
N	3,264		2,804	
Adj. R^2	0.016		0.024	
Control variables	YES		YES	
Firm/Year/ Announcement-type fixed effects	YES		YES	

Note. This table reports the results for the subsample partitioned based on the institutional ownership in firms and the rerun of Model 4.4 estimated over the matched sample. The dependent variable is *either CAR(-1,+1) or CAR(-1,+3). POST* is set to 1 for observations since 2013. *TREAT = 1* (*TREAT = 0*) indicates the most (least) impacted firms that experience a greater (lesser) increase in the use of boilerplate disclosure post-GN8 revision. All continuous variables are winsorised at the 1st and 99th percentiles. Regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for both columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 4.7: Financial analysts

Variable	|*Revision*|	*ln*|*Revision*|
	(1)	(2)
Constant	1.628***	0.970***
	(4.139)	(4.525)
POST	0.001	-0.011
	(0.010)	(-0.472)
TREAT	0.082	0.057*
	(1.480)	(1.774)
POST*TREAT	**-0.076**	**-0.029**
	(-1.135)	**(-0.716)**
N	6,009	6,009
Adj. R^2	0.176	0.293
Control variables	YES	YES
Firm/Year/ Announcement-Type fixed effects	YES	YES

Note. This table reports the analysis of the relation between analysts' earnings forecast and reduced nonperiodic announcement readability post-GN8 revision. The dependent variable is either |*Revision*| or *ln*|*Revision*|. *POST* is set to 1 for observations since 2013. *TREAT = 1* (*TREAT = 0*) indicates the most (least) impacted firms that experience a greater (lesser) increase in the use of boilerplate disclosure post-GN8 revision. All continuous variables are winsorised at the 1st and 99th percentiles. Regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for both columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 4.8: Alternative measure of readability

	Full sample			Matched sample		
Variable	*FOG*	*FLESCH*	*Ln(File_Size)*	*FOG*	*FLESCH*	*Ln(File_Size)*
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	18.990***	10.843***	6.417***	17.802***	10.190***	7.188***
	(16.902)	(14.363)	(9.431)	(14.040)	(12.477)	(9.791)
POST	**0.701*** **	**0.505*** **	**0.767*** **	0.616***	0.367**	0.709***
	(4.390)	**(3.919)**	**(10.800)**	(2.815)	(2.397)	(7.284)
TREAT	-	-	-	-0.152	-0.106	-0.113
	-	-	-	(-0.820)	(-0.765)	(-1.061)
POST*TREAT	-	-	**-**	**0.320***	**0.356****	**0.308*** **
				(1.828)	**(2.382)**	**(2.920)**
N	9,898	9,898	9,898	6,022	6,022	6,022
Adj. R^2	0.120	0.108	0.160	0.103	0.096	0.177
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm/Year/ Announcement-type fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table reports the results of the alternative measures of readability using both the full sample and matched sample. *POST* is set to 1 for observations since 2013. *TREAT = 1* (*TREAT = 0*) indicates the most (least) impacted firms that experience a greater (lesser) increase in the use of boilerplate disclosure post-GN8 revision. All continuous variables are winsorised at the 1st and 99th percentiles. Regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for both columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 4.9: Placebo tests

Variable	Date = 1 May 2011	Date = 1 May 2012	Date = 1 July 2015
	BOG	*BOG*	*BOG*
	(1)	(2)	(3)
Constant	87.061***	85.619***	89.739***
	(8.824)	(8.103)	(7.751)
POST	3.953*	3.519*	2.400
	(1.971)	(1.792)	(1.194)
TREAT	-1.314	0.015	-0.994
	(-0.611)	(0.008)	(-0.750)
POST*TREAT	**1.645**	**1.460**	**2.795**
	(0.776)	**(0.738)**	**(1.177)**
N	5,096	5,184	4,504
Adj. R^2	0.085	0.091	0.071
Control variables	YES	YES	YES
Firm/Year/ Announcement-type fixed effects	YES	YES	YES

Note. This table reports the Model (4) results across several placebo tests where the date of the regulation is changed to different pseudo-event dates. *POST* is set to 1 for observations since 2013. *TREAT = 1* (*TREAT = 0*) indicates most (least) impacted firms that experience a greater (lesser) increase in the use of boilerplate disclosure post-GN8 revision. The dependent variable is *BOG*. All continuous variables are winsorised at the 1st and 99th percentiles. Regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for both columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Chapter Five:

Textual Complexity of Corporate Announcements and Information Processing Role of Regulated Stock Message Boards

5.1 Introduction

This chapter investigates the information processing role of regulated stock message boards for textually complex disclosures and how it may affect price informativeness. Recent studies suggest that textually complex disclosures can influence investors to rely on alternative sources (e.g., analysts, news and social media) for firm-specific information (Asay et al., 2017; Miller, 2010). With the emergence of social media, investors can tap into the 'wisdom of crowds', where the aggregation of information discussed by non-expert individuals can often collectively solve the problem more accurately than experts, thus making it distinct from traditional media (Bartov et al., 2018; Chen et al., 2014; Lawrence, Ryans, & Sun, 2017; Lerman, 2020). Despite the positive role, false and misleading posts by general users,[58] experts (e.g., nonprofessional analysts) and firms' CEOs[59] can turn social media into a rumour mill and cause significant market disruption (Campbell et al., 2019; Jia et al., 2020; Lei et al., 2019; Sabherwal et al., 2011). With the recent

[58] For example, SEC v. Carol McKeown, Daniel F. Ryan, Meadow Vista Financial Corp., and Downshire Capital, Inc. and SEC v. Wall Street Capital Funding LLC, Philip Cardwell, Roy Campbell, and Aaron Hume. In Australia, see the media release "Jonathan Moylan Convicted" in regard to the Whitehaven hoax at https://asic.gov.au/about-asic/news-centre/find-a-media-release/2014-releases/14-179mr-jonathan-moylan-convicted/.

[59] In August 2018, a tweet by Tesla's CEO, Elon Musk, about taking Tesla private resulted in a 6% increase in Tesla's stock price, which later turned out to be misleading information and Musk was charged with securities fraud by the SEC.

GameStop stock manipulation caused by rumours on Reddit's WallStreetBets, market commentators urged regulators for greater scrutiny of shared investment-related social media posts through strict regulations.[60] However, restricting CEOs and experts from sharing investment advice via social media can offset processing benefits (Blankespoor, 2018; Campbell et al., 2019; Drake et al., 2022; Lei et al., 2019). Therefore, before greater regulatory control is imposed, this chapter utilises an Australian setting where stock message boards are regulated by Regulatory Guidance 162 (RG162) to provide insight into this policy debate by examining the following questions: (1) Does textual complexity within disclosures affect the extent to which investors engage in stock message board activities? If so, (2) Do higher levels of discussion on a regulated stock message board reduce stock price synchronicity for firms with textually complex disclosures?

RG162 was amended in 2007 to restrict CEOs and experts from engaging in stock message boards, and in 2013 GN8 was updated to require listed firms to monitor for potential rumours and misinformation across all social media. Therefore, the Australian market presents a strong setting to examine how a stock message board that is both 'free' of CEOs' and experts' opinions and regulated for misinformation can enable investors to process textually complex disclosures and influence stock price informativeness. Likewise, I first predict greater stock message board activity, namely views and discussions, around textually complex disclosures.

[60] Various regulatory warnings following the GameStop crisis include "Staff Report on Equity and Options Market Structure Conditions in Early 2021" by the SEC, "Episodes of Very High Volatility in Trading of Certain Stocks" by the European Securities and Market Authority (ESMA) and "Lessons to Learn from the GameStop Episode" by the UK Financial Conduct Authority (FCA). Notable regulatory initiatives towards regulating social media after the GameStop event include "Call for Evidence: On the European Commission Mandate on Certain Aspects Relating to Retail Investor Protection" by ESMA and "Guide for Finfluencers" by Financial Market Authority (FMA) New Zealand.

Second, CEOs' and experts' posts are more concentrated towards the industry they are specialised in and tend to be influential but also have various incentives to provide biased information (Drake et al., 2017; Eickhoff & Muntermann, 2016; Lei et al., 2019; Xu et al., 2021). However, Golub and Jackson (2010) propose a social network model in which a large naïve society converges on an accurate estimation when the most influential agents disappear. Thus, if RG162 diminishes CEOs' and experts' biases and GN8 reduces misinformation, investors can incorporate more credible firm-specific stock message board discussions for textually complex disclosures at lower processing costs, leading to lower stock price synchronicity (Hutton et al., 2009; Jin & Myers, 2006; Morck et al., 2000).

I further supplement these predictions by investigating how different levels of stock message board activity in processing textually complex periodic and nonperiodic disclosures may influence stock price informativeness. Unlike periodic disclosures, which provide anticipated earning performances, nonperiodic disclosures provide information on unanticipated material events (Debreceny et al., 2021; Li & Tan, 2022). However, it is challenging to detect whether the lower stock price synchronicity associated with stock message board discussions for firms with complex disclosures may be driven by misinformation and noise rather than fundamental information processing dynamics (Drake et al., 2017; Jia et al., 2020). Furthermore, gauging the information processing role of stock message boards in developed capital markets is challenging because retail investors' social media activity makes a small contribution to overall trading activity (Xu et al., 2021).

I use data from HotCopper, the most popular Australian stock message board regulated by RG162, which represents Australian retail investor populations in the absence of CEOs and experts. Further, HotCopper allows me to link each specific market announcement (periodic/nonperiodic) to a discussion thread, directly linking

stock message board activity to an announcement and the one which was not possible for the US data used in previous studies. I use a sample of 24,809 periodic and nonperiodic material announcements downloaded from the ASX website and a Python program I designed to extract user-generated announcement-specific views and discussions from HotCopper threads from 2010 to 2018. Using the number of views and discussions on HotCopper for each announcement-specific thread as a measure of stock message board activity allows me to link it with market participants' processing of complex disclosures. Further, I mainly use two textual complexity measures. First, I use a commercial software program, *StyleWriter*, to estimate the Bog Index (*BOG*) that captures the readability of announcements, and a higher *BOG* level reflects lower readability. I also include *Ln(TOTAL_WORDS)*, measured as the logarithm of the number of words in each price-sensitive announcement, to capture the textual quantity of disclosure. Since readability and length components significantly influence investors' processing costs (Blankespoor et al., 2020), these two measures serve the purpose of this study more appropriately.

My main findings are as follows. First, for the full sample analysis, I find greater stock message board views and discussions surrounding less readable announcements, but there is no such association for longer announcements after controlling for professional intermediaries (e.g., news media, analysts). Next, when I partition the periodic and nonperiodic announcements, stock message board views and discussions are driven by less readable and longer nonperiodic announcements rather than periodic announcements. This suggests that investors consider stock message boards to be a more meaningful channel for processing complex nonperiodic announcements than periodic announcements because supplementary information is not available in advance for these unanticipated material events. Next, I test whether regulated stock message boards improve stock price informativeness for firms with

less readable and longer announcements. I follow Roll (1988) to measure stock price synchronicity with R^2 from the market model regression and focus only on message board discussions because greater numbers of views do not mean better information processing (Lerman, 2020). Consistent with my prediction, I find a negative and significant association between higher numbers of stock message board discussions and stock price synchronicity for firms with longer and less readable announcements, and the association is more pronounced for nonperiodic announcements. These findings suggest that the regulated stock message board that is both 'free' of CEOs' and experts' influence and regulated for misinformation improves stock price informativeness, particularly in processing complex nonperiodic announcements.

My findings are robust to alternative readability and length measures and by excluding announcements within takeover and merger rumours windows in an alternative regression specification. To strengthen my findings, I also analyse samples of message board discussions that surfaced during non-trading windows and employ an instrumental variable approach. Collectively, these tests alleviate the endogeneity concern and provide confidence that the main results may be driven by information processing dynamics via the 'wisdom of crowds' rather than misinformation and noise. In an additional analysis, my results remain significant in firms with lower institutional ownership, suggesting that the average retail investor appears to rely more on the regulated stock message board for interpreting less readable and longer unanticipated information. However, I fail to find sufficient evidence on the professional intermediaries' role in interpreting longer and less readable periodic announcements when they fail to do that through message board discussions.

This study contributes to the literature in four ways. Firstly, I show that textually complex announcements, such as less readable and longer disclosures, can influence investors to rely on alternative channels for processing them at lower cost.

This adds to the literature that explores investors' information processing for textually complex disclosures (Asay et al., 2017: Blankespoor, 2018; Blankespoor et al., 2020; Miller, 2010).

Secondly, it contributes to the growing literature that examines the determinants and production of user-generated information on social media (Blankespoor, 2018; Lawrence, Ryans, & Sun, 2017; Lawrence, Ryans, Sun, & Soni, 2017; Lei et al., 2019; Lerman, 2020) by providing evidence that investors' reliance on stock message boards could be to help them interpret longer and less readable disclosures. In addition, I emphasise that prior evidence on higher stock message board activity surrounding 8-Ks (Debreceny et al., 2021; Lawrence, Ryans, Sun, & Soni, 2017; Lerman, 2020) is driven by retail investors using them as a more effective and timelier channel to process longer and less readable unanticipated material information.

Thirdly, my study contributes to the policy debate about regulating social media. A host of recent studies emphasise that unregulated social media can bias investors' discussions and distort stock price informativeness (Campbell et al., 2019; Chen et al., 2014; Farrell et al., 2021; Jia et al., 2020; Lei et al., 2019). This study shows that the stock message board that is free of experts and regulated for misinformation can provide more credible firm-specific information in processing textually complex disclosures by diminishing the bias in discussions, leading to lower stock price synchronicity. However, the lack of evidence in processing periodic disclosures in the absence of experts and the recent growing influence of 'finfluencers' and 'nonprofessional analysts' as experts in the capital market raises concerns because RG162 has not been updated to reflect the way social media have evolved. Therefore, this study provides valuable insight to ASIC, along with international securities regulators, in revisiting whether they should regulate nonprofessional

analysts because their posted research may complement or substitute that produced by experts (Campbell et al., 2019; Drake et al., 2022) while defusing finfluencer's influences.

Finally, I provide new insights into the determinants of stock price synchronicity (Ding et al., 2020; Huang et al., 2013; Jin & Myers, 2006; Morck et al., 2000; Roll, 1988) by highlighting the incremental role of regulated stock message boards. Notably, this research adds to the work of Ding et al. (2019) by highlighting that the textual complexity within nonperiodic disclosures can influence investors' stock message board activity rather than opaque discretionary accruals by confirming inferences in a more regulated setting. Further, my study differs from Huang et al. (2022) on the effect of Guba messages on lower stock price synchronicity in China, whereby I find such an association for regulated stock message board setting by highlighting its information processing role for textually complex disclosures. I conclude that a regulated stock message board can serve as a complementary information processing channel for formal disclosure.

The remainder of this chapter is organised as follows. Section 5.2 presents the regulatory settings, background literature and hypothesis development. Section 5.3 describes the data and variable construction procedure. Section 5.4 describes and research design and reports the results of the main regressions, while Section 5.5 reports the results of robustness checks. In Section 5.6, I perform additional analyses. The final section concludes the chapter.

5.2 The regulatory setting, review of literature and hypothesis development

5.2.1 Regulatory setting

Listed companies in Australia must comply with disclosure requirements in Listing Rules 3.1, including periodic announcements for anticipated financial results and nonperiodic announcements for major unanticipated corporate events or transactions. These announcements must be first disclosed via the ASX website before being disseminated through other channels, including social media.[61] ASIC views IDSs (e.g., stock message boards) as a more interactive platform rather than only a dissemination channel (e.g., Twitter) (ASIC, 2007). ASIC amended RG162 in 2007, intending to facilitate inexpensive IDSs for investors who are not securities industry professionals to exchange information, advice, and opinions. RG162 further clarifies that IDSs involved in providing professional securities advice (e.g., newswire reporters, professional and nonprofessional analysts) can only be operated with an Australian Financial Services licence. This clarification is intended to protect investors and ensure market integrity by minimising the risk of IDSs being used for market manipulation, insider trading or other misleading behaviour. Non-compliance with RG162 breaches the Australian Corporations Act 2001 and may result in enforcement actions. In essence, RG162 broadly limits the influence of professional advisors and companies in IDSs, such as stock message boards.

[61] In Australia, under Listing Rule 15.7, listed entities are restricted in releasing announcements to any other channels (e.g. press, financial analysts, or social media) other than ASX, unless and until it has been lodged with ASX and the entity has received an acknowledgement from ASX that the information has been released to the market. But in the US, listed companies can release any new material information via press release, and since 2013 they have been allowed to use social media as the primary channel of corporate disclosure (Prokofieva, 2015).

Despite the regulatory restrictions, anecdotal evidence suggests that social media in Australia can be a channel whereby false information can adversely affect stock prices (Clarkson et al., 2006; Prokofieva, 2015). For example, in 2013, The *Sydney Morning Herald* reported that Whitehaven Coal and David Jones experienced a substantial drop in stock price due to market rumours spread over social media channels. These cases provided the impetus for ASX to implement a series of obligations in their revised GN8 of Listing Rule 3.1 for posting and sharing on social media channels in May 2013 (Price, 2012). Specifically, the revised guidance requires listed entities to monitor well-known social media feeds for rumours or potential announcement leaks to avoid misinformation driving a 'false market' situation.[62] Therefore, Australian listed entities must ensure there is no false market situation by responding to speculation and market rumours on social media.

5.2.2 Stock message boards activity surrounding textually complex disclosures

Prior evidence suggests that the market reacts less strongly to longer and less readable disclosures (Lawrence, 2013; Li, 2008; Miller, 2010) because information that is more difficult and costly to extract is less completely reflected in the stock price (Bloomfield, 2002; Grossman & Stiglitz, 1980). Under such circumstances, investors can search for and expand efforts to obtain firm-related information through various alternative sources to minimise processing costs (e.g., analysts, news and social media) (Asay et al., 2017; Blankespoor, 2018; Blankespoor et al., 2020; Drake et al.,

[62] The term "false market" refers to a situation where there is material misinformation or materially incomplete information in the market. This situation may arise if (a) a listed entity makes a false or misleading announcement; (b) there is other false or misleading information, including a false rumour, market speculation or media comment; and (c) a segment of the market is trading based on market sensitive information that is not available to the market as a whole. Under such circumstances, placing a trading halt can minimise the likelihood that the stock is traded on ASX on the basis of misinformation.

2012). Despite the informational benefit of traditional information intermediaries, recent evidence suggests that less sophisticated investors are increasingly relying on low-cost interactive social media to support investment decisions (Bartov et al., 2018; Drake et al., 2017; Eickhoff & Muntermann, 2016; Farrell et al., 2021; Lawrence, Ryans, Sun, & Soni, 2017; Lerman, 2020). However, unlike microblogging platforms (e.g., Twitter), stock message boards are not subject to text length limitations[63] (Lerman, 2020) and have predominantly served as an interaction hub for independent and diverse retail investors to process information collectively (Blankespoor et al., 2020; Chen et al., 2014; Lawrence, Ryans, Sun, & Soni, 2017).

Prior studies document that user-generated discussions on stock message boards have a strong predictive and problem-solving capacity via the 'wisdom of crowds' and can improve stock price efficiency. Using data from HotCopper, an Australian stock message board, Leung and Ton (2015) found that stock prices react quickly to higher message board discussions for small-capitalisation stocks, facilitating the provision of value-relevant information to investors. Chen et al. (2014) and Campbell et al. (2019) documented that user-generated research articles with stipulated discussions from other users on the Seeking Alpha portal help predict future stock returns and earnings surprises. In some cases, evidence suggests estimation through collective discussions can beat professional analysts in making financial predictions (Eickhoff & Muntermann, 2016). Further, evidence suggests that stock message board discussions provide more firm-specific information for firms with poor information environments (Lawrence, Ryans, Sun, & Soni, 2017; Lerman, 2020), resulting in lower stock price comovement (Ding et al., 2020). Building on the above literature, I predict greater announcement-specific views and

[63] Before 2020, each tweet was limited to a maximum of 140 characters, and now the limit is 280 characters.

discussions on the stock message board surrounding longer and less readable ASX announcements because greater search (Lawrence Ryans, & Sun, 2017; Xu et al., 2021) and collective interpretation (Bartov et al., 2018; Chen et al., 2014) efforts may allow investors to process information at a lower cost. However, despite the stock message boards' continual efforts to help users detect high- versus low-quality content, this user-generated information could be noisy, unregulated, inaccurate and less credible (Antweiler & Frank, 2004; Bartov et al., 2018; Campbell et al., 2019; Drake et al., 2017; Lei et al., 2019). Therefore, it is difficult to infer whether the observed stock message board views and discussions are driven by fundamental information processing or misinformation/noise. My first set of hypotheses, in alternative forms, are:

$H_{5.1a}$: *There is a negative association between stock message board activity and the readability of disclosures.*

$H_{5.1b}$: *There is a positive association between stock message board activity and longer disclosures.*

Periodic announcements predominantly deliver anticipated financial results, and investors can access various alternative sources to comprehend them (i.e., analysts' reports). In contrast, nonperiodic announcements are sporadic material events (Debreceny et al., 2021; Li & Tan, 2022), thus they cannot gather supplementary information in advance or seek clarification from management through follow-up conference calls (Lawrence, Ryans, & Sun, 2017; Lerman, 2020; Li & Tan, 2022). Therefore, I expect a comparatively greater number of stock message board views and discussions surrounding textually complex nonperiodic announcements than periodic announcements. However, nonperiodic announcements may attract less retail investor attention because media coverage and analysts' commentaries are less pronounced surrounding these material events

compared to periodic announcements (e.g., earnings) (Lawrence, Ryans, & Sun, 2017; Lerman, 2020). This may result in lower numbers of stock message board views and discussions from investors in processing unanticipated nonperiodic announcements. On the balance of probabilities, I state my second set of hypotheses in alternative forms:

$H_{5.2a}$: *The negative association between stock message board activity and the readability of disclosures is stronger around unanticipated events than anticipated events.*

$H_{5.2b}$: *The positive association between stock message board activity and longer disclosures is stronger around unanticipated events than anticipated events.*

5.2.3 Role of regulated stock message board in processing textually complex disclosures and stock price synchronicity

The discussions on the stock message board appear to be meaningfully associated with better information processing (Lerman, 2020). Despite the positive role of discussions on stock message boards, prior studies have focused on settings where such platforms are unregulated (Campbell et al., 2019; Chen et al., 2014; Lei et al., 2019). An unregulated social media platform can introduce persuasion bias into naïve investors' discussions (DeMarzo et al., 2003; Jia et al., 2020) because when they collectively fail to verify the validity of repetitive information deriving from different sources, they become susceptible to 'influential agents' or experts for validation (Becker et al., 2017; Lorenz et al., 2011). However, evidence suggests that CEOs' opinions on social media are influential but can bias information to hide bad news (Lei et al., 2019; Xu et al., 2021). Further, analysts and newswire reporters tend to incorporate more of the industry or market-specific information they are specialised in (Chan & Hameed, 2006; Crawford et al., 2012; Drake et al., 2017; Piotroski & Roulstone, 2004) and recommend close to their consensus (Drake et al., 2014; Eickhoff & Muntermann, 2016). Therefore, allowing influential agents to

engage in stock message boards may bias investors' discussions by facilitating the introduction of more market and industry-wide information into investors' collective information sets, leading to higher stock price synchronicity.

In the Australian setting, where CEOs and professional and nonprofessional experts are restricted from engaging in stock message board discussions, companies must monitor those discussions. Hence I expect a very low level of influential agents' involvement in stock message boards. Consistent with the social network model of Golub and Jackson (2010), which highlights the point that collective discussions are more effective without influential agents involved, this provides a strong setting for examining the benefits of collective information processing. Thus, if the value of investors' collective discussions holds in this setting, I expect a stronger relationship between the stock message board discussions and stock price synchronicity for firms with less readable and longer announcements under RG162 and GN8 rules. By contrast, given the anecdotal evidence on the rumour mill role of social media in Australia, despite the enforcement of RG162, higher investors' discussions could still be undermined by biased information. On the balance of probabilities, my hypothesis is as follows:

$H_{5.3a}$: *The higher the number of stock message board discussions for less readable and longer disclosures, the lower the stock price synchronicity*

$H_{5.3b}$: *The higher the number of stock message board discussions for longer disclosures, the lower the stock price synchronicity*

Because being unanticipated aggravate naïve investors' processing capacity to comprehend textually complex nonperiodic announcements as they can not gather supplementary firm-specific information in advance, as they typically do for periodic announcements (Debreceny et al., 2021; Lawrence, Ryans, & Sun, 2017; Li & Tan, 2022). Under such circumstances, stock message boards can facilitate investors to

access user-generated information and use them to interpret textually complex nonperiodic announcements more effectively than periodic ones. Therefore, I expect the association between the number of stock message board discussions and stock price synchronicity to be more pronounced for textually complex nonperiodic announcements. Conversely, unlike Seeking Alpha, HotCopper does not provide analysts' reports. The user-generated information could only be useful to naïve investors if a sufficient number of users share their ideas, which is very unlikely for all announcements. Consequently, lower accessibility of firm-specific via HotCopper can influence investors to access the market and industry-wide information to interpret textually complex nonperiodic announcements and can price informativeness (Hutton et al., 2009; Jin & Myers, 2006). Despite the competing argument above, my final hypothesis is as follows:

$H_{5.3b}$: *The negative association between the number of stock message board discussions and stock price synchronicity is more pronounced for firms with less readable and longer nonperiodic disclosures.*

5.3 Data and variable description

5.3.1 Data

My sample is drawn from all ASX price-sensitive announcements by S&P/ASX 200-listed companies from 2010 to 2018. The initial sample comprises 24,809 price-sensitive announcement documents covering periodic and nonperiodic material events, and is downloaded from the ASX website in PDF format.[64] I first employ the Microsoft VBA program to convert all the PDF files into docx files and

[64] In Australia, all price-sensitive material announcements must be first released via the Signal G platform, and the Signal G database acts as a repository of all announcements made to ASX. The Morningstar DataAnalysis database uses the Signal G database to classify all announcements by date and time of release, according to announcement type and whether ASX highlighted such announcements as price-sensitive.

convert all docx files into plain text files using a Python program to conduct the parsing procedure. Following Bonsall et al. (2017), I exclude all the tables, header/title/bottom contact info (tagged with 'contact or further information' or 'about …'), markup tags (e.g., HTML), bullet point signs and special characters (e.g.? #$).[65] Prior to conducting textual analysis, periodic and nonperiodic announcement documents are dropped if they (1) only contain presentation slides, tables, graphs, or pictures, (2) only contain appendix tables (e.g., 3B, 3C) and are related to admission to official quotation, (3) contain both nonperiodic and periodic information in a single document,[66] (4) are nonreadable by *StyleWriter* software (e.g., when the file is corrupted or is a scanned PDF), or (5) contain less than 300 words.[67] My final sample contains 17,080 firm-announcement observations from 184 firms,[68] and Table 5.1 summarises the details of the sample selection criteria. Periodic and nonperiodic announcements are partitioned under different categories using the Morningstar DataAnalysis database. I collect firm fundamentals, stock returns, and analyst coverage data from Thomson Reuters Eikon. Daily news coverage data for firm *i* on day *d* to *d+1* is hand-collected from the Factiva database.[69]

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[65] The program also eliminates all the blank spaces and single non-alphabetic paragraphs within this procedure to ensure that all the tables and tabulated text are excluded. For detail, see Bonsall et al. (2017).

[66] I can draw one such example from the announcement made by Ausdrill Ltd on 15/08/2018 titled "FY18 Outstanding Results and Strategic Barminco Acquisition."

[67] The sample announcements with more than 300 words represents the upper 70% of the total announcement sample. However, the results remain consistent with the 5% variation in the cut-off point.

[68] To construct the sample, I verify the listed companies for each year over the sample period to ensure that my sample firms remained in the top S&P/ASX200 list during the study period for consistency. This process reduces the sample size from 200 to 184 firms.

[69] Since news articles in the Factiva database are not tagged by company name or a stock ticker, I formulate a search query to find matched news articles for each firm from January 2010 to December 2018. I start with each company's name as it appears in the S&P/ASX200 list and require the company name to show up in the news article. I filter for any news released from ASX and NZX

[Insert Table 5.1 about here]

5.3.2 Measures of textual complexity

I use two complexity measures. First, I use *BOG* to capture the writing clarity component of readability. I use *StyleWriter* to derive *BOG* for all announcements, with a higher score reflecting poorer document readability. I choose *BOG* because it overcomes the major criticism of the Fog Index related to capturing the word complexity based on using its proprietary 200,000-word list dictionary instead of syllable count alone (Bonsall et al., 2017).[70] Second, I employ a quantity-based measure, *Ln(TOTAL_WORDS)*, calculated as the natural logarithm of the total number of words in an announcement, to capture the information quantity component of readability. The underlying notion is that investors incur higher information processing costs for firms with longer and more detailed disclosures (Lawrence, 2013; Li, 2008).

5.3.3 Stock message board data

For my stock message board data, I use HotCopper, Australia's largest stock message board[71] with over 250,000 registered members, 200,000 unique visitors and 21 million page impressions per month. HotCopper operates under a strict code of

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newswires. Further, if a company changes its name during the sample period, I query all possible names and combine the search results. I also check the date of combined search results to ensure no overlapping between these news. Despite these best efforts, the matching of announcement-specific message board activity with the corresponding Factiva articles during that day is not perfect, and I acknowledge the noise in the matching procedure.

[70] For example, Loughran and McDonald (2014a) raised this concern by showing that all words with three or more syllables that Fog Index identified as 'complex' (e.g., company) should be easily understood by the least sophisticated investors. However, in additional tests, I show my results are robust to using the Fog Index as an alternative measure of readability and file size as an alternative measure of length.

[71] As of 2019, Alexa, a web traffic analysis company owned by Amazon, ranked HotCopper as the sixth most popular financial service site for investors after ASX and ASIC. See https://hotcopper.com.au.

conduct to comply with RG162, moderating any message board posting that does not comply, suspending users and retaining the right to take legal actions against any user for unethical or illegal use of the forum.[72] My primary construct of interest in this study is announcement-specific views and discussion data on HotCopper. This data is distinct from most prior research using US-based platforms (e.g., Yahoo Finance! and Seeking Alpha) as each item is tied to a specific ASX announcement. Therefore, examining my research questions using HotCopper allows me to provide additional insight by directly linking stock message board views and discussions as a channel to process specific market announcements, which was not possible in the US setting.

To understand the nature of posting on HotCopper and the interaction between users, Figures 5.1 and 5.2 provide two typical examples. An initial search using the ASX stock code would initially lead users to the firm's page containing threads/posts, as illustrated in Figure 5.1. Each thread comes with the company's ticker/tag symbol, subject, post starter, number of comments and views associated with the thread and date. The starter named 'ASX News' represents the threads related to ASX announcements. Figure 5.2 shows that each announcement-specific thread contains the names of all users who participated in discussions, the thread's title, the sentiment of the poster (whether they want to buy, sell, or hold the stock), and the stock price at the time of each user's discussion. Further, I interpret the users' interactions within these threads on HotCopper (see Figure 5.2) as a source of essential research and information interpretation, and as a dissemination tool.

[Insert Figure 5.1 about here]

[72] For details, see https://hotcopper.com.au/about/.

[Insert Figure 5.2 about here]

I designed a Python program to extract all data from the HotCopper website, including company ticker, date, announcement title, post starter, total views and discussions for each thread from January 2010 to December 2018. This results in an initial 134,980 threads comprising both private and announcement-specific data.[73] I then designed another Python program to identify announcement-specific threads by matching the sample announcement data described in section 5.4.1 based on stock ticker, announcement title, and release date. My final sample contains 17,080 announcement-specific threads on HotCopper. I use two measures of stock message board activity. Firstly, $VIEWS_{i,d}$ is the natural logarithm of one plus the number of views on a thread for a firm-specific announcement for firm i on day d.[74] Secondly, $DISCUSSIONS_{i,[d,d+1]}$ is the natural logarithm of one plus the number of announcement-specific discussions on the thread for firm i over days d to $d+1$, otherwise zero if there were no discussions (Chen et al., 2014).[75]

[73] Following a periodic or nonperiodic price-sensitive announcement being posted on the ASX website, the announcement is instantaneously available at HotCopper under a single thread and investors can start interacting under the title of the announcement or can start discussing it by opening a new thread. For the purpose of this study, I exclude the information content of private threads and focus on threads surrounding public price-sensitive announcements.

[74] Given that it is difficult to differentiate the number views within the first two days of the announcement released, I take the total views of each announcement.

[75] I choose a two-day discussion window because 67% of discussions occurred on the released day of the price-sensitive announcement, followed by an additional 19.3% discussions which occurred on the next day, while the remaining discussions occurred sporadically over the ensuing weeks. Similar to Chen et al. (2014), based on my reading of a random sample of 100 discussions that occurred out of the two-day window, I also find them to be less relevant to the released material announcement.

5.3.4 Defining stock price synchronicity

Following Roll (1988), I estimate $SYN_{i,[d+1,d+30]}$ for a 30-day window following the announcements,[76] using the R^2 from the following market model:

$$RET_{i,d} = \beta_0 + \beta_1 MKTRET_{i,d} + \beta_4 MKTRET_{i,d-1} + \beta_5 INDRET_{i,d} + \beta_6 INDRET_{i,d-1} + \epsilon_{i,d} \quad (5.1)$$

where $RET_{i,d}$ is the daily stock return of firm i on day d. $MKTRET_{i,d}$ $(INDRET_{i,d})$ is the daily return calculated as the value-weighted return on S&P/ASX200 at day d (value-weighted GICS code industry return). The lag returns ($MKTRET_{i,d-1}$ and $INDRET_{i,d-1}$) are included to tackle potential non-synchronous trading biases resulting from daily returns for estimating the market model. I run a regression (1) across each firm day for a rolling window of 40 days with a minimum of 30 daily observations. Following Morck et al. (2000), I estimate stock price synchronicity ($SYN_{i,d}$) as:

$$SYN_{i,[d+1,d+30]} = In\left[\frac{R^2}{1-R^2}\right] \quad (5.2)$$

where $SYN_{i,[d+1,d+30]}$ is the synchronicity index of firm i calculated over 30 days. R^2 is the coefficient of determination from the market model in Equation (5.1). To circumvent the bounded nature of R^2 within [0,1], I use a logistic transformation of R^2. By construction, a higher value of $SYN_{i,[d+1,d+30]}$ indicates that a firm's stock return is more closely tied to market and industry returns (higher return comovement).

5.3.5 Control variables

For the set used to test $\mathbf{H_{5.1}}$ and $\mathbf{H_{5.2}}$, consistent with prior literature, I control for a set of variables that have been identified as affecting the stock message board activity (Chen et al., 2014; Lawrence, Ryans, Sun, & Soni, 2017; Leung & Ton,

[76] For announcements made outside of trading hours, day zero is set to be the first business day after the announcement. For details, see Lerman (2020).

2015). To distinguish the impact of traditional intermediaries[77] on stock message board activity, I include $NEWS_{i,[d,d+1]}$ calculated as the natural logarithm of one plus the number of news articles recorded by Factiva about firm *i* over days *d* to *d+1* (a two-day window); I also include $ANALYSTS_{i,d}$ measured as the natural logarithm of one plus the number of unique analysts providing a forecast (from the I/B/E/S) for firm *i* on the day earliest in the month during the fiscal year. I control several return-based measures for high visibility/attention-grabbing stocks. Both abnormal returns ($RET_{i,[d-90,d-15]}$) and abnormal trading volume ($TURN_{i,[d-90,d-15]}$) are added to capture pre-announcement stock performance for firm *i* over the windows of *d-90* to *d-15*. To capture pre-announcement volatility, I also add $SRV_{i,d-90}$ measured as the standard deviation of monthly stock returns for firm *i* over the past 90 days. To differentiate the effect of textual sentiment from readability, I add $TONE_{i,d}$ measured as the number of positive words less the number of negative words divided by the total number of words in an announcement.[78]

All annual report data are from the most recent fiscal year as at the time of the announcement. Following Chen et al. (2014) and Leung and Ton (2015), I also add yearly firm control variables. These are: *SIZE*, defined as the natural logarithm of a firm's market value of equity as of the fiscal year-end; *LEVERAGE*, the total debt divided by total assets as of the fiscal year-end; *ROA*, the income before extraordinary items divided by total assets as of the fiscal year-end; *MTB*, the market capitalisation divided by the book value of equity as of the fiscal year-end; *M&A*, a binary variable

[77] Consistent with the prior literature, I argue that by controlling for the impact of traditional media, the effects of HotCopper activities against less readable announcements can then be interpreted as incremental to the effects of traditional media. See Jia et al. (2020) for more detail.

[78] In the same vein as prior literature, I use word dictionaries developed explicitly for the financial context by Loughran and McDonald (2011) to estimate announcement tone. I thank Tim Loughran and Bill Mcdonald for making sentiment word lists and Python code publicly available at https://sraf.nd.edu/textual-analysis/code/.

equal to 1 if the firm engaged in merger and acquisition transactions in the fiscal year and 0 otherwise; and *SEO*, a binary variable equal to 1 if the firm engaged in a seasoned equity offering in the fiscal year and 0 otherwise. Given that various industries might have different disclosure practices,[79] I also include three industry dummies, *HIGHTECH*, *REGULATED* and *RESOURCE*, and set each to 1 if the firm is in a high tech, a regulated or a resource industry, and 0 otherwise.

For stock price synchronicity analysis (**$H_{5.3a}$** and **$H_{5.3b}$**), in addition to the above control variables, I also control several other variables that prior studies find important. These are: *BIG4*, a binary variable to record whether firms are audited by Big 4 accounting firms; $ZERO\_RET_{i,d}$, the frequency of zero return day in a fiscal year for firm *i* on day *d* to control stock illiquidity and minimise the measurement error of using the market model in stock price synchronicity analysis (Gassen et al., 2020); *NIND*, the natural logarithm of the number of firms in the industry to which a firm belongs; and *HERFSALE*, the sum of the squared terms of the proportion of a firm's revenue to total revenue in the industry at the end of the previous fiscal year. To mitigate the potential influence of outliers, I winsorised all continuous variables at the top and bottom 1%. The definitions of all variables are given in Appendix C.

5.4 Research design and empirical results

5.4.1 Descriptive statistics and bivariate analysis

Panel A in Table 5.2 presents sample announcement frequency, number of views, and number of discussions across ASX announcement types, while Panel B

[79] For example, in Australia, listed mining exploration entities are exempt from the ASX's requirements to release half-yearly and preliminary final reports, but they are required to file quarterly reports detailing mining production, development and exploration activities. Due to their aggressive accounting techniques, they are more likely to attract a larger than average risk of shareholder lawsuits and thus required to generate additional disclosures (Prokofieva, 2015).

shows the distribution across industries. Regarding the frequency of announcement types, the largest group relates to progress (29.78%) and periodic reports (23.71%). However, announcements on 'other' reports and quarterly activity reports get the most views (3486.48 and 2149.62 views, respectively), while the number of discussions is highest for ASX Query and quarterly activity report announcements (6.884 and 6.488, respectively). The higher numbers of views and discussions for quarterly activity reports are not surprising because those reports are mandatorily prepared by mining, oil- and gas-producing entities with a detailed technical summary of exploration activities and incurred expenditures. From the industry analysis in Panel B, it is noteworthy that firms from the information technology and consumer staples industries generate the most views (4,391.49 and 2,989.62 views, respectively) and discussions (10.10 and 7.36 discussions, respectively).

[Insert Table 5.2 about here]

[Insert Table 5.3 about here]

Table 5.3 provides the descriptive statistics of all variables used in regression models. For the full sample in Panel A, the synchronicity measure ($SYN_{[d,\ d+30]}$) has a mean (median) of -0.806 (-0.748) and varies from -1.658 (25th percentile) to 0.007 (75th percentile). The mean (median) value of the *BOG* is 75.659 (76), and the mean (median) *Ln(TOTAL_WORDS)* is 7.258 (6.762), which translates into a mean (median) of 4,098 (797) words. The mean (median) $VIEWS_{i,d}$ (unlogged) is 1,268(260), whereas the mean (median) $DISCUSSIONS_{i,[d,d+1]}$ (unlogged) is 3.463(0.000). The mean (median) of *BIG4* is 0.866 (1.000), indicating that more than 86.6% of the sample firms have a Big 4 firm as their auditor. Of firms included in the sample, 4.4% are in the high-tech sector (*HIGHTECH*), 29.2% are regulated industries (*REGULATED*), and 26.6% are from resource industries (*RESOURCE*)

Panel B presents the bivariate analysis of the different mean values between periodic and nonperiodic announcements. In all cases, the differences in means are statistically significant. The mean value of *BOG* [*Ln(TOTAL_WORDS)]* for the periodic announcements is 80.478 (7,429) and 73.063 (2,244) for the nonperiodic announcements, suggesting that regular periodic reports are more textually complex. Nonperiodic announcements have higher $VIEWS_{i,d}$ (unlogged) and $DISCUSSIONS_{i,[d,d+1]}$ (unlogged) than periodic announcements (mean = 1354 compared to mean = 1110 views, and mean = 3.669 compared to mean = 3.081 discussions), suggesting that investors' demand/search and collective interpretation efforts are more concentrated toward unanticipated material events. However, periodic announcements have higher media coverage ($NEWS_{i,[d,d+1]}$) and analyst following ($ANALYSTS_{i,d}$) than nonperiodic announcements (mean = 1.187 compared to mean = 1.112 media items; mean = 2.31 compared to mean = 2.21 analyst reports), indicating that on average, more experts' resources are available for complex periodic announcements.

I also plot the association between the *BOG* [*Ln(TOTAL_WORDS)]*, and $VIEWS_{i,d}$ and $DISCUSSIONS_{i,[d,d+1]}$ for both periodic and nonperiodic announcements to illustrate their relationship on a bivariate basis. A review of Figure 5.3 shows that, on average, with the increase in *BOG* [*Ln(TOTAL_WORDS)]* over the sample period, there is a substantial increase in the $VIEWS_{i,d}$ and $DISCUSSIONS_{i,[d,d+1]}$ on HotCopper for both announcements, suggesting the growing influence of stock message boards in the investment community over the years.

[Insert Figure 5.3 about here]

5.4.2 Multivariate results

The research design for the multivariate analysis consists of two stages. To test the sets of hypotheses $\mathbf{H_{5.1}}$ and $\mathbf{H_{5.2}}$, the first stage examines the announcement-specific views and discussions on the stock message board surrounding less readable and longer announcements. In the second stage, I capture the effect of social media regulation on stock message board discussions in information processing by examining the association between textually complex announcements, stock message board discussions, and stock price synchronicity to test $\mathbf{H_{5.3}}$. I define the stock message board activity window *d* to *d+1* and the incorporation window over the ensuing 30 days as explained in Figure 5.4.

[Insert Figure 5.4 about here]

5.4.2.1 Stock message board activity surrounding textually complex announcements

To test the first and second sets of hypotheses, I construct the following ordinary least square regression model:

$$\begin{aligned} VIEWS_{i,d} \text{ or } DISCUSSIONS_{i,[d,d+1]} = {} & \beta_0 + \beta_1 COMPLEX + \beta_2 NEWS_{i,[d,d+1]} \\ & + \beta_3 ANALYSTS_{i,d} + \beta_4 RET_{i,[d-90,d-15]} + \beta_5 TURN_{i,[d-90,d-15]} + \beta_6 SRV_{i,d-90} \\ & + \beta_7 TONE_{i,d} + Firm\_Control_{i,y} + \sum \alpha_i FIRM_i + \sum \alpha_j YEAR_j + \\ & \sum \alpha_k ANNOUNCMENT\_TYPE_i + \epsilon_{i,d} \end{aligned} \quad (5.3)$$

where $VIEWS_{i,d}$ is the natural logarithm of one plus the number of announcement-specific views for firm *i* on day *d*, and $DISCUSSIONS_{i,[d,d+1],}$ is the natural logarithm of one plus the number of announcement-specific discussions for firm *i* over days *d* to *d+1*, and zero otherwise. *COMPLEX* is the primary variable of interest in Model (5.3), representing either *BOG* or *Ln(TOTAL_WORDS)*. I expect the higher *BOG* or *Ln(TOTAL_WORDS)* to influence higher stock message board activity – views, and discussions – and that such associations are stronger for nonperiodic announcements. Therefore, I predict β_1 to be positive. Besides the yearly firm control variables ($Firm\_Control_{i,y}$), I include three fixed effect dummies to control firm-specific,

announcement-specific and time trend variations. The reported *t*-statistics are adjusted using standard error clustered by the firm (Petersen, 2009). The definitions of all variables are given in Appendix C.

Table 5.4, Panel A, shows that both $VIEWS_{i,d}$ and $DISCUSSIONS_{i,[d,d+1]}$ are positive and significantly associated with lower readability (*BOG*) (0.004, t = 2.744; 0.002, t = 1.887 respectively) in columns 1 and 3. However, there is no significant association between either measure of the stock message board activity and *Ln(TOTAL_WORDS)*. In Panel B, I rerun the analysis, splitting the sample based on whether the announcement is periodic or nonperiodic. For the periodic announcement subsample, *BOG* is not significant, while *Ln(TOTAL_WORDS)* is negative and significantly associated with both $VIEWS_{i,d}$ and $DISCUSSIONS_{i,[d,d+1],}$ (-0.042, t = -2.537; -0.031, t = -2.560, respectively) in columns 6 and 8. In contrast, *BOG* remains positive and significantly associated with both types of stock message board activity for nonperiodic announcements (0.004, t = 3.194; 0.003, t = 2.303) in columns 9 and 11, and *Ln(TOTAL_WORDS)* is also positive and significant (0.053, t = 2.863 and 0.037, t = 2.059) in columns 10 and 12. My results show that poor readability and length are important for driving stock message board use in processing nonperiodic announcements, likely due to their unanticipated nature and lower coverage by traditional sources. Further, a one-standard-deviation increase in *BOG[Ln(TOTAL_WORDS)]* for nonperiodic announcements results in a 6.49% (4.12%) increase in the announcement-specific $VIEWS_{i,d}$ and a 4.87% (2.88%) increase in the announcement-specific $DISCUSSIONS_{i,[d,d+1]}$.[80] Overall, my findings are consistent with prior literature (Lawrence, Ryans, & Sun, 2017; Lerman, 2020)

[80] [16.245*(0.004) = 6.49%; 0.779*(0.053) = 4.12%] and [16.245*(0.003) = 4.87%; 0.779*(0.037) = 2.88%] where 16.245 (0.779) is the standard deviation of *BOG[Ln(TOTAL_WORDS)]* for nonperiodic announcements presented in Panel B, Table 5.3.

and provide confidence that these results are statistically and economically significant.

However, I offer two explanations to increase the understanding of the negative association of *Ln(TOTAL_WORDS)* with stock message board activity for periodic announcements in contrast to nonperiodic announcements' positive association. Firstly, from an untabulated analysis, I manually check and find that longer periodic reports belong to larger companies (e.g., Commonwealth Bank of Australia, Telstra Corporation Ltd, National Australia Bank Ltd) that get greater media coverage and analyst following.[81] Therefore, retail investors may rely more on the experts to interpret longer information rather than on themselves (Lawrence, Ryans, & Sun, 2017; Li & Tan, 2022). Secondly, the underlying theoretical argument is that relatively longer announcements may limit investors' ability and willingness to extract information due to higher information processing costs (Blankespoor et al., 2020; Bloomfield, 2002; Grossman & Stiglitz, 1980).

[Insert Table 5.4 about here]

5.4.2.2 Stock price synchronicity analysis

To test the hypothesis set of $\mathbf{H_{5.3}}$, I propose the following models to examine the interplay between textually complex announcements, stock message board discussions and stock price synchronicity under RG162:

[81] To provide confidence in the findings, I focus on top 20 firms, which represent more than 50% of the market capitalisation of the 184 sample firms. I manually check the five most lengthy periodic reports and, of these five, three (Commonwealth Bank of Australia, Telstra Corporation Ltd and National Australia Bank Ltd) belong to top 20 firms. The descriptive analysis shows that the mean number of words is 10,614 for the top 20 firms with mean news coverage (analyst following) of 1.836(2.792). In contrast, the mean number of words is 9,457 for the rest of the sample firms, with mean news coverage (analyst following) of 1.074(2.121).

$$SYN_{i,[d+1,d+30]} = \beta_0 + \beta_1 DISCUSSIONS_{i,[d,d+1]} + \beta_2\ NEWS_{i,[d,d+1]} + \beta_3 ANALYSTS_{i,d} + \beta_4 TURN_{i,[d-90,d-15]} + \beta_5 ZERO\_RET_{i,d} + \beta_6 BIG4_{i,d} + Firm\_Control_{i,y} + \sum \alpha_i FIRM_i + \sum \alpha_j YEAR_j + \sum \alpha_k ANNOUNCMENT\_TYPE_i + \epsilon_{i,d} \quad (5.4)$$

$$SYN_{i,[d+1,d+30]} = \beta_0 + \beta_1 DISCUSSIONS_{i,[d,d+1]} + \beta_2\ COMPLEX\_DUMMY + \beta_3 DISCUSSIONS_{i,[d,d+1]} * COMPLEX\_DUMMY + \beta_4 NEWS_{i,[d,d+1]} + \beta_5 ANALYSTS_{i,d} + \beta_6 TURN_{i,[d-90,d-15]} + \beta_7 ZERO\_RET_{i,d} + \beta_8 BIG4_{i,d} + Firm\_Control_{i,y} + \sum \alpha_i FIRM_i + \sum \alpha_j YEAR_j + \sum \alpha_k ANNOUNCMENT\_TYPE_i + \epsilon_{i,d} \quad (5.5)$$

where the variable *COMPLEX_DUMMY* can be either *BOG_DUMMY* or *Ln(TOTAL_WORDS)_DUMMY*. *BOG_DUMMY* [*Ln(TOTAL_WORDS)_DUMMY]* is a binary variable equal to one if the *BOG [Ln(TOTAL_WORDS)]* is above the top quartile value of *BOG[Ln(TOTAL_WORDS)]*. The coefficient of the interaction terms between these dummy variables and $DISCUSSIONS_{i,[d,d+1]}$, in Model (5.5) is the primary variable of interest. If firms with more stock message board discussions surrounding complex announcements have lower stock price synchronicity and if such an association is more pronounced for nonperiodic announcements, I expect it to be negative. Besides the yearly firm control variables ($Firm\_Control_{i,y}$), I also include three fixed effect dummies to control firm-specific, announcement-specific and time trend variations. The reported *t*-statistics are adjusted using standard errors clustered by firm. The definitions of all variables are given in Appendix C.

Table 5.5 reports the regression results of stock price synchronicity analyses. I first run Model (5.4) and show that $DISCUSSIONS_{i,[d,\ d+1]}$ is negative and significantly associated with stock price synchronicity ($SYN_{i,[d+1,d+30]}$) in column 1 at the 1% level (-0.026, t = -3.391) after controlling for news coverage ($NEWS_{i,[d,d+1]}$) and analyst following ($ANALYSTS_{i,d}$). These results provide initial confirmation that stock message board discussions contain credible firm-specific information that is different from the public news and facilitates incorporating such information into the stock

price to a greater extent. Specifically, a one-standard-deviation increase in $DISCUSSIONS_{i,[d,\ d+1]}$ results in a 2.576% decrease in stock price synchronicity. As this is 3.196% of the average $SYN_{i,[d+1,d+30]}$ across the sample firms, it suggests that the magnitude of the results is economically significant.[82] Consistent with $\mathbf{H_{5.3a}}$, I find that the coefficient for both interaction terms [$BOG\_DUMMY*DISCUSSIONS_{i,[d,d+1]}$ and $Ln(TOTAL\_WORDS)\_DUMMY*DISCUSSIONS_{i,[d,d+1]}$] are negative and significantly associated with stock price synchronicity in the full sample (-0.034, t = -2.329; -0.018, t = -2.316). When I rerun the analysis based on a subsample determined by whether the announcement is periodic or nonperiodic, I find that results for both interaction terms only hold for nonperiodic announcements (-0.038, t = -2.529; -0.032, t = -2.189), which is consistent with $\mathbf{H_{5.3b}}$.

Overall, my findings suggest that the regulated stock message board appears to play a more significant and timely role for investors in processing unanticipated complex nonperiodic announcements compared to periodic announcements, leading to greater incorporation of firm-specific information into the stock price. While these findings may indicate greater numbers of stock message board discussions facilitating the incorporation of complex nonperiodic information into prices, it may also reflect investors increasing their level of discussion in response to more frequent nonperiodic announcements that they find to be value relevant (Gassen et al., 2020).[83] This leads me to conduct further tests to understand the causal link between the numbers of

[82] -2.576% [=0.991*(-0.026)] and 3.196% [=0.991*(-0.026)/-0.806] where 0.991 is the standard deviation of $DISCUSSIONS_{i,[d,\ d+1]}$ and -0.806 is the mean of $SYN_{[d,\ d+30]}$ presented in Panel A, Table 5.3.

[83] Gassen et al. (2020) concluded that the information mechanisms on the price formation process using synchronicity metrics based on R^2 tend to be conceptually more affected by settings with a frequent flow of different disclosures.

stock message board discussions and stock price synchronicity for firms with textually complex nonperiodic announcements, and these are reported in section 5.5.

[Insert Table 5.5 about here]

5.5 Robustness checks

5.5.1 Alternative measure of readability and length

I rerun the stock price synchronicity analysis using alternative announcement readability and length measures from prior studies, as shown in Table 5.6. Following Bonsall et al. (2017) and Li (2008), I use the Fog Index (*FOG*) as a proxy for the clarity component of readability and file size [*Ln(File_Size)]* for the information quantity component of readability. Higher values of *FOG* and *Ln(File_Size)* reflect less readability and longer disclosure, respectively. Similarly, using alternative measures, I construct *FOG_DUMMY [Ln(File_Size)_DUMMY*] as a binary variable equal to one if the *FOG [Ln(File_Size)*] is above the top quartile value of the *FOG [Ln(File_Size)*] and interact it with $DISCUSSIONS_{i,[d,\ d+1]}$. Table 5.6 shows that the coefficient of both interaction terms is negative and significant for nonperiodic announcements in columns 5 and 6, while there is no such association for periodic announcements. This confirms that my main results for stock price synchronicity analysis are robust to alternative measures of readability and length.

[Insert Table 5.6 about here]

5.5.2 Takeover and merger rumours

Prior studies show that higher market reactions surrounding takeover rumours are accompanied by greater stock message board discussions (Clarkson et al., 2006), and merger rumours are accompanied by Twitter discussions (Jia et al., 2020). Beyond the rumours window, stocks that are frequently on stock message boards can

also be manipulated through a two-day pump followed by a two-day dump in the market (Sabherwal et al., 2011). Therefore, it raises concerns about whether the association between synchronicity and stock message board discussions for firms with less readable and longer announcements in Table 5.5 is driven by takeover or merger rumours surrounding material announcements. To explore this possibility, I collect takeover rumour data from Thomson Reuter Eikon and exclude announcement-specific discussions that coincide with takeover or merger rumour events from the analysis. A message board discussion is classified as coinciding if such a discussion occurs within a three-day window (*d-1to d+1*) relative to the takeover or merger rumours date. About 884 announcement-specific discussions are excluded as a result. Table 5.7 reports that $DISCUSSIONS_{i,[d,\ d+1]}$ remains negative and significant with $SYN_{i,[d+1,d+30]}$. Further, the coefficient of both interaction terms is negative and significant for the full sample, and this association is stronger for the nonperiodic announcements. Overall, this provides confidence that the results for the stock price synchronicity analysis in Table 5.5 are robust and are not driven by discussions surrounding concurrent takeover or merger rumours.

[Insert Table 5.7 about here]

5.5.3. Endogeneity

My inference that stock message board discussions for firms with less readable and longer announcements affect stock price synchronicity may be confounded by two important endogeneity concerns: reverse causality and unobservable omitted correlated variables.

First, while there is no compelling reason to believe that stock message board discussions are caused by stock price synchronicity, one cannot completely rule out the possibility of reverse causality. To mitigate this concern, I analyse the

announcement-specific discussions on the stock message board that surface during the non-trading windows. Despite the market being closed, stock message board users can still discuss textually complex announcements; thus, by construction, these discussions cannot be driven by stock price comovement. I test this intuition by running the stock price synchronicity analysis and dividing all announcements into two subsamples based on whether they were weekend or weekday (Monday–Friday) announcements. I identify 2,697 announcements that were discussed over the weekend or holidays.[84] The results in Table 5.8 suggest that the stock message board discussions show no difference based on the time of announcement release. The weekend/weekdays subsample analysis confirms that my results in Table 5.5 are not likely to derive from stock price synchronicity being driven by stock message board discussions for firms with less readable and longer nonperiodic announcements. Therefore, my main results are unlikely to be driven by reverse causality.

[Insert Table 5.8 about here]

Second, I employ two instrumental variables (IVs) for stock message board discussions to further mitigate concerns around endogeneity that might arise from unobservable correlated omitted variables. Following Ding et al. (2020), I use the annual advertising expenditures of a firm (*ADV_EXP*), measured as the natural log of one plus the firm's annual advertising expenditure. I expect message board discussions to be positively correlated with firms with higher advertising expenditures because they may attract more attention from both investors in general and registered users of HotCopper. I also collect data on HotCopper interruptions during my sample period from the HotCopper website to capture the possible exogenous shocks to its

[84] If the discussions associated with an announcement surfaced on Friday after the close of the market, then I estimate the announcement-specific discussions for Friday aftermarket, Saturday and Sunday, otherwise only for the weekend.

operations, as system-wide interruptions would negatively affect users' access to the stock message board. I follow a similar procedure as Jia et al. (2020) to identify HotCopper outages into the following categories: (1) sites crashes, (2) login/access/stability issues, (3) local issues arising from a network (e.g., Telstra outage) or power outage (e.g., 2016 South Australian blackout), and (4) other miscellaneous issues. I extract all the discussions tagged with disruption/interruption or outage at HotCopper and their timestamp and then manually review each discussion to identify potentially relevant threads explaining HotCopper interruptions.[85] After excluding insignificant interruption events (e.g., those lasting less than 45 minutes), 849 announcements are identified that overlap with the system-wide interruption events. I create a binary variable *INTERRUPT* to denote announcements that coincide with stock message board discussions related to HotCopper interruptions in the sample.

Column 1 of Table 5.9 reports the first-stage regression results, and I find that *ADV_EXP* (*INTERRUPT*) is significantly and positively (negatively) associated with stock message board discussions. The reported first-stage Kleibergen-Paap *rk* LM statistic rejects the null hypothesis, "that the instrument is under-identified", at the 1% level. Further, my reported Kleibergen-Paap *rk* Wald *F*-statistic (F= 82.967) and Cragg–Donald Wald *F*-statistic (F= 76.595) are greater than the critical value of the Stock–Yogo test, rejecting the weak-instrument hypothesis of the IV. Finally, Hansen's *J*-test for over-identification is 2.582 (p = 0.1081), which fails to reject the null hypothesis of the over-identification of the IV. In the second stage, I interact

[85] For power and network outages, I cross-check the HotCopper discussions with news coverage to establish the relevance of the disruptions. For example, I crosschecked a thread titled "Another Mobile Outage" at HotCopper against news reported at *The Guardian* on 21 May 2018 titled "Telstra mobile outage affects national network" to verify the disruption.

BOG_DUMMY [Ln(TOTAL_WORDS)_DUMMY] with the predicted number of stock message board discussions and rerun the stock price synchronicity analysis. Columns 3(4), 5(6) and 7(8) report the second-stage regression results and the negative and significant effect of the interaction terms *[BOG_DUMMY*PRED_DISCUSSIONS]* and *[Ln(TOTAL_WORDS)_DUMMY* PRED_DISCUSSIONS]* on $SYN_{i,[d+1,d+30]}$ for the full sample, and nonperiodic announcement subsample remains, therefore corroborating the main results in Table 5.5.

[Insert Table 5.9 about here]

5.6 Additional analysis

5.6.1 Investor types

Prior studies document that retail investors are more affected by longer and less readable disclosures than sophisticated investors (Lawrence, 2013; Miller, 2010). Evidence suggests that retail investors are increasingly expanding their processing efforts in a poorer information environment via low cost, easily accessible social media channels (Blankespoor et al., 2020; Lawrence, Ryans, Sun, & Soni, 2017; Lei et al., 2019; Lerman, 2020), while sophisticated investors can 'instantaneously' obtain information through various subscription sources (Drake et al., 2017). However, given the unfiltered and unverified nature of user-generated information on stock message boards, existing literature has labelled such information as noisy, inaccurate, or biased (Antweiler & Frank, 2004; Campbell et al., 2019; Jia et al., 2020). In contrast, HotCopper's operation under RG162 restricts professional intermediaries and CEOs from sharing their investment advice, and daily users on such stock message boards represent a large Australian retail investor population, not professional investors. Thus, it presents a stronger setting in which to examine the value of the stock message board discussions in a regulated environment, specifically

from the retail investors' perspective. I partition the sample based on whether the firm's institutional ownership is below or above the sample median, to investigate whether the benefits of processing less readable and longer announcements via the stock message board are driven by less sophisticated investors. I obtain institutional ownership data from Thomson Reuters Eikon and measure institutional ownership as the aggregate number of shares held by institutions, scaled by outstanding shares, at the beginning of the fiscal year.

I rerun the stock price synchronicity analysis. Table 5.10 reports that the coefficient of both interaction terms is only negative and significant for the low institutional ownership subsample in columns 3 and 4 and is stronger for nonperiodic announcements in columns 7 and 8. This suggests that the benefits of stock message board discussions are more pronounced for less sophisticated investors who do not have access to professional services to process textually complex announcements. Further, the reduced engagement of professional intermediaries and CEOs under the RG162 setting suggests that user-generated information on a regulated platform can facilitate the provision of unbiased information to retail investors for information processing, which contrasts with the prior findings in unregulated settings (Antweiler & Frank, 2004; Jia et al., 2020).

[Insert Table 5.10 about here]

5.6.2 The role of professional intermediaries

Prior accounting literature has documented that professional financial intermediary such as financial analysts (Campbell et al., 2019; Eickhoff & Muntermann, 2016; Lawrence, Ryans, & Sun, 2017), the business press (Drake et al., 2014) and newswire reporters (Drake et al., 2017) play an important role in creating and disseminating information for market participants. Prior evidence suggests that

retail investors rely on professional intermediaries to interpret periodic reports rather than go through entire documents (Lawrence, Ryans, & Sun, 2017; Lehavy et al., 2011). Given the complexity of periodic announcements and the limited processing capacity of retail investors, it is important to investigate whether professional intermediaries use their expertise to provide more useful information. However, within an RG162 setting, I argue that small investors' demand for and use of such external information would be contextual, specifically when they fail to interpret such information collectively on stock message boards. To test this research question, I only focus on periodic announcements. I interact *BOG_DUMMY [Ln(TOTAL_WORDS)_DUMMY]* with news media coverage ($NEWS_{i,[d,d+1]}$) and the number of analysts following ($ANALYSTS_{i,d}$). Table 5.11 reports that the coefficients of both interaction terms for the analyst are positive and significant, but no such association is found for news media. This is consistent with the previous findings that analysts increase the relative amount of industry and market-level information (Chan & Hameed, 2006; Piotroski & Roulstone, 2004), resulting in greater comovement in the firm-level security price. While I am hesitant to draw strong conclusions on analysts' role in interpreting less readable and longer periodic reports, there is a burgeoning literature on analysts' role; thus, I leave further investigation of this issue for future research.

[Insert Table 5.11 about here]

5.7 Conclusion

With the growing debate about regulating social media, this study investigates the role of the regulated stock message board in processing complex disclosures and how it may reduce stock price synchronicity. I utilise data from HotCopper, Australia's largest stock message board, which operates under RG162 restrictions on

CEOs' and experts' engagement, and GN8 regulation of misinformation. First, there is a significant increase in stock message board views and discussions surrounding complex disclosures, mainly driven by nonperiodic announcements covering a wide range of unanticipated material events. Consistent with Golub and Jackson's (2010) model, higher number of discussions on the regulated stock message board, which is free of CEOs and experts, reduce stock price synchronicity by facilitating more credible firm-specific information at lower costs for processing complex disclosures. However, such an association is more pronounced for processing complex nonperiodic announcements. Further, the processing benefit in respect of textually complex nonperiodic announcements appears stronger for firms with low institutional ownership. My findings contribute to the international debate on regulating social media by highlighting how regulated stock message boards can play a vital role in information processing, particularly for retail investors, in processing unanticipated material information.

Figure 5.1: Stock message board page for Beach Energy Limited (BPT)

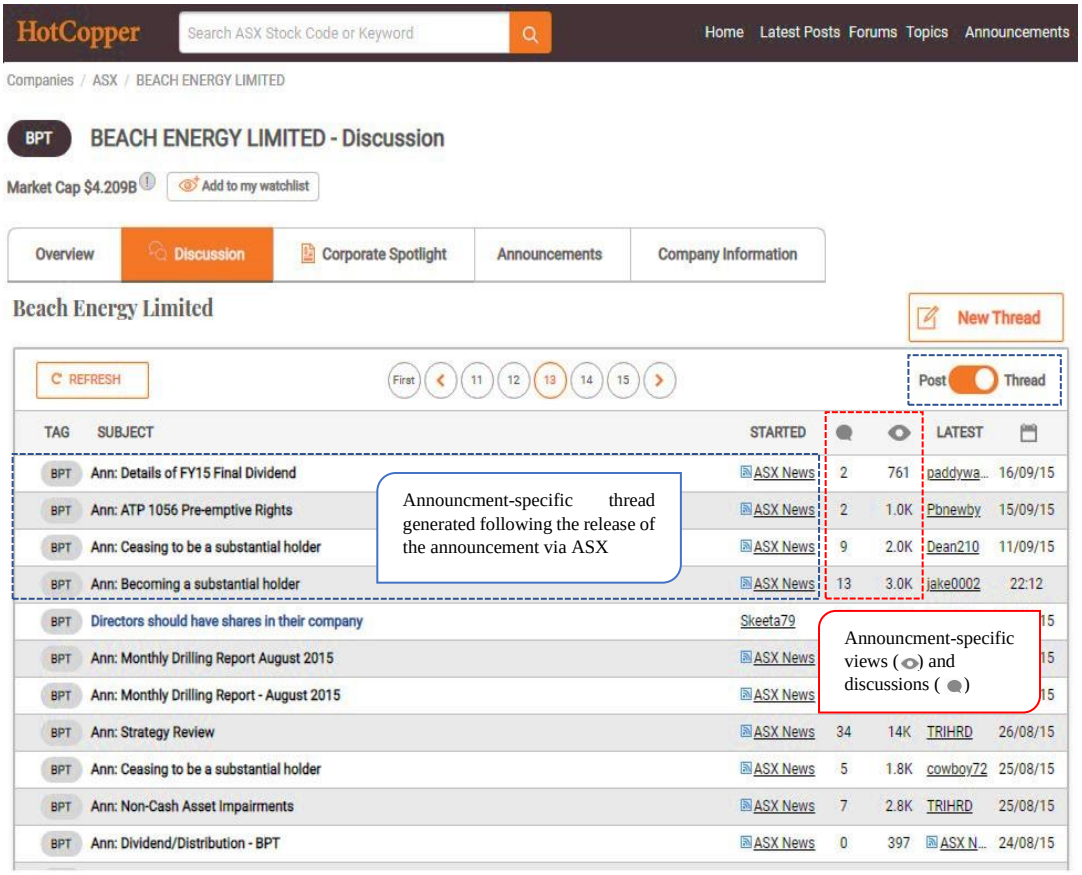


Figure 5.2: Stock message board discussions on an announcement

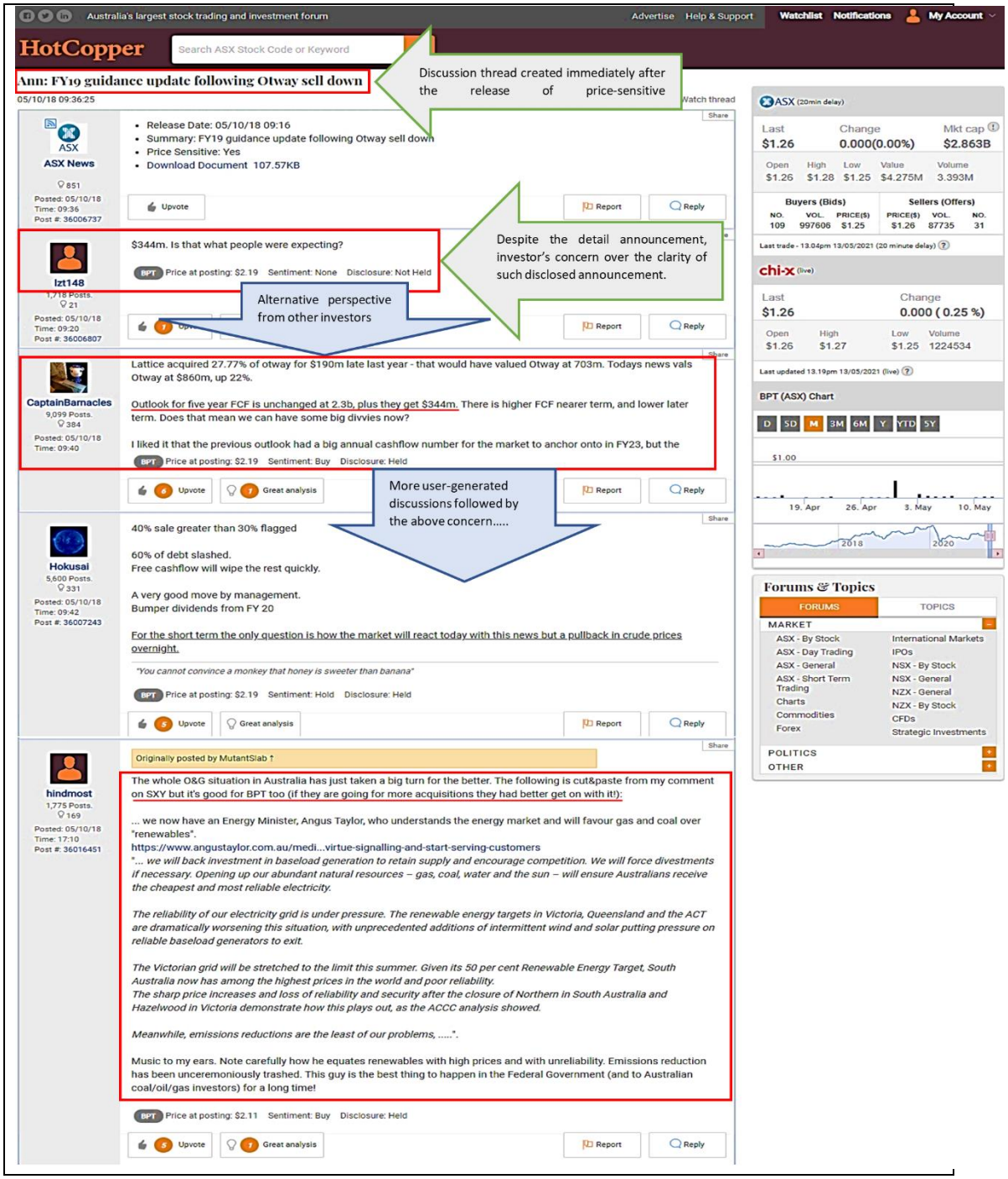
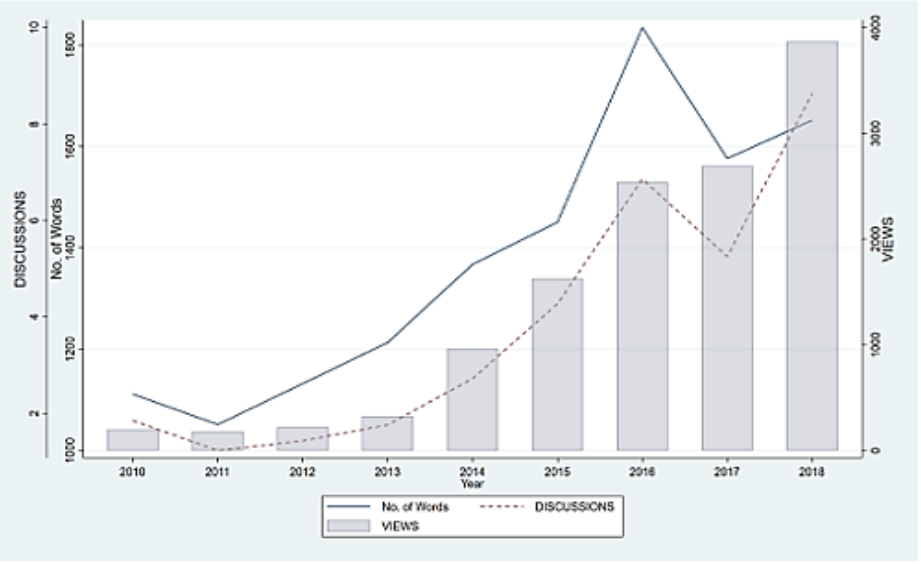


Figure 5.3: The trend in BOG (No. of Words), VIEWS and DISCUSSIONS on the stock message board over the sample period for periodic and nonperiodic announcements



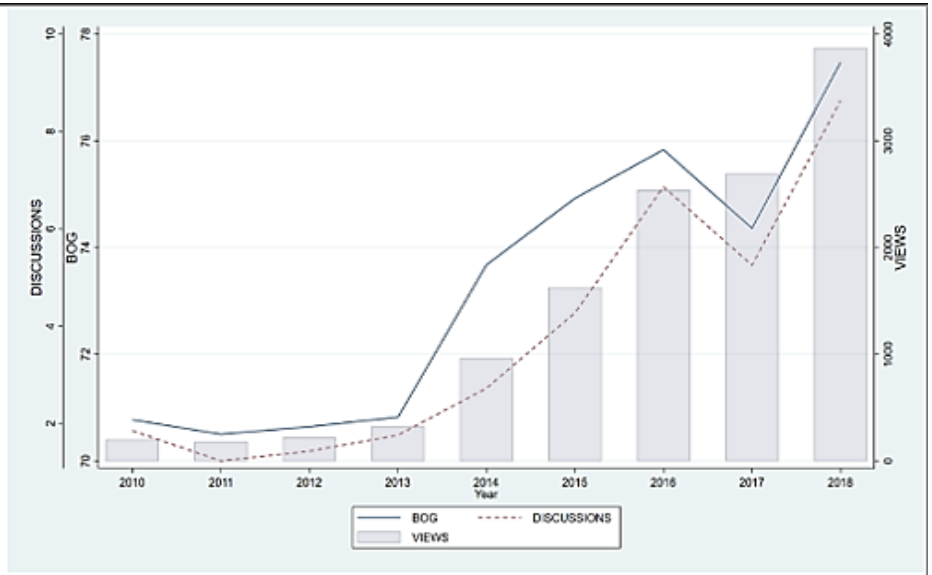
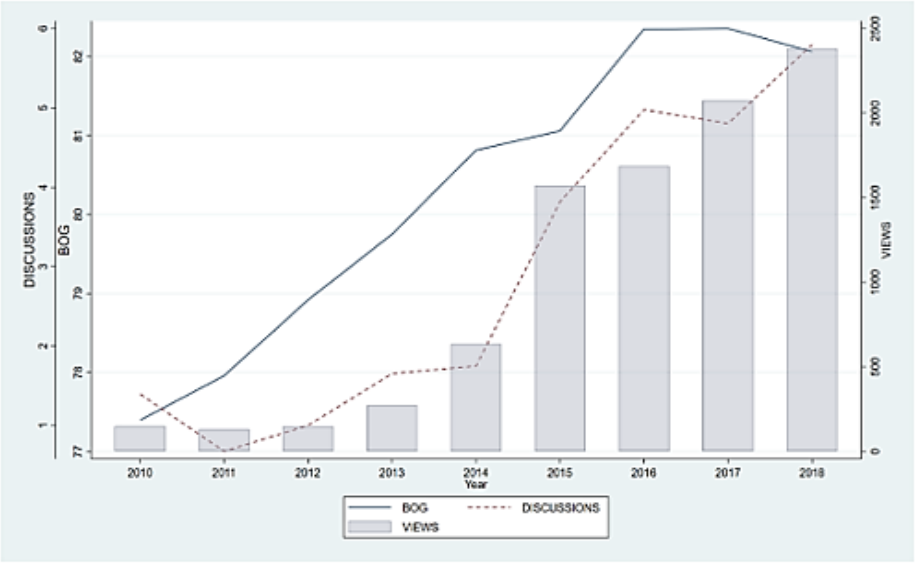


Figure 5.3.1 . The trend in *BOG* (*No. of Words*), *VIEWS* and *DISCUSSIONS* at stock message board over the sample period for nonperiodic announcements



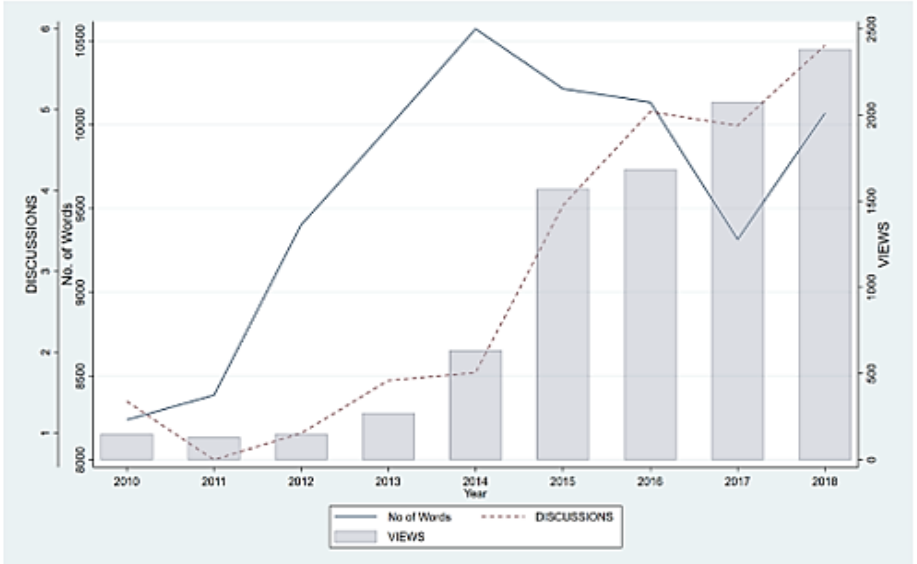
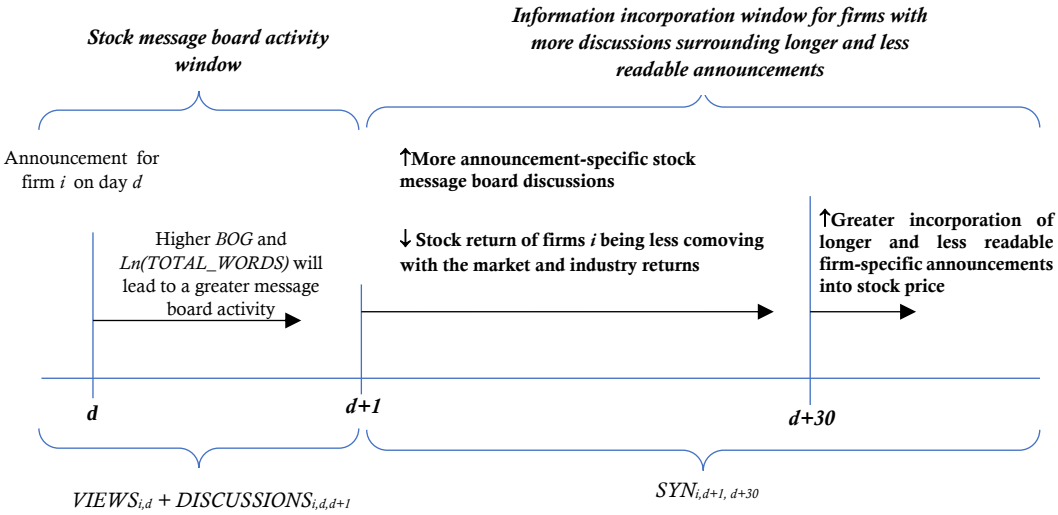


Figure 5.3.2 . The trend in *BOG* (*No. of Words*), *VIEWS* and *DISCUSSIONS* at stock message board over the sample period for periodic announcements

Figure 5.4: Timeline of stock message board activity surrounding longer and less readable announcements and information incorporation window



Note. The message board activity window starts on day *d* of the announcement, and the intensity continues for *d+1* based on the writing clarity and information quantity of the announcement. Therefore, a higher level of *BOG* and *Ln(TOTAL_WORDS)* for such announcements will influence investors to increase search and process efforts for complex announcements. The incorporation window for the frequently discussed announcements will begin from d+1 and continue over the ensuing 30 days. If the higher amount of discussion facilitates investors' ability to process longer and less readable announcements, I expect a greater (lower) incorporation of firm-specific information (market/industry-wide information), thus lower stock price synchronicity.

Table 5.1: Sample selection

Description	Observations
Total Price-sensitive announcements	24,809
Less: If an announcement only contains presentation slides, tables, graphs or pictures	1,002
Less: If an announcement only contains appendix tables (e.g., 3B, 3C) and are related to admission to official quotation	194
Less: If an announcement contains both nonperiodic and periodic information in a single document	102
Less: If an announcement is not file readable	83
Less: If an announcement contains less than 300 words	6,348
The final sample	**17,080**

Note. This table reports data on sample selection. The sample comprises all the periodic and nonperiodic announcements released during the sample period from 2010 to 2018.

Table 5.2: Sample distribution by announcement types and industries

Panel A: Distribution of announcement-specific views and discussions by announcement type

ASX Codes	Announcement Type	# of Annc.	% of Annc	Mean Views	Mean Discussions
	Periodic Announcements				
3	Periodic reports (including earnings announcements)	5,881	23.71	878.42	2.15
4	Quarterly activities report	1,192	4.80	2,149.62	6.48
5	Quarterly cash flow report	273	1.10	1,673.53	4.22
8	Notice of meeting	49	0.20	446.84	1.14
10	Dividend announcement	625	2.52	401.77	0.71
15	Chairman's address	270	1.09	683.37	1.46
	Total periodic announcements (1)	**8,290**	100%		
	Nonperiodic Announcements				
1	Takeover announcements	1,431	5.77	1,091.08	2.47
2	Shareholder details	284	1.14	1,349.54	3.14
6	Issued capital	2,621	10.56	870.36	2.13
7	Asset acquisition and disposal	2,394	9.65	859.56	2.07
9	Stock exchange announcement	860	3.47	2,035.04	5.47
11	Progress report	7,388	29.78	1,494.05	4.06
12	Company administration	1,110	4.47	1,207.81	3.33
13	Notice of call	12	0.05	2,21.24	0.31
14	Other	237	0.96	3,486.48	3.71
16	Letter to shareholders	16	0.06	964.87	3.75
17	ASX Query	158	0.64	2,128.39	6.88
18	Warrants	8	0.03	324.22	0.46
	Total nonperiodic announcements (2)	**16,519**	100%		

Panel B: Distribution of sample announcements' specific views and comments by industry

GICS Codes	Industry group	# of Annc.	% of Annc.	Mean Views	Mean Discussions
1000-1499	Energy	3744	15.09	887.12	2.82
1500-1999	Materials	6561	26.44	2,596.73	6.85
2000-2499	Industries	3453	13.91	713.44	1.63
2500-2999	Consumer Discretionary	1769	7.13	805.63	1.79
3000-3499	Consumer Staples	964	3.88	2,989.62	7.36
3500-3999	Health Care	1100	4.43	1,713.92	3.99
4000-4499	Financial	2452	9.88	841.29	1.97
4500-4999	Information Technology	738	2.97	4,391.49	10.10
5000-5499	Communication Services	1095	4.41	1,952.62	4.53
5500-5999	Utilities	677	2.72	461.55	1.47
6000-6499	Real Estate	2256	9.09	314.18	0.37
	Total Price-sensitive announcements (1) +(2)	**24,809**	100%		

Note. This table reports the distribution of announcements by ASX primary category codes and by GICS Codes. ASX primary categories are based on Signal G, which organises the announcement based on 18 primary codes. The total sample includes 24,809 price-sensitive announcements of S&P/ASX200 firms from 2010 to 2018.

Table 5.3: Descriptive statistics

Variable	Panel A						Panel B								Mean Diff.
	Full sample						Periodic announcements				Nonperiodic announcements				
	N	Mean	SD	p25	p50	P75	N	Mean	SD	p50	N	Mean	SD	p50	
$SYN_{[d, d+30]}$	17,032	-0.806	1.351	-1.658	-0.748	0.007	5,964	-0.834	1.282	-0.791	11,068	-0.791	1.385	-0.722	0.043**
BOG	17,032	75.659	15.529	65	76	87	5,964	80.478	12.778	80	11,068	73.063	16.245	73	-7.414***
TOTAL_WORDS	17,032	4,098	10,127	493	797	2,451	5,964	7,429	11,265	3,197	11,068	2,244	8,543	587	-5,185***
Ln(TOTAL_WORDS)	17,032	7.258	1.266	6.216	6.762	7.996	5,964	8.239	1.406	8.318	11,068	6.731	0.779	6.428	-1.509***
$VIEWS_{i,d}$ *(unlogged)*	17,032	1,268	6,059	128	260	437	5,964	1,110	4,371	247	11,068	1,354	6,796	269	-3,017***
$VIEWS_{i,d}$	17,032	5.692	1.252	4.859	5.564	6.082	5,964	5.621	1.225	5.513	11,068	5.731	1.264	5.598	0.199***
$DISCUSSIONS_{i,[d,d+1]}$ *(unlogged)*	17,032	3.463	15.582	0.000	0.000	1.000	5,964	3.081	13.089	0.000	11,068	3.669	16.795	0.000	0.588***
$DISCUSSIONS_{i,[d,d+1]}$	17,032	0.488	0.991	0.000	0.000	0.693	5,964	0.424	0.959	0.000	11,068	0.523	1.004	0.000	0.099***
$NEWS_{i,[d,d+1]}$	17,032	1.138	0.906	0.000	1.098	1.791	5,964	1.189	0.929	1.097	11,068	1.113	0.893	1.098	-0.076***
$ANALYSTS_{i,d}$	17,032	2.246	0.777	2.079	2.564	2.772	5,964	2.315	0.695	2.564	11,068	2.213	0.811	2.564	-0.101***
$RET_{i,[d-90,d-15]}$	17,032	0.004	0.051	-0.019	0.002	0.026	5,964	0.007	0.057	0.004	11,068	0.003	0.048	0.001	-0.003***
$TURN_{i,[d-90,d-15]}$	17,032	0.006	0.006	0.001	0.003	0.006	5,964	0.006	0.007	0.004	11,068	0.005	0.006	0.003	-0.001***
$SRV_{i,d-90}$	17,032	0.021	0.011	0.013	0.018	0.025	5,964	0.022	0.099	0.017	11,068	0.021	0.099	0.018	0.000***
TONE	17,032	0.003	0.012	-0.003	0.002	0.011	5,964	0.001	0.009	-0.000	11,068	0.004	0.012	0.004	0.003***
SIZE	17,032	21.811	1.678	20.731	21.792	22.961	5,964	21.839	1.541	21.796	11,068	21.814	1.737	21.793	-0.024
LEVERAGE	17,032	0.203	0.162	0.066	0.191	0.301	5,964	0.211	0.166	0.199	11,068	0.199	0.157	0.191	-0.011***
ROA	17,032	0.052	0.131	0.012	0.054	0.106	5,964	0.058	0.126	0.057	11,068	0.049	0.133	0.053	-0.008***
MTB	17,032	3.031	3.545	1.161	1.831	3.203	5,964	3.163	3.675	1.853	11,068	2.958	3.469	1.821	-0.205***
HIGHTECH	17,032	0.044	0.206	0.000	0.000	0.000	5,964	0.042	0.199	0.000	11,068	0.044	0.206	0.000	0.043
REGULATED	17,032	0.292	0.454	0.000	0.000	0.000	5,964	0.306	0.461	0.000	11,068	0.284	0.451	0.000	-0.022***
RESOURCE	17,032	0.266	0.442	0.000	0.000	1.000	5,964	0.242	0.429	0.000	11,068	0.279	0.449	0.000	0.037***
M&A	17,032	0.285	0.452	0.000	0.000	1.000	5,964	0.239	0.427	0.000	11,068	0.399	0.463	0.000	0.072***
SEO	17,032	0.591	0.492	0.000	1.000	1.000	5,964	0.581	0.493	1.000	11,068	0.597	0.491	1.000	0.015**
BIG4	17,032	0.866	0.344	1.000	1.000	1.000	5,964	0.884	0.319	1.000	11,068	0.856	0.351	1.000	-0.028***
NIND	17,032	4.747	1.266	3.988	4.543	6.475	5,964	4.663	1.269	4.454	11,068	4.794	1.262	4.543	0.131***
HERFSALE	17,032	3.339	0.219	3.152	3.326	3.457	5,964	3.338	0.224	3.302	11,068	3.339	0.216	3.328	0.002
$ZERO\_RET_{i,d}$	17,032	0.077	0.076	0.027	0.055	0.103	5,964	0.076	0.069	0.056	11,068	0.079	0.079	0.055	0.003**

Note. This table reports the descriptive statistics of the variables. Panel A provides descriptive statistics for the full sample containing 17,080 firm-announcement observations for all the announcements over the sample period from 2010 to 2018. In Panel B, I partition the sample into subsamples based on periodic and nonperiodic announcements. The subsample of periodic announcement includes 5,964 firm-announcement observations and the subsample of nonperiodic announcement includes 11,068 firm-announcement observations over the sample period. P25(P75) is the 25th (75th) percentile of the variable's distribution. All continuous variables are winsorised at the 1st and 99th percentiles. Superscripts ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively, for two-tailed tests. In Panel B, *t*-statistics are presented in parentheses. See Appendix C for variable definition.

Table 5.4: Stock message board activities surrounding textually complex announcements

Variable	Hyp. Sign	Panel A: Full Sample Analysis				Panel B: Nonperiodic vs Periodic announcement							
						Periodic announcements				Nonperiodic announcements			
		$VIEWS_{i,d}$		$DISCUSSIONS_{i,[d, d+1]}$		$VIEWS_{i,d}$		$DISCUSSIONS_{i,[d, d+1]}$		$VIEWS_{i,d}$		$DISCUSSIONS_{i,[d, d+1]}$	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	?	4.427***	4.755***	-0.748**	-0.547	4.348***	4.806***	-0.633	-0.369	4.248***	4.218***	-0.981***	-1.031***
		(10.767)	(11.243)	(-2.157)	(-1.518)	(9.552)	(12.116)	(-1.576)	(-1.007)	(9.751)	(9.126)	(-2.664)	(-2.635)
BOG	**+**	**0.004*** **		**0.002***		0.001		0.000		**0.004*** **		**0.003****	
		(2.744)		**(1.887)**		(0.743)		(0.229)		**(3.194)**		**(2.303)**	
Ln(TOTAL_WORDS)			-0.007		-0.006		**-0.042****		**-0.031****		**0.053*** **		**0.037****
			(-0.548)		(-0.560)		**(-2.537)**		**(-2.560)**		**(2.863)**		**(2.059)**
$NEWS_{i,[d,d+1]}$	+	0.008	0.010	0.030*	0.031**	-0.027	-0.015	-0.008	0.000	0.024	0.023	0.048***	0.047***
		(0.431)	(0.534)	(1.955)	(2.051)	(-0.999)	(-0.601)	(-0.357)	(0.014)	(1.212)	(1.085)	(2.798)	(2.670)
$ANALYSTS_{i,d}$	+	0.058	0.063	0.005	0.008	-0.028	-0.031	-0.054	-0.057	0.091*	0.098**	0.028	0.032
		(1.132)	(1.195)	(0.122)	(0.181)	(-0.429)	(-0.473)	(-0.888)	(-0.939)	(1.969)	(2.090)	(0.739)	(0.849)
$RET_{i,[d-90,d-15]}$	+	0.013	0.020	0.038	0.042	-0.179	-0.158	-0.270	-0.255	0.124	0.137	0.249	0.257
		(0.064)	(0.099)	(0.194)	(0.216)	(-0.705)	(-0.626)	(-1.075)	(-1.016)	(0.494)	(0.554)	(0.998)	(1.038)
$TURN_{i,[d-90,d-15]}$	+	11.427***	11.267***	10.637***	10.549***	14.242***	14.183***	12.008***	12.012***	9.736***	9.396***	9.787***	9.563***
		(4.335)	(4.288)	(4.824)	(4.767)	(3.908)	(3.911)	(3.540)	(3.495)	(3.149)	(3.064)	(3.458)	(3.405)
$SRV_{i,d-90}$	+	16.943***	16.888***	20.082***	20.042***	14.302***	13.936***	16.894***	16.591***	18.658***	18.545***	22.008***	21.946***
		(6.142)	(6.191)	(8.155)	(8.202)	(5.159)	(5.085)	(7.050)	(6.893)	(5.788)	(5.813)	(7.340)	(7.368)
TONE	?	2.292*	1.402	2.109*	1.565	3.628*	1.289	3.058	1.525	1.835	1.466	1.799	1.614
		(1.751)	(1.072)	(1.791)	(1.327)	(1.679)	(0.543)	(1.636)	(0.785)	(1.348)	(1.147)	(1.419)	(1.305)
SIZE	+	-0.015	-0.021	0.020	0.016	0.000	-0.003	0.028	0.026	-0.016	-0.022	0.022	0.019
		(-0.731)	(-1.013)	(1.199)	(0.970)	(0.011)	(-0.168)	(1.439)	(1.375)	(-0.753)	(-1.033)	(1.331)	(1.089)
LEVERAGE	+	-0.084	-0.083	-0.114	-0.114	-0.127	-0.126	-0.182	-0.182	-0.055	-0.044	-0.072	-0.064
		(-0.546)	(-0.536)	(-0.980)	(-0.976)	(-0.714)	(-0.725)	(-1.387)	(-1.393)	(-0.323)	(-0.253)	(-0.542)	(-0.480)
ROA	+	-0.156	-0.162	-0.161	-0.164	0.097	0.124	0.023	0.044	-0.299	-0.312	-0.261	-0.269
		(-0.611)	(-0.630)	(-0.683)	(-0.693)	(0.539)	(0.688)	(0.131)	(0.247)	(-0.939)	(-0.973)	(-0.877)	(-0.901)
MTB	+	0.013*	0.014*	0.009	0.010*	0.009	0.009	0.005	0.005	0.014*	0.015*	0.011*	0.011*
		(1.801)	(1.862)	(1.619)	(1.662)	(1.350)	(1.296)	(0.853)	(0.831)	(1.668)	(1.794)	(1.681)	(1.771)
HIGHTECH	+	0.317**	0.331**	0.226*	0.234*	0.295***	0.303***	0.190*	0.196*	0.320*	0.338**	0.237	0.248
		(2.333)	(2.509)	(1.748)	(1.846)	(2.629)	(2.728)	(1.704)	(1.743)	(1.906)	(2.064)	(1.507)	(1.607)
REGULATED	+	0.046	0.055	0.134**	0.140***	0.027	0.026	0.091	0.088	0.059	0.071	0.160***	0.167***
		(0.700)	(0.833)	(2.550)	(2.619)	(0.403)	(0.384)	(1.644)	(1.627)	(0.773)	(0.924)	(2.741)	(2.838)

Table 5.4. continued

RESOURCE	+	0.163*	0.179**	0.188**	0.198***	0.126	0.150*	0.158**	0.174**	0.177*	0.176*	0.196**	0.194**
		(1.895)	(2.063)	(2.529)	(2.646)	(1.610)	(1.887)	(2.237)	(2.403)	(1.737)	(1.740)	(2.295)	(2.305)
M&A	+	-0.038	-0.037	-0.010	-0.009	-0.038	-0.038	0.006	0.005	-0.028	-0.030	-0.009	-0.010
		(-1.175)	(-1.110)	(-0.324)	(-0.293)	(-0.809)	(-0.807)	(0.145)	(0.120)	(-0.776)	(-0.820)	(-0.278)	(-0.315)
SEO	+	0.032	0.034	0.021	0.022	-0.006	-0.010	-0.004	-0.007	0.060	0.063	0.041	0.043
		(0.672)	(0.702)	(0.510)	(0.531)	(-0.116)	(-0.198)	(-0.102)	(-0.177)	(1.037)	(1.101)	(0.874)	(0.914)
N		17,032	17,032	17,032	17,032	5,964	5,964	5,964	5,964	11,068	11,068	11,068	11,068
Adj. R^2		0.385	0.383	0.119	0.118	0.365	0.366	0.111	0.112	0.396	0.394	0.123	0.122
Firm/Year/ Announcement-Type fixed effects		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note. This table provides the results of OLS regressions examining the effect of the less readable and longer announcement on stock message board activity based on Equation (5.3). The dependent variables are either $VIEWS_{i,d}$ or $DISCUSSIONS_{i,[d,\ d+1]}$. Panel A presents the regression results using the full sample of 17,032 firm-announcement observations from 2010 through 2018. Panel B provides the regression results using a subsample of nonperiodic and periodic announcements. The subsample of periodic announcements includes 5,964 firm-announcement observations, and the subsample of nonperiodic announcements includes 11,068 firm-announcement observations over the sample period. All continuous variables are winsorised at the 1st and 99th percentiles. The regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for all the columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 5.5: Stock price synchronicity analysis

Variable	Full Sample			Periodic announcements		Nonperiodic announcements	
	$SYN_{i,[d+1,d+30]}$			$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-11.081***	-10.585***	-10.615***	-11.142***	-11.054***	-10.027***	-10.082***
	(-18.286)	(-5.984)	(-6.025)	(-5.775)	(-5.743)	(-5.171)	(-5.186)
***DISCUSSIONS*$_{i,[d, d+1]}$**	**-0.026*** **	0.018	-0.000	0.002	-0.003	0.021	0.003
	(-3.391)	(1.413)	(-0.001)	(0.078)	(-0.172)	(1.484)	(0.274)
BOG_DUMMY		0.021		0.038		0.017	
		(1.105)		(0.986)		(0.780)	
***BOG_DUMMY* DISCUSSIONS*$_{i,[d, d+1]}$**		**-0.034** ** **(-2.329)**		-0.009 (-0.385)		**-0.038** ** **(-2.529)**	
Ln(TOTAL_WORDS)_DUMMY			0.013		0.009		0.016
			(0.929)		(0.348)		(0.871)
***Ln(TOTAL_WORDS)_DUMMY * DISCUSSIONS*$_{i,[d, d+1]}$**			**-0.018** ** **(-2.316)**		-0.004 (-0.164)		**-0.032** ** **(-2.189)**
$NEWS_{i,[d,d+1]}$	0.011*	0.002	0.002	0.007	0.008	0.001	0.001
	(1.921)	(0.169)	(0.126)	(0.407)	(0.399)	(0.102)	(0.068)
$ANALYSTS_{i,d}$	0.027*	0.056	0.058	0.160**	0.161**	0.020	0.022
	(1.867)	(0.542)	(0.561)	(2.571)	(2.595)	(0.183)	(0.202)
$TURN_{i,[d-90,d-15]}$	-0.391	-0.888	-0.818	-5.021*	-5.018*	0.164	0.247
	(-0.461)	(-0.448)	(-0.409)	(-1.899)	(-1.901)	(0.086)	(0.129)
$ZERO\_RET_{i,d}$	-3.006***	-2.844***	-2.841***	-3.211***	-3.212***	-2.699***	-2.694***
	(-17.063)	(-4.679)	(-4.672)	(-6.005)	(-6.006)	(-3.673)	(-3.675)
BIG4	-0.064*	-0.103	-0.104	-0.040	-0.041	-0.140	-0.142
	(-1.806)	(-0.427)	(-0.430)	(-0.162)	(-0.168)	(-0.625)	(-0.630)
SIZE	0.418***	0.397***	0.396***	0.415***	0.414***	0.389***	0.387***
	(26.463)	(6.233)	(6.192)	(6.792)	(6.775)	(5.994)	(5.961)
LEVERAGE	0.057	0.054	0.052	0.022	0.022	0.095	0.092
	(1.025)	(0.262)	(0.253)	(0.126)	(0.125)	(0.400)	(0.388)
ROA	-0.183***	-0.194	-0.194	-0.393**	-0.397**	-0.085	-0.082
	(-3.882)	(-1.111)	(-1.109)	(-2.257)	(-2.273)	(-0.481)	(-0.466)
MTB	0.012***	0.010	0.011	0.007	0.007	0.010	0.010
	(5.035)	(1.176)	(1.195)	(0.735)	(0.751)	(1.056)	(1.068)
NIND	-0.674***	-0.408***	-0.395***	-0.503***	-0.515***	-0.369***	-0.345***
	(-8.338)	(-3.749)	(-3.682)	(-3.952)	(-4.166)	(-3.413)	(-3.205)
HERFSALE	0.805***	0.542	0.543	0.781**	0.782**	0.381	0.376
	(8.609)	(1.340)	(1.344)	(1.993)	(1.991)	(0.842)	(0.832)
N	17,032	17,032	17,032	5,964	5,964	11,068	11,068
Adj. R^2	0.838	0.795	0.795	0.766	0.766	0.850	0.850
Firm/Year/ Announcement-Type fixed effects	YES	YES	YES	YES	YES	YES	YES

Note. This table reports the results of the interplay between the textually complex announcements, stock message board activity and stock price synchronicity based on Equation (5.5). The full sample contains 17,032 firm-announcement observations over the period 2010-2018 when $SYN_{i,[d+1,d+30]}$ is the dependent variable. The subsample of periodic announcements includes 5,964 firm-announcement observations, and the subsample of nonperiodic announcements includes 11,068 firm-announcement observations over the sample period. All continuous variables are winsorised at the 1st and 99th percentiles. Regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for all the columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 5.6: Alternative measures of readability and length

Variable	Full Sample		Periodic announcements		Nonperiodic announcements	
	$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-10.997***	-11.003***	-12.335***	-12.286***	-10.226***	-10.216***
	(-18.107)	(-18.094)	(-13.317)	(-13.262)	(-13.303)	(-13.287)
$DISCUSSIONS_{i,[d, d+1]}$	-0.001	0.000	-0.135***	-0.005	0.012	0.004
	(-0.138)	(0.065)	(-2.990)	(-0.292)	(1.082)	(0.521)
FOG_DUMMY	-0.009		0.088		-0.011	
	(-0.695)		(1.600)		(-0.730)	
FOG_DUMMY*	-0.012		-0.031		**-0.023***	
DISCUSSIONSi,[d, d+1]	(-1.049)		(-0.573)		**(-1.841)**	
Ln(File_Size)_DUMMY		0.014		0.013		0.015
		(1.261)		(0.629)		(1.041)
Ln(File_Size)_DUMMY*		**-0.023****		-0.022		**-0.024****
DISCUSSIONSi,[d, d+1]		**(-2.544)**		(-1.167)		**(-2.152)**
N	17,032	17,032	5,964	5,964	11,068	11,068
Adj. R^2	0.838	0.838	0.819	0.818	0.850	0.850
Control Variables	YES	YES	YES	YES	YES	YES
Firm/Year/ Announcement-Type fixed effects	YES	YES	YES	YES	YES	YES

Note. This table reports the results from the stock price synchronicity analysis based on Equation (5.5) using alternative measures of announcement readability (*FOG*) and length [*Ln(File_Size)]*. The full sample contains 17,032 firm-announcement observations over the period 2010-2018 when $SYN_{i,[d+1,d+30]}$ is the dependent variable. The subsample of periodic announcements includes 5,964 firm-announcement observations, and the subsample of nonperiodic announcements includes 11,068 firm-announcement observations over the sample period. All continuous variables are winsorised at the 1st and 99th percentiles. The regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for all the columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 5.7: Takeover and merger rumours

Variable	Full Sample			Periodic announcements		Nonperiodic announcements	
	$SYN_{i,[d+1,d+30]}$			$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-10.790***	-10.833***	-10.756***	-12.133***	-12.136***	-9.964***	-9.824***
	(-17.217)	(-17.298)	(-17.117)	(-12.869)	(-12.871)	(-12.442)	(-12.215)
DISCUSSIONS$_{i,[d, d+1]}$	**-0.014*** **	0.010	-0.002	-0.044*	-0.008	0.024**	0.002
	(-2.755)	(0.999)	(-0.333)	(-1.862)	(-0.521)	(2.187)	(0.285)
BOG_DUMMY		0.001		0.005		0.003	
		(0.115)		(0.185)		(0.223)	
Ln(TOTAL_WORDS)_DUMMY			0.009		0.004		0.019
			(0.773)		(0.202)		(1.265)
BOG_DUMMY* DISCUSSIONS$_{i,[d, d+1]}$		**-0.030*** **		0.025		**-0.045*** **	
		(-2.732)		(1.011)		**(-3.513)**	
Ln(TOTAL_WORDS)_DUMMY * DISCUSSIONS$_{i,[d, d+1]}$			**-0.028*** **		-0.019		**-0.040*** **
			(-3.016)		(-1.089)		**(-3.291)**
N	16,159	16,159	16,159	5,759	5,759	10,400	10,400
Adj. R^2	0.835	0.835	0.835	0.816	0.816	0.847	0.846
Control Variables	YES	YES	YES	YES	YES	YES	YES
Firm/Year/ Announcement-Type fixed effects	YES	YES	YES	YES	YES	YES	YES

Note. This table reports results from the stock price synchronicity analysis based on Equation (5.5) by excluding the takeover and merger rumours for 16,159 firm-announcement observations over the period 2010-2018, when $SYN_{i,[d+1,d+30]}$ is the dependent variable. The subsample of periodic announcements includes 5,759 firm-announcement observations, and the subsample of nonperiodic announcements includes 10,400 firm-announcement observations over the sample period. All continuous variables are winsorised at the 1st and 99th percentiles. The regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for all the columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 5.8: Stock message board discussions on non-trading windows

Variable	Panel A: Announcements on non-trading days						Panel B: Announcements on trading days					
	Subsample		Periodic announcements		Nonperiodic announcements		Subsample		Periodic announcements		Nonperiodic announcements	
	$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	-12.006***	-11.900***	-14.261***	-14.225***	-11.011***	-10.853***	-10.804***	-10.739***	-12.312***	-12.292***	-9.939***	-9.807***
	(-7.030)	(-6.977)	(-5.014)	(-5.005)	(-5.324)	(-5.256)	(-16.692)	(-16.517)	(-12.195)	(-12.159)	(-11.931)	(-11.716)
$DISCUSSIONS_{i,[d, d+1]}$	0.048	0.011	0.080	0.060	0.036	-0.004	0.007	-0.004	-0.053**	-0.024	0.023**	0.002
	(1.291)	(0.719)	(1.116)	(1.509)	(1.340)	(-0.212)	(0.703)	(-0.573)	(-2.070)	(-1.277)	(1.981)	(0.216)
BOG_DUMMY	0.063**		0.165**		0.048		-0.006		-0.010		-0.003	
	(2.174)		(2.017)		(1.496)		(-0.494)		(-0.343)		(-0.224)	
BOG_DUMMY*	**-0.074*** **		-0.100		**-0.072** **		**-0.024** **		0.035		**-0.039*** **	
***DISCUSSIONS**$_{i,[d, d+1]}$*	**(-2.735)**		(-1.335)		**(-2.338)**		**(-2.077)**		(1.288)		**(-2.894)**	
Ln(TOTAL_WORDS)_DUMMY		0.046		0.102*		0.047		-0.000		-0.011		0.002
		(1.591)		(1.758)		(1.308)		(-0.026)		(-0.446)		(0.134)
Ln(TOTAL_WORDS)_DUMMY*		**-0.051** **		**-0.090***		**-0.046***		**-0.017***		0.001		**-0.023***
***DISCUSSIONS**$_{i,[d, d+1]}$*		**(-2.304)**		**(-1.949)**		**(-1.758)**		**(-1.734)**		(0.069)		**(-1.822)**
N	2,697	2,697	800	800	1,897	1,897	14,335	14,335	5,164	5,164	9,171	9,171
Adj. R^2	0.853	0.853	0.831	0.830	0.864	0.863	0.836	0.836	0.818	0.818	0.848	0.848
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm/Year/ Announcement-Type fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note. This table reports the results of the analysis of subsamples divided between the announcement released on non-trading days and trading days. The non-trading day subsample contains 2,697 firm-announcement observations from 2010 to 2018. All continuous variables are winsorised at the 1st and 99th percentiles. The regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for all the columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 5.9: An instrumental variable approach

Variable	Stage 1	Stage 2						
		Full sample			Periodic announcements		Nonperiodic announcements	
	$SYN_{i,[d+1,d+30]}$	$SYN_{i,[d+1,d+30]}$			$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.977***	-9.059***	-9.087***	-9.104***	-7.423***	-7.379***	-11.268***	-11.322***
	(4.557)	(-12.344)	(-12.357)	(-12.301)	(-7.039)	(-6.961)	(-10.339)	(-10.376)
ADV_EXP	**0.004*** **							
	(3.432)							
INTERRUPT	**-0.074****							
	(-2.411)							
***PRED_ DISCUSSIONS*$_{i,[d, d+1]}$**		**-0.803*****	-0.742**	-0.689**	-1.342**	-1.317**	-0.467	-0.416
		(-2.721)	(-2.493)	(-2.282)	(-2.083)	(-2.041)	(-1.263)	(-1.105)
***BOG_DUMMY* PRED_ DISCUSSIONS*$_{i,[d, d+1]}$**			**-0.060***		-0.014		**-0.198****	
			(-1.699)		(-0.280)		**(-1.976)**	
***Ln(TOTAL_WORDS)_DUMMY* PRED_ DISCUSSIONS*$_{i,[d, d+1]}$**				**-0.078****		-0.069		**-0.216*****
				(-2.227)		(-1.494)		**(-2.668)**
N	17,032	17,032	17,032	17,032	5,964	5,964	11,068	11,068
Adj. R^2	0.812	0.795	0.812	0.812	0.767	0.767	0.811	0.811
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm/Year/ Announcement-Type fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Kleibergen-Paap rk LM statistic		14.495***						
P-val		(0.000)						
Cragg-Donald Wald F statistic		82.967						
Kleibergen-Paap rk Wald Fstatistic		76.595						
Hansen J statistic		2.582						
P-val		(0.1081)						

Note. This table reports the two-stage least squares (2SLS) results. I use two instrumental variables: *ADV_EXP* is the natural log of 1 plus the firm's annual advertisement expenditure; *INTERRUPT* is a binary variable equal to 1 if an announcement coincides with a generic outage that lasts longer than 45 minutes, 0 otherwise. The full sample contains 17,032 firm-announcement observations over the period 2010-2018 when $SYN_{i,[d+1,d+30]}$ is the dependent variable. The subsample of periodic announcements includes 5,964 firm-announcement observations, and the subsample of nonperiodic announcements includes 11,068 firm-announcement observations over the sample period. All continuous variables are winsorised at the 1st and 99th percentiles. Regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in parentheses for all the columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 5.10: Investor type

Variable	High Institutional Ownership		Low Institutional Ownership					
	Subsample		Subsample		Periodic announcements		Nonperiodic Announcements	
	$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-11.838***	-11.824***	-12.776***	-12.625***	-13.237***	-13.256***	-11.837***	-11.716***
	(-17.033)	(-16.989)	(-15.191)	(-14.946)	(-4.868)	(-4.938)	(-4.131)	(-4.146)
DISCUSSIONSi,[d, d+1]	0.018*	0.005	0.008	-0.009	0.140***	0.035	0.031	-0.007
	(1.684)	(0.649)	(0.523)	(-0.991)	(3.767)	(0.921)	(0.998)	(-0.477)
BOG_DUMMY	0.009		0.009		0.114		0.061	
	(0.713)		(0.541)		(0.872)		(1.372)	
BOG_DUMMY* DISCUSSIONSi,[d, d+1]	-0.017		**-0.033****		**-0.157*****		**-0.060***	
	(-1.401)		**(-2.126)**		**(-3.809)**		**(-1.863)**	
Ln(TOTAL_WORDS)_DUMMY		-0.007		-0.010		0.112		0.014
		(-0.494)		(-0.616)		(0.653)		(0.648)
Ln(TOTAL_WORDS)_DUMMY* DISCUSSIONSi,[d, d+1]		0.002		**-0.037*****		-0.054		**-0.035****
		(0.157)		**(-2.952)**		(-1.226)		**(-2.308)**
N	8,592	8,592	8,440	8,440	3,115	3,115	5,325	5,325
Adj. R^2	0.865	0.865	0.837	0.838	0.770	0.770	0.804	0.804
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm/Year/ Announcement-Type fixed effects	YES	YES	YES	YES	YES	YES	YES	YES

Note. This table reports the association between stock price synchronicity and stock message board discussions for textually complex announcements partitioned by high and low institutional ownership (i.e., institutional and non-institutional investors). All continuous variables are winsorised at the 1st and 99th percentiles. Regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in parentheses for all the columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Table 5.11: Professional intermediaries

Variable	News Media		Analysts	
	$SYN_{i,[d+1,d+30]}$		$SYN_{i,[d+1,d+30]}$	
	(1)	(2)	(3)	(4)
Constant	-21.293***	-21.235***	-20.855***	-21.125***
	(-10.192)	(-10.168)	(-9.974)	(-10.070)
DISCUSSIONS	-0.038	-0.022	-0.041	-0.023
	(-1.557)	(-1.198)	(-1.613)	(-1.214)
BOG_DUMMY	0.007		-0.224**	
	(0.198)		(-2.019)	
Ln(TOTAL_WORDS)_DUMMY		-0.004		-0.137
		(-0.120)		(-1.435)
BOG_DUMMY DISCUSSIONS*	0.021		0.023	
	(0.792)		(0.854)	
Ln(TOTAL_WORDS)_DUMMY DISCUSSIONS*		0.002		0.002
		(0.090)		(0.102)
*BOG_DUMMY*NEWS*$_{i,[d,d+1]}$	0.007			
	(0.391)			
*Ln(TOTAL_WORDS)_DUMMY*NEWS*$_{i,[d,d+1]}$		0.006		
		(0.297)		
*BOG_DUMMY*ANALYSTS*			**0.102****	
			(2.215)	
*Ln(TOTAL_WORDS)_DUMMY*ANALYSTS*				**0.061***
				(1.671)
N	5,964	5,964	5,964	5,964
Adj. R^2	0.817	0.817	0.818	0.817
Control Variables	YES	YES	YES	YES
Firm/Year/ Announcement-Type fixed effects	YES	YES	YES	YES

Note. This table reports the results from professional intermediaries only using the periodic announcement subsample. OLS regressions are run separately for news media and analysts using the entire subsample of periodic announcements. All continuous variables are winsorised at the 1st and 99th percentiles. Regressions include firm, year, and announcement-type fixed effects. The *t*-statistics based on standard errors clustered by the firm are reported in the parentheses for all the columns. Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using a two-tailed test. See Appendix C for variable definitions.

Chapter Six:

Conclusion and Future Research Directions

6.1 Research summary

An important consideration in a company's decision to use complex language in its disclosures is the ability of investors to understand the information provided (Blankespoor, 2018). Because market participants have limited capacity to process complex disclosures (Lawrence, 2013; F. Li, 2008; Miller, 2010), they often rely on alternative sources such as analysts, news media and social media to get alternative perspectives at lower costs, so as to be able to process information (Asay et al., 2017). Social media has been found to allow more investors to access the 'wisdom of crowds' through third-party-generated information related to a company, and to use this information to make decisions (Bartov et al., 2018; Chen et al., 2014; Lawrence, Ryans, Sun, & Soni, 2017). However, the impact of social media on investors' information processing, particularly when dealing with textually complex periodic and nonperiodic disclosures, has not been extensively studied. This thesis explores the role of a regulated stock message board in the processing of textually complex corporate disclosures, particularly focusing on nonperiodic corporate announcements.

The first study (Chapter 3) investigates whether the textual complexity of nonperiodic disclosures differs from periodic disclosures in terms of determinants. Using textual analysis of periodic and nonperiodic disclosures, my initial analysis shows that nonperiodic disclosures tend to be more readable, shorter and less boilerplate but have a more positive tone than periodic disclosures. However, while both types of disclosures became increasingly complex over the study period, the

complexity of nonperiodic disclosures increased more notably, particularly after the 2013 revision of GN8. Industry analysis shows that firms in resource, financial, and regulated industries tend to have more textually complex structures, business models, and disclosure practices, resulting in more textually complex periodic and nonperiodic disclosures. In terms of determinants, time trends, market-to-book ratio, gearing, and special items have a greater impact on the textual complexity of nonperiodic disclosure than on periodic disclosures, but this is not due to poor performance. Finally, I find that managers tend to produce more textually complex nonperiodic disclosures when they are releasing bad news on the last trading day or outside of regular trading hours, when investors are less attentive.

The second study (Chapter 4) addresses whether managers' strategic reporting to ease litigation risk for timeliness and completeness results in decreased readability. I test this on the GN8 revision, and the results show that treated firms that use greater boilerplate disclosure in nonperiodic disclosures to meet regulatory pressure experience a larger reduction in readability than control firms. The study finds a negative association between market reactions and firms with greater use of boilerplate disclosure post-GN8 revision, particularly for firms with lower institutional ownership. My findings imply that managers' strategic use of boilerplate is particularly useful in nonperiodic disclosure settings, allowing them to meet 'immediate' and complete disclosure pressure while minimising the risk of breaching GN8 of Listing Rule 3.1. However, the added boilerplate in nonperiodic disclosures post-GN8 revision is more costly for retail investors to extract relevant information due to decreased readability. Sensitivity tests confirm the robustness of the results.

The third (Chapter 5) study examines the role of regulated stock message boards in improving the informativeness of stock prices for complex disclosures by allowing investors to process such disclosures at lower costs. Using data from HotCopper,

Australia's largest stock message board, the study finds that discussions and views on the stock message board increase with complex disclosures and that nonperiodic disclosures mainly drive this association. The study also shows that higher levels of discussion on the regulated stock message board reduce stock price synchronicity, particularly for nonperiodic disclosures, by providing investors with more credible firm-specific information at lower cost. Further, the processing benefit of textually complex nonperiodic announcements appears to be stronger for firms with low institutional ownership. In summary, this study adds to the discussion on the regulation of social media and the literature on archival accounting by showing that regulated platforms can play a crucial role in providing retail investors with the ability to process complex and unanticipated material information at a lower cost.

Overall, the thesis contributes to the literature on textual complexity, nonperiodic disclosures, and social media by showing a connection between the causes and effects of periodic and nonperiodic disclosures' textual complexity and how the regulated stock message board can aid in processing these textually complex disclosures at a lower cost.

6.2 Implications

The findings of the research questions of this thesis have critical implications, particularly for ASIC, ASX, directors of ASX-listed firms, and market participants. In response to ASIC's concerns over the growing textual complexity of financial reporting (Price, 2015), the study provides evidence of the growing textual complexity of periodic disclosure in the Australian setting. My findings on comparative analysis can provide a broader understanding of textual complexity for both periodic and nonperiodic disclosure in terms of determinants. Further, I show managers can strategically prepare textually complex nonperiodic disclosures when

they contain bad news and are released after trading hours or on weekends, when investors pay less attention. Overall, my findings provide important insights for the regulators to allow them to address the growing textual complexity of nonperiodic disclosures and emphasise listed firms to make them simpler and less boilerplate so that naïve investors could find them more useful for their decisions.

The findings of the second study have direct implications for the long-running regulatory debate about whether the clarification of 'immediate' disclosure eases the litigation risk for timely and complete disclosure requirements for nonperiodic disclosures. My findings indicate that adding boilerplate to provide complete disclosure appears to be more beneficial for firms to minimise litigation risk, even with ASIC's strict view on the application of timeliness post-GN8 revision. But lower readability for firms with more boilerplate disclosures is the downside that retail investors mainly carried in the form of higher processing costs, as evidenced by lower levels of market reactions. Despite negative market outcomes, growing numbers of shareholder class actions for misleading and deceptive conduct in recent years could be a salient factor in firms' attempts to make disclosure more complete by adding boilerplate disclosure for better legal protection. Recently, the Australian Federal Government has passed the Treasury Laws Amendment (2021 Measures No. 1) Bill 2021 to provide directors with greater certainty for disclosures to the market without apprehensions about speculative shareholder class actions for misleading and deceptive conduct. Therefore, my findings could be of interest to Australian regulators, particularly in investigating the textual complexity within nonperiodic disclosure following the 2021 Bill. This is because if the 2021 Bill eases the litigation risk for misleading and deceptive conduct, regulators may expect firms to rely less on the thoroughness of disclosure using boilerplate, thus leading to significantly improved disclosure readability.

The findings of the third study provide important insights for Australian and international regulators, particularly before revising regulations or imposing stricter regulations on social media. My findings demonstrate that the regulated stock message board appears to be more useful in processing nonperiodic disclosures. Thus, Australian regulators should consider a better approach to allow investors to process textually complex periodic disclosures. One way is to introduce nonprofessional security analysts (NSAs), like the US-based stock message board Seeking Alpha. This is because, instead of providing investment advice, NSAs produce various articles, including earnings forecasts, that mainly reflect the personal approach to stock picking and portfolio management. However, to improve the scrutiny of NSAs, RG162 needs to be revised immediately because social media has evolved significantly and created new challenges over the last few years.

6.3 Limitations and suggestions for future research

This thesis is subject to several limitations. Addressing these limitations may provide several promising future research avenues.

Firstly, despite focusing on a broad set of textual measures in the thesis, I acknowledge the limitations of these textual measures in capturing the meaningful aspects of disclosures. Specifically, most of these measures are primarily used for the periodic disclosure context; therefore, using them for nonperiodic disclosures raises concerns about whether these measures capture the specific context of various unanticipated material events. Because nonperiodic disclosures encompass various unexpected material events, the way textual content is utilised may vary for each event. For instance, firms embroiled in unanticipated legal disputes may use announcements categorised as ‘others’; therefore, those types of announcements tend to contain more complex legal language than other types. Therefore, future research

could investigate using more suitable measures with validation for textual complexity in nonperiodic disclosures, which could improve the accuracy of comparisons between various unexpected material events.

Secondly, nonperiodic announcements cover several unanticipated material events, which may be dissimilar in terms of their economic significance (Watkins, 2022). For example, takeover announcements may not carry similar economic significance to asset acquisition and disposal announcements or company administration announcements to investors. Chapters 3 and 4 delve into the causes and consequences of the textual complexity of nonperiodic disclosure using a full sample, while Chapter 5 looks into how these textually complex disclosures can be processed via a regulated stock message board. Therefore, this raises the question of whether the findings in these chapters are driven by specific unanticipated material events. Thus, future research should address this issue and develop a research design to test these events individually to provide confidence in their empirical results.

Thirdly, though Chapters 4 and 5 are motivated by Australian regulatory settings, they do not explore the overall cost and benefit of the GN8 revision of CDR and social media regulation. Regarding Chapter 4, my study is limited only to the readability effects of the GN8 revision. While I proxy regulatory pressure for timely and complete disclosure post-GN8, I cannot comment on the overall net benefit because of the limited analysis. Secondly, over-emphasis on boilerplate disclosure does not clarify how litigation risk might trigger firms to focus on specific textual characteristics to minimise future litigation risk. For example, Humphery-Jenner et al. (2019) pointed out that firms that experienced litigation risk appear to alter their 10-K reporting by using more complex words, legal words and uncertain words to minimise future lawsuits, but the downside is that it worsens report readability. In future research, examining the net benefit of the GN8 revision may be worthwhile,

with a particular focus on whether strategic boilerplate disclosure is more beneficial for firms that had experienced litigation before the GN8 revision compared to those that had not. Regarding Chapter 5, although my inferences reflect the notion that higher levels of discussion on regulated stock message boards can facilitate the production of credible firm-specific information at lower costs for the processing of textually complex disclosures, this study is still limited in assessing the role of professional investors on a regulated platform. Because of the limited evidence on the interpretation role of regulated platforms for periodic disclosures in the absence of experts, future research can explore other social media platforms in order to examine this issue. Secondly, despite the robust approach in the research methodology, separating rumour mill effects from investors' information processing efforts is difficult, particularly when I use total discussions as a proxy for collective investors' processing efforts. To mitigate these concerns in a regulated setting, future research can apply natural language processing techniques to identify and classify relevant discussions to relate them more accurately to investors' collective information processing.

Finally, this thesis primarily attempts to establish a link between investors' use of social media in response to textually complex disclosures and market outcomes. However, moving from the firms' disclosures to investors' responses, management must then choose their reaction to investors' responses. As with any disclosure decision, management evaluates the potential advantages and drawbacks in the capital market, such as direct disclosure expenses, proprietary expenses, and the risk of litigation, prior to selecting a disclosure response. Therefore, firms' responses via disclosures, corporate policy, or the role of corporate governance in responding to investors' reactions in the market could be several potential areas to which future research can contribute.

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APPENDICES

Appendix A: Regulatory enforcement relating to CDR Listing Rule 3.1 contraventions up to 31/12/2019

Company	Press Release Time	Type of material events	Context of the alleged breach	Regulatory compliance fails to meet	Area of enforcement
Solbec Pharmaceuticals Limited*	1 August 2005	Nonperiodic	Fined $33,000 for allegedly failing to fully disclose the nature of the animal study results relating to the company's cancer drug.	Disclosure completeness/ accuracy	Infringement Notice
QRSciences Holdings Limited*	17 February 2006	Nonperiodic	Fined $33,000 for allegedly failing to notify ASX immediately about an underwriter that withdrew its fundraising on 31 January 2005.	Disclosure timeliness	Infringement Notice
Fortescue Metals Group Limited#	2 March 2006	Nonperiodic	ASIC alleged that Fortescue overstated framework agreements as enforceable agreements with three major state-owned Chinese companies to build, finance and transfer the railway, port and mine. Fortescue and its chairman won its case.	Misleading and deceptive conduct	Court Actions Fortescue Metals Group Ltd v ASIC Forrest v ASIC
SDI Limited*	21 April 2006	Periodic	Fined $33,000 for allegedly failing to update the company's earnings forecast.	Disclosure timeliness	Infringement Notice
Avastra Limited*	15 May 2006	Nonperiodic	Fined $33,000 for allegedly failing to notify ASX in a timely way of a significant delay in publishing the results of a clinical trial on 26 April 2005.	Disclosure timeliness	Infringement Notice
Astron Limited*	18 July 2006	Nonperiodic	Fined $66,000 for allegedly failing to notify ASX in a timely way of an increase in the mineral resource estimate for its Donald Mineral Sands Project.	Disclosure timeliness	Infringement Notice
Citrofresh International Limited#	25 August 2006	Nonperiodic	ASIC alleged that on 27 September 2005, Citrofresh issued an ASX release containing false claims that the product promoted by Citrofresh was a vaccine for various diseases (HIV and STDs) rather than a disinfectant.	Misleading and deceptive conduct	Court Actions Case: ASIC v Citrofresh International

			At the penalty hearing on 29 March 2010, the chief executive officer received a seven-year banning order and a pecuniary penalty of $20,000.		
Avantogen Limited*	8 December 2006	Nonperiodic	Fined $33,000 for allegedly failing to disclose in a timely way the unsuccessful results regarding the phase II clinical trial of its Pentrys anti-cancer vaccine.	Disclosure timeliness	Infringement Notice
Multiplex Group	20 December 2006	Periodic	ASIC alleged that Multiplex failed to disclose a substantial change in profits immediately, and the undertaking secured a $32 million compensation fund for affected investors.	Disclosure timeliness	Enforceable undertaking
James Hardie Industries Limited#	15 February 2007	Nonperiodic	ASIC commenced civil penalty proceedings against James Hardie for failing to disclose the information relating to a deed of covenant and indemnity; and for failing to disclose the ABN 60 Foundation information.	Misleading and deceptive conduct	Court Actions Case: ASIC v James Hardie
Promina Group Limited*	20 March 2007	Nonperiodic	Fined $100,000 for allegedly failing to inform ASX in a timely way of a takeover proposal from Suncorp Metway Limited.	Disclosure timeliness	Infringement Notice
Raw Capital Partners Limited*	1 August 2007	Nonperiodic	Fined $33,000 for allegedly failing to inform ASX in a timely way of the loss of an important IT service contract.	Disclosure timeliness	Infringement Notice
Centrex Metals Limited*	12 March 2008	Nonperiodic	Fined $33,000 for allegedly failing to notify ASX in a timely way about signing a binding Heads of Agreement with Baotou Iron and Steel Company Limited to supply hematite.	Disclosure timeliness	Infringement Notice
Sub-Sahara Resources NL*	29 March 2008	Nonperiodic	Fined $33,000 for allegedly failing to adequately disclose metallurgical test results.	Disclosure completeness/ accuracy	Infringement Notice
Rio Tinto Limited*	5 June 2008	Nonperiodic	Fined $100,000 for allegedly failing to inform ASX in a timely way about the acquisition of Alcan Inc.	Disclosure timeliness	Infringement Notice
TZ Limited*	4 July 2008	Periodic	ASIC alleged that TZ failed to disclose material information, and the undertaking required the company to engage an external consultant to ensure proper disclosure.	Disclosure completeness/ accuracy	Enforceable undertaking

The Commonwealth Bank of Australia Limited*	14 October 2009	Nonperiodic	Fined $100,000 for allegedly failing to notify ASX in a timely way of the company's expected loan impairment expense.	Disclosure timeliness	Infringement Notice
Citigold Corporation*	22 September 2010	Nonperiodic	Fined $33,000 for allegedly failing to inform the market in a timely way about its forecast gold production revisions at its Charters Towers goldfield in Queensland.	Disclosure timeliness	Infringement Notice
Nufarm Limited*	1 December 2010	Periodic	Fined $66,000 for allegedly failing to inform investors in a timely way about the expected financial results.	Disclosure timeliness	Infringement Notice
Nexbis Limited*	12 August 2011	Nonperiodic	Fined $33,000 for allegedly failing to inform the market in a timely way about a completed agreement to receive the right to supply the Nexcode security suite to the General Administration of Quality Supervision and Inspection and Quarantine of the People's Republic of China.	Disclosure timeliness	Infringement Notice
BioProspect Limited*	8 March 2012	Nonperiodic	Fined $33,000 for allegedly misleading the market regarding the interest of acquiring 25% equity of Frontier Gasfields Pty Ltd.	Disclosure detail	Infringement Notice
BC Iron Limited*	8 March 2012	Nonperiodic	Fined $66,000 for allegedly failing to disclose information about the termination rights in terms of an arrangement scheme with Regent Pacific Group Limited.	Disclosure completeness/ accuracy	Infringement Notice
Leighton Holdings Limited*	18 March 2012	Nonperiodic	Fined $100,000 for allegedly failing to disclose in a timely way the deterioration of the financial position of the Airport Link Project.	Disclosure timeliness	Infringement Notice
Leighton Holdings Limited*	18 March 2012	Nonperiodic	Fined $100,000 for allegedly failing to disclose in a timely way information concerned with the increased costs of the Victorian Desalination Project.	Disclosure timeliness	Infringement Notice
Leighton Holdings Limited*	18 March 2012	Nonperiodic	Fined $100,000 for allegedly failing to disclose in a timely way the decreased evaluation of the Al Habtoor Leighton Group investment.	Disclosure timeliness	Infringement Notice

Navigator Resources Limited*	15 June 2012	Nonperiodic	Fined $33,000 for allegedly releasing misleading statements which implied that Patersons Securities Limited was legally bound to underwrite Navigator's renounceable rights issue.	Disclosure completeness/ accuracy	Infringement Notice
Northern Iron Limited*	19 December 2012	Nonperiodic	Fined $66,000 for allegedly failing to immediately disclose the nonbinding indicative offer from Essel to acquire 100% equity in Northern Iron Limited.	Disclosure timeliness	Infringement Notice
ZYL Limited*	20 September 2013	Nonperiodic	Fined $66,000 for allegedly failing to disclose in a timely way the earlier repayment date of a $2 million bridging facility as to a convertible note agreement; and an alleged failure to disclose the results of the confirmed decrease in reserves from the mining ratification workshop.	Disclosure timeliness	Infringement Notice
Central Asia Resources Limited*	14 October 2013	Nonperiodic	Fined $33,000 for allegedly failing to disclose its actual gold equivalent production figures immediately at the Dalabai operations.	Disclosure timeliness	Infringement Notice
Stone Resources Australia Limited*	3 December 2013	Nonperiodic	Fined $33,000 for allegedly failing to disclose the increased gold resource immediately.	Disclosure timeliness	Infringement Notice
Diploma Group Limited*	10 February 2014	Nonperiodic	Fined $33,000 for allegedly failing to immediately disclose its entry into the contract for the sale of 69 Adelaide Terrace, East Perth, for $4.86 million.	Disclosure timeliness	Infringement Notice
Reward Minerals Limited*	13 June 2014	Nonperiodic	Fined $33,000 for allegedly failing to immediately disclose the analysis results showing samples of near-surface brines taken from lakes in Western Australia's Telfer-Lake Disappointment area contained encouraging potassium levels.	Disclosure timeliness	Infringement Notice
Newcrest Mining Limited#	18 June 2014	Nonperiodic	ASIC alleged Newcrest briefed analysts on its expected gold production for the 2013–14 financial year and its expected capital expenditure for the 2013–14 financial year ahead of it being disclosed to the market. The Federal Court imposed a $1.2 million penalty on Newcrest Mining Limited.	Disclosure timeliness	Court Actions Case: ASIC v Southcorp Limited
NuSep Holdings Limited	19 December 2014	Nonperiodic	ASIC alleged NuSep released inaccurate information related to corporate governance issues. The company agreed to have its continuous	Disclosure completeness/ accuracy	Enforceable undertaking

			disclosure and corporate governance procedures reviewed and rectified by an independent consultant.		
Rhinomed Limited[#]	10 June 2015	Nonperiodic	Fined $33,000 for allegedly failing to immediately disclose an agreement with Fitness First concerning a promotional campaign.	Disclosure timeliness	Infringement Notice
Padbury Mining Limited[#]	24 June 2015	Nonperiodic	ASIC alleged that Padbury's announcement on 11 April 2014 about the $6 billion funding agreement for the development of the Oakajee port and rail project was misleading because the funding agreement was subject to a conditions precedent that had not yet been met. The Federal Court in Perth on August 2016 banned two of Padbury's directors from managing corporations for three years and ordered they each pay a $25,000 fine.	Misleading and deceptive conduct	Court Actions ASIC V Padbury Mining Limited
Coal Fe Resources Ltd[#]	3 July 2015	Nonperiodic	Fined $33,000 for allegedly failing to provide complete disclosure on the valuation report of the Abadi Coal Project.	Disclosure completeness/ accuracy	Infringement Notice
Waterberg Coal Company Limited (WCC) and Firestone Energy Limited (FSE)[#]	27 July 2015	Nonperiodic	Each company was fined $33,000 for allegedly failing to disclose immediately a new loan agreement between them valued at up to $3 million.	Disclosure timeliness	Infringement Notice
Living Cell Technologies Limited[#]	18 December 2015	Nonperiodic	Fined $33,000 for allegedly failing to immediately disclose an *NTCELL* poster presentation at the International Congress of Parkinson's Disease and Movement Disorders, where they were to discuss the Phase I/IIa study findings to investors.	Disclosure timeliness	Infringement Notice
Australia Samly Holdings Limited[#]	25 January 2016	Periodic	Fined $33,000 for allegedly failing to inform investors in a timely way about its operating profit/loss of mainland China-based subsidiaries for the half-year ending 31 December 2014.	Disclosure timeliness	Infringement Notice
ZhongHuanYun Holdings Group[#]	25 January 2016	Periodic	Fined $33,000 for allegedly failing to inform investors in a timely way about the operating	Disclosure timeliness	Infringement Notice

			profit/loss of mainland China-based subsidiaries for the half-year ending 31 December 2014.		
Continental Coal Limited (CCC)#	4 March 2016	Periodic	Following the ASIC application, the Federal Court of Australia ordered the winding up of CCC by appointing an official liquidator as they allegedly failed to lodge audited accounts and hold an annual shareholder meeting.	Disclosure timeliness	Court Actions
Rhinomed Limited#	10 June 2016	Nonperiodic	Followed by a penalty of $33,000 for failing to inform investors in a timely way about the terminated distribution agreement with ResMed. ASIC has accepted an enforceable undertaking (EU) from Rhinomed.	Disclosure timeliness	Enforceable undertaking
Sanhe Building Materials Technology Company Limited#	20 September 2016	Periodic	Fined $33,000 for allegedly failing to inform investors in a timely way about its operating financial result for the full year to 31 December 2015.	Disclosure timeliness	Infringement Notice
Sirtex Medical Limited#	20 September 2017	Periodic	Fined $100,000 for allegedly failing to inform investors in a timely way about its projected dose sales growth for 2017.	Disclosure timeliness	Infringement Notice
Bellamy's Australia Limited#	11 October 2017	Periodic	Fined $66,000 for allegedly failing to inform in a timely way that it was unlikely to achieve market consensus forecasts for the 2017 financial year.	Disclosure timeliness	Infringement Notice
Adairs Limited#	20 October 2017	Periodic	Fined $66,000 for allegedly failing to inform investors in a timely way about its forecast figures for EBITDA, EBIT and NPAT for the full financial year 2017.	Disclosure timeliness	Infringement Notice
MG Responsible Entity Limited (MGRE)#	16 November 2017	Periodic	ASIC alleged the MGRE, in contravention of Section 674(2) of the Corporations Act 2001 (Cth), failed to notify ASX that circumstances had arisen, a consequence of which MGRE was unlikely to achieve its forecast stated in the February Announcements. MGRE has admitted to the alleged contravention, and the Federal Court fined it $650,000.	Disclosure completeness/ accuracy	Court Actions

Murray River Organics Group Limited#	11 December 2017	Periodic	Fined $33,000 for allegedly failing to inform ASX in a timely way about its revenue, EBITDA and PBT for the 2017 financial year were likely to be materially below the forecasts contained in its prospectus.	Disclosure timeliness	Infringement Notice
Gold Mountain Limited#	7 August 2018	Periodic	Fined $33,000 for allegedly failing to comply with the JORC Code while preparing additional disclosure on production targets and revenue forecasts.	Disclosure completeness/ accuracy	Infringement Notice
Australia and New Zealand Banking Group Limited (ANZ)#	14 September 2018	Nonperiodic	ASIC alleged that ANZ contravened Section 674(2) of the Corporations Act 2001 by failing to inform ASX that approximately $791 million of the $2.5 billion of ANZ shares offered in the Placement was to be acquired by its underwriters rather than placed with investors.	Disclosure completeness/ accuracy	Court Actions

Source: *North (2013), pp. 80-84 and pp. 134-142.
ASIC media release downloaded from https://asic.gov.au/about-asic/news-centre/find-a-media-release/

Appendix B: List of securities class actions concerning breaches of CDR's misleading and deceptive conduct regulations

No.	Defendant company	Industry	Type of topic	Nature of allegations	Nature of event	Year Filed	Year Settled	Settlement Amount ($ Million)
1	GIO Australia Holdings Limited	Financials	Takeover	Misleading representations in a takeover, reinsurance losses, business risk	Nonearnings	1999	2003	112
2	Aristocrat Leisure	Consumer discretionary	Overstating its profits and failing to meet earnings forecasts	Misleading or deceptive conduct about profit downgrade	Earnings	2003	2008	144.5
3	Concept Sports Limited	Information technology	Issuing a prospectus that did not warn investors of some very significant risks	Misleading statements in the prospectus	Nonearnings	2004	2006	3
4	Harris Scarfe Holdings Ltd	Consumer discretionary	Inflating the group's reported profits.	Misleading or deceptive conduct about the corporate collapse	Nonearnings	2002	2006	3
5	Multiplex Group	Real Estate	Progress report – failed to tell the market about the cost overruns and the consequent impact on profits and revenue in relation to three projects – Wembley, the West India Quay hotel and apartment project in the UK, and the Qantas heavy maintenance hangar at Brisbane Airport.	Misleading or deceptive conduct about profit downgrade	Earnings	2006	2010	110

6	Telstra Group Limited	Communication service	The legal action concerns a briefing that Telstra gave to the Federal Government on August 11, 2005, which was not disclosed to the Australian stock exchange until September 7.	Misleading or deceptive conduct regarding business risk	Nonearnings	2006	2007	5
7	Downer EDI Limited	Industrials	Progress report – Downer EDI knew a blow-out of costs and delays had put the project 12 months behind schedule and $117 million over budget more than a year before telling the market of its troubles with the contract.	Misleading or deceptive conduct about profit downgrade	Earnings	2007	2008	18.25
8	Village Life Ltd	Real Estate	Village Life investors claim the company failed to meet forecasts on future profits and construction timetables laid down at the time of the float.	Misleading statements in the prospectus	Nonearnings	2008	2009	3
9	Sons of Gwalia Limited	Materials	Shareholders being misled into acquiring or holding on to shares ("shareholder damages claims"), raised the issue of whether that claim is entitled to be treated as an ordinary unsecured claim (as with any other damages claim) or whether that claim is a claim of a member seeking to claim the loss or part of the loss of its investment.	Misleading or deceptive conduct about the corporate collapse	Nonearnings	2005	2009	70

10	AWB Limited	Consumer staples	AWB's failure to disclose Iraqi kickbacks under the United Nations' Oil For Food Program.	Misleading or deceptive conduct regarding business risk	Nonearnings	2007	2010	40
11	Centro Properties Group	Real Estate	The misclassification of debt by which CNP's current debt was understated, and its non-current debt was overstated.	Misleading or deceptive conduct about debt position	Nonearnings	2008	2012	200
12	Media World Communications Limited	Information technology	Media World was placed into administration in September after its "breakthrough" Adams Platform compression technology was revealed to be a fake.	Misleading or deceptive conduct about profit downgrade	Earnings	2005	2010	0
13	OZ Minerals Limited	Materials	The claim includes the alleged failure by Oxiana and OZ Minerals to disclose the true debt position of OZ Minerals during the period.	Misleading or deceptive conduct about debt position	Nonearnings	2009	2011	39
14	OZ Minerals Limited	Materials	OZ Minerals understated true debt position.	Misleading or deceptive conduct about debt position	Nonearnings	2009	2011	21
15	OZ Minerals Limited	Materials	OZ Minerals understated true debt position.	Misleading or deceptive conduct about debt position	Nonearnings	2009	2016	32.5
16	Credit Corp Group Limited	Financials	Unknown	Misleading or deceptive conduct about profit downgrade	Earnings	2010	2012	6.5
17	National Australia Bank	Financials	The lawsuit, launched in late 2010, claimed NAB had failed to diligently disclose the true extent of its exposure to toxic subprime investments.	Misleading or deceptive conduct about business risk	Nonearnings	2010	2012	115

18	Sigma Healthcare Limited	Health care	Sigma engaged in misleading or deceptive conduct in relation to the guidance provided on 7 and 14 September 2009 by providing guidance concerning its NPAT for the year ending 31 January 2010 without a reasonable basis, overstating its first-half result of $32.2m by between 20% and 35%.	Misleading or deceptive conduct about profit downgrade	Earnings	2010	2012	58
19	Cleanaway Waste Management Limited	Industrials	Profit downgrade	Misleading or deceptive conduct about profit downgrade	Earnings	Settled before filing	2012	35
20	Nufarm	Materials	Nufarm managing director Doug Rathbone is accused of repeatedly misleading investors with optimistic forecasts.	Misleading or deceptive conduct about profit downgrade	Earnings	2011	2012	47
21	GPT Group	Real Estate	Overstated earnings forecast for the 2008 year.	Misleading or deceptive conduct about profit downgrade	Earnings	2011	2013	75
22	Triangle Energy (Global) Limited	Energy	Unknown	Misleading statements in the prospectus	Nonearnings	2012	2014	3
23	Allco Finance Group Limited	Financials	Between August 2007 and February 2008, Allco did not disclose its true current liabilities to the market.	Misleading or deceptive conduct about debt position	Nonearnings	2013	2017	40

24	Great Southern Mining Limited	Materials	The class action had sought to void more than $300 million of loans taken out with Bendigo and Javelin Asset Management to fund the schemes on the basis that investors were misled by Great Southern and later they collapsed.	Misleading or deceptive conduct about debt position	Nonearnings	2013	2014	23
25	CIMIC Group Limited	Industrials	It alleged the company's former management failed to disclose problems at its biggest projects ahead of a $907 million group write-down.	Misleading or deceptive conduct regarding project progress	Nonearnings	2013	2014	70
26	Rivercity Motorway Group	Industrials	The class action was against AECOM Australia, which did the traffic forecasts for the tunnel, and two RiverCity Motorway companies were funded by IMF Bentham, which overstated the forecast of making a $29 million profit from the proceedings.	Misleading or deceptive conduct about the forecast	Earnings	2014	2016	121
27	Newcrest Mining Limited	Materials	Newcrest was alleged to engage in misleading or deceptive conduct by providing production guidance without reasonable grounds during the profit downgrade claim period.	Misleading or deceptive conduct about profit downgrade	Earnings	2014	2014	36
28	Downer EDI Limited	Industrials	Alleging the company misled investors by failing to disclose issues with its Waratah Train Project in 2010 adequately.	Misleading or deceptive conduct regarding project progress	Nonearnings	2011	2014	28

29	Downer EDI Limited	Industrials	Alleging the company misled investors by failing to disclose issues with its Waratah Train Project in 2010 adequately. (second claim).	Misleading or deceptive conduct about project progress	Nonearnings	2014	2016	11
30	Billabong International Limited	Consumer discretionary	The class action alleged that during the period of 18 February 2011 to immediately prior to the publication of a trading update on 19 December 2011, Billabong provided guidance for FY11 and FY12 without a reasonable basis.	Misleading or deceptive conduct about profit downgrade	Earnings	2015	2016	45
31	BrisConnections Unit Trusts	Industrials	BrisConnections forecasts about airport traffic were not reliable.	Misleading or deceptive conduct about forecast	Earnings	2014	2015	Confidential
32	Gunns Limited	Materials	Gunns was aware and failed to inform investors on 31 August 2009 that its results would be significantly worse in this reporting period as compared to the first half of the 2009 financial year.	Misleading or deceptive conduct about profit downgrade	Earnings	2011	2016	16
33	Treasury Wine Estates Limited	Consumer staples	Alleged for failing to inform investors the actual financial position. Law firm Maurice Blackburn filed the lawsuit in 2014 after the world's biggest listed stand-alone winemaker announced a surprise A$190 million write-down, partly to cover the cost of pouring out millions of bottles of unsold wine.	Misleading or deceptive conduct about business risk	Nonearnings	2014	2017	49

34	QBE Insurance Group Limited	Financials	QBE announced in Dec. 9, 2013 that it was not going to meet earlier profit and financial performance guidance – mostly because of losses in its North American operations. After downgrading the profit, QBE shares plummeted more than 30% over two days, which wiped A$5 billion (US$3.9 billion) off the company's market value.	Misleading or deceptive conduct about profit downgrade	Earnings	2015	2017	132.5
35	Slater & Gordon Limited	Consumer discretionary	Shareholders launched the class action against Slater and Gordon after its disastrous acquisition of British firm Quindell led to $1 billion-plus write-downs, a string of financial losses and a major investigation by ASIC.	Misleading representations in takeover,	Nonearnings	2016	2017	36.5
36	Tamaya Resources Limited	Materials	Failed to disclose financial position, the true value of Tamaya's shares and the purpose of two capital raisings.	Misleading or deceptive conduct about business risk	Nonearnings	2014	2017	6.75
37	Lionhub Group Limited	Real Estate	Failed to disclose the financial position.	Misleading or deceptive conduct regarding business risk	Nonearnings	2012	2018	19.25

38	Kagara Limited	Materials	Kagara's directors were alleged to make misleading representations to the market concerning Kagara's net profit (or loss) and net assets. They did not disclose certain information to the market in Half Yearly and Annual Reports from 29 September 2010.	Misleading or deceptive conduct about profit downgrade	Earnings	2016	2018	3
39	Macmahon Holdings Limited	Materials	A number of shareholders launched the Federal Court action in 2015, alleging the contractor breached stock market rules by not telling them about the financial impact of delays with the Pilbara rail and bridge project.	Misleading or deceptive conduct regarding project delay	Nonearnings	2015	2018	6.7
40	Forge Group Limited	Industrials	Forge was alleged to have three profit write-downs between late November 2012 and the end of January 2013, stemming largely from the problems with power station projects in the Pilbara and northwestern Queensland.	Misleading or deceptive conduct regarding project progress	Nonearnings	2014	2019	16.5

41	Worley Limited	Energy	In August 2013, Worley Limited (Worley) released earnings guidance that estimated net profit after tax (NPAT) in excess of $322 million in the financial year ending 30 June 2014. Revised earnings guidance was published in November 2013 with a forecast NPAT between $260-300 million, leading to a 26% reduction in the Worley share price.	Misleading or deceptive conduct about profit downgrade	Earnings	2015		N/A
42	Myer Holdings Limited	Consumer discretionary	In September 2014, Myer made a forecast that net profit after tax (NPAT) for the financial year would be in excess of the prior year's $98.5 million result. In March 2015, Myer updated the market on its forecasts, saying its NPAT would be between $75 million and $80 million, sending its shares diving 31%. As a result, more than 1500 shareholders joined a class action against the retailer, claiming it misled investors by not correcting Mr Brookes' comment.	Misleading or deceptive conduct about profit downgrade	Earnings	2015	2020	0

43	QRxPharma Limited	Health care	The complaint alleges that QRx Pharma issued false and misleading public statements and omitted material facts concerning the commercial prospects for its experimental drug Moxduo. Specifically, the complaint alleges that QRx Pharma failed to disclose to investors that it received a "no agreement letter" from the Food and Drug Administration ("FDA") regarding its Moxduo trials and further misrepresented and concealed other material facts concerning its attempts to get Moxduo approved. Upon the disclosure of an FDA memo that denied QRx Pharma's application to get Moxduo approved, the price of QRx Pharma ADRs plummeted by over 83% on April 23, 2014.	Misleading or deceptive conduct about a drug trial	Nonearnings	2015	2020	7
44	Ashley Services Group Limited	Industrials	The claim arises from allegedly misleading statements and material omissions made in Ashley's prospectuses issued prior to its listing and allegedly misleading conduct and failures to comply with continuous disclosure obligations by Ashley, which occurred after its listing.	Misleading statements in the prospectus	Nonearnings	2016	2019	14.6

45	Vocation Limited	Consumer discretionary	Vocation made misleading or deceptive statements and omitted information that was required to be disclosed, thereby causing loss to persons who acquired an interest in ordinary Vocation shares during the period 27 November 2013 and 4 December 2014 (inclusive).	Misleading statements in the prospectus	Nonearnings	2016	2021	50
46	Australian Zircon NL	Materials	The key allegations in the Endeavour River Class Action are that Murray Goulburn and MGRE engaged in misleading and deceptive conduct when MGRE issued a product disclosure statement on 29 May 2015, particularly concerning the financial forecast for the financial year ending 30 June 2016 (FY16).	Misleading or deceptive conduct about profit downgrade	Earnings	2016	2019	42
47	UGL Limited	Industrials	A long-running class-action between CIMIC-owned engineering firm UGL and litigation funder IMF Bentham, alleging poor disclosure over cost blowouts for the Ichthys gas project, has reached a conditional settlement.	Misleading or deceptive conduct regarding project progress	Nonearnings	2017	2019	8.3
48	Sirtex Medical Limited	Health care	The claims arise from allegedly misleading statements made by Sirtex to ASX in 2016 concerning its earnings and sales growth.	Misleading or deceptive conduct about profit downgrade	Earnings	2017	2019	N/A

49	Bellamy's Australia Limited	Consumer staples	It was alleged that on and from 14 April 2016, Bellamy knew or ought to have known that market consensus concerning forecasts for its FY17 revenue and EBIT margin were materially inconsistent. Bellamy failed to disclose this information until 2 December 2016 and 11 January 2017, respectively. When the market became aware of this information, BAL's shares dropped $5.57 per share and $2.67 per share, respectively.	Misleading or deceptive conduct about profit downgrade	Earnings	2017	2019	49.7
50	Commonwealth Bank of Australia	Financials	The class action follows CBA's $700m settlement with Austrac over widespread breaches of the Anti-Money Laundering and Counter-Terrorism Financing Act. CBA was aware or should have been aware of its non-compliance with these requirements from at least June 2014. Despite that, CBA did not disclose any AML/CTF concerns to investors until they were forced to do so by Austrac's announcement on 3 August. CBA's share price then fell markedly. Several enquiries into CBA's conduct were announced in the wake of the	Misleading or deceptive conduct regarding business risk	Nonearnings	2017	2022	50

			Austrac announcement, including by ASIC and APRA.					
51	Spotless Group Holdings Limited	Industrials	The class action alleged Spotless had engaged in misleading and deceptive conduct when it provided its FY16 Guidance on 25 August 2015.	Misleading or deceptive conduct about profit downgrade	Earnings	2017	2020	95
52	Surfstitch Group Limited	Consumer discretionary	The claim alleges that the public downgrades came too late and should have been issued in 2015 when it was clear SurfStitch would be unlikely to meet the optimistic forecasts that were in place.	Misleading or deceptive conduct about profit downgrade	Earnings	2017	2021	0.91
53	Crown Resorts Limited	Consumer discretionary	Crown engaged in misleading or deceptive conduct and breached its continuous disclosure obligations concerning its operations in China, where it failed to inform its shareholders of the business risks and threats it posed to its revenue streams.	Misleading or deceptive conduct regarding business risk	Nonearnings	2017	2021	125
54	Shine Metals Limited	Industrials	Failed to disclose the progress of the project.	Misleading or deceptive conduct regarding business risk	Nonearnings	2017	2021	unknown

55	Quintis Ltd	Materials	Overstating in the FY15 and FY16 Financial Reports the value of Quintis' biological assets, its profit attributable to its recognition of certain establishment fees as revenue, and its recognition of optional annual fees as intangible assets. This had the effect of materially overstating Quintis' assets and revenue.	Misleading or deceptive conduct about profit overstating	Earnings	2017	2022	4.7
56	DSHE Holdings Limited	Consumer discretionary	Failed to disclose a rebate-focused inventory buying policy which was one of the main triggers of the company's collapse, according to a subsequent creditors' report.	Misleading or deceptive conduct about debt position	Nonearnings	2017	2021	25
57	AMP Limited	Financials	At the Financial Services Royal Commission, AMP was revealed to have misled ASIC 20 times about the extent and nature of the fee-for-no-service scandal.	Misleading or deceptive conduct in business operation	Nonearnings	2018		
58	GetSwift Limited	Information technology	The class action settlement comes over two years after GetSwift said it could not forecast when it would achieve profitability due to its ongoing legal expenses. At the time, the company faced the shareholder class action and proceedings brought forward by ASIC and had paid $2.17 million in legal expenses during its half-year results.	Misleading or deceptive conduct about profit downgrade	Earnings	2018	2021	unknown

59	Iluka Resources Limited	Materials	The court was tasked with determining whether Iluka had "reasonable grounds" for its sales guidance and whether the company was aware that its forecast sales would be "materially less" than the figures forecasted between April and July 2012.	Misleading or deceptive conduct about profit overstating	Earnings	2018	2022	dismissed
60	BHP Group Limited	Materials	BHP failed to provide true news of the Fundão tailings dam collapse on 5 November 2015 at the Germano mine releasing a mudflow that killed 19 people and caused catastrophic damage to downstream communities and the environment.	Misleading or deceptive conduct regarding business risk	Nonearnings	2018	N/A	N/A
61	Commonwealth Bank of Australia	Financials	The class action against the CBA alleges contraventions concerning its non-compliance with the AML/CTF Act, information that a reasonable person would expect to have a material effect on the price or value of CBA shares.	Misleading or deceptive conduct regarding business risk	Nonearnings	2018	N/A	N/A
62	Brambles Limited	Industrials	The disclosure violations, it is alleged, prompted Brambles to suddenly slash its sales and profit forecasts, triggering two major share price plunges at the beginning of 2017 and significantly harming its shareholders.	Misleading or deceptive conduct about profit downgrade	Earnings	2018	N/A	N/A

63	CIMIC Group Limited	Industrials	It was alleged to have used controversial financing techniques to mislead investors about its cash flows and did not fully disclose the financial problems in its Middle Eastern joint venture.	Misleading or deceptive conduct about profit overstating	Earnings	2018	N/A	N/A
64	Woolworths Group	Consumer staples	Woolworths breached its continuous disclosure obligations and engaged in misleading conduct by overstating profit forecasts to investors in 2014.	Misleading or deceptive conduct about profit downgrade	Earnings	2018	2021	44.5

Appendix C: Variable definitions and data sources

Variable	***Definition***	Source
Textual complexity measures		
BOG	*BOG* is computed for each downloaded ASX announcement using Editor Software's *StyleWriter 4*: *BOG = Sentence Bog + Word Bog - Pep* *Sentence Bog* identifies readability issues stemming from sentence length, whereas *Word Bog* captures the plain English style problems and word difficulty. *BOG's* final component, *Pep*, identifies writing attributes that facilitate readers' understanding of texts. A higher value of *BOG* for a nonperiodic announcement implies a lower readability level. For details, see Bonsall et al. (2017).	ASX Website
TOTAL_WORDS	Represents announcement length and is measured as the total number of words in a nonperiodic announcement.	ASX Website
Ln(TOTAL_WORDS)	Natural logarithm of the number of words in each announcement.	ASX Website
File_Size	An alternative disclosure quantity measure calculated as the number of kilobytes used by the entire announcement.	
Ln(File_Size)	Natural logarithm of the number of kilobytes used by the entire announcement.	
BOILER_WORDS	The number of boilerplate words in standardised sentences in a nonperiodic announcement. The standardised sentences are flagged based on a list of identified three-word phrases (trigrams) in nonperiodic announcement sentences for all firms in the same six-digit GICS industry.	ASX Website
BOILER_WORDS_CHANGE	The percentage change in *BOILER_WORDS* in a nonperiodic announcement from pre-GN8 to post-GN8 revision.	ASX Website

BOILER	The total number of words in the identified standardised sentences is divided by the total number of words in the announcement.	ASX Website
FACTOR1	The first factor produced in factor analysis of main textual attributes is influenced mostly by *BOG* and *BOILER*.	ASX Website
Announcement type and Time trend variable		
NONPRD	A binary variable is set to 1 if the price-sensitive announcement is nonperiodic.	*Self-estimation*
TREND	A variable that increments by 1 each year starting from 2010 to capture the time-series trend in textual attributes (Dyer et al., 2017).	*Self-estimation*
Measures of stock message board activities		
$VIEWS_{i,d}$	Natural logarithm of the number of views on a thread for a firm-specific announcement for firm *i* on day *d* plus one.	HotCopper
$DISCUSSIONS_{i,[d,\ d+1]}$	Natural logarithm of the number of announcement-specific discussions on the thread for firm *i* over days *d* to *d+1* plus one, otherwise zero if there were no discussions.	HotCopper
Regulatory variable		
POST	A binary variable set to 1 (0) if the observation is after (before) the effective date of the GN8 revision (1 May 2013).	*Self-estimation*
TREAT	A binary variable set to 1 for treatment firms that experienced a greater increase in the use of boilerplate disclosure and 0 otherwise.	*Self-estimation*
Market outcome variables		
$\lvert CARs_{i,t}(m,n) \rvert$	The absolute cumulative abnormal return, which is the sum of abnormal returns for firm *i* on day *t* for three day *(-1,+1)* and five day *(-1,+3)* windows.	Thomson Reuters Eikon
$SYN_{i,[d+1,d+30]}$	Logarithmic transformation of R^2 defined as log (R^2/(1-R^2)), where R^2 is from a regression of firm *i*'s daily return $RET_{i,d}$ on the current and prior days' value-weighted market return ($MKTRET_{i,d}$ and $MKTRET_{i,d-1}$) and on current and prior days' value-weighted industry return ($INDRET_{i,d}$ and $INDRET_{i,d-1}$).	Thomson Reuters Eikon

Firm characteristics and other control variables		
SIZE	Natural logarithm of a firm's market value of equity.	Thomson Reuters Eikon
LEVERAGE	Total debt scaled by total assets.	Thomson Reuters Eikon
ROA	Income before extraordinary items scaled by total assets.	Thomson Reuters Eikon
MTB	The ratio of the market value of equity to book value of equity.	Thomson Reuters Eikon
AGE	Natural logarithm of the number of years elapsed since the firm first appeared in the Morningstar database.	Thomson Reuters Eikon
LNBSEG	Natural logarithm of the number of business segments.	Thomson Reuters Eikon
LNGSEG	Natural logarithm of the number of geographical segments.	Thomson Reuters Eikon
SPECIAL	Total amount of special items scaled by total assets.	Thomson Reuters Eikon
M&A	A binary variable set to 1 if the firm engaged in merger and acquisition transactions during the fiscal year and 0 otherwise	Thomson Reuters Eikon
SEO	A binary variable set to 1 if the firm had a common equity offering in the secondary market during the fiscal year and 0 otherwise.	Thomson Reuters Eikon
HIGHTECH	A binary variable set to 1 when the firm belongs to Drugs, R&D Services, Programming, Computers, or Electronics sectors; and 0 otherwise.	Thomson Reuters Eikon
REGULATED	A binary variable set to 1 when the firm belongs to the Telephone, TV, Cable, Communications, Gas, Electricity, Water, or Financial sectors; and 0 otherwise.	Thomson Reuters Eikon
RESOURCE	A binary variable set to 1 when the firm belongs to Energy and Material sector and 0 otherwise.	Thomson Reuters Eikon

VOLATILITY	The standard deviation of the average daily stock return during the (0, -90) day pre-event window, where day 0 is the date the nonperiodic announcement is released.	Thomson Reuters Eikon
BIG4	A binary variable set to 1 if the audit firm is one of the big four or 0 otherwise.	Thomson Reuters Eikon
ANALYSTS	Natural logarithm of 1 plus the number of unique analysts providing a forecast from the I/B/E/S for the 12 months ending on the day the nonperiodic announcement is released.	Thomson Reuters Eikon
NONPERD	A binary variable set to 1 if another nonperiodic announcement is released by the firm on day *t-1* to *t*, 0 otherwise.	*Self-estimation*
PERD	A binary variable set to 1 if the periodic announcement is released by firm *i* on day *t-1* to *t*, 0 otherwise.	*Self-estimation*
$NEWS_{i,[d,d+1]}$	Natural logarithm of the number of news articles recorded by Factiva (using the company name as the search criterion) for firm *i* over day *d* to day *d+1* (two-day window) plus one.	Factiva
$ANALYSTS_{i,d}$	Natural logarithm of the number of unique analysts providing a forecast (from the I/B/E/S) for firm *i* on the day earliest in the month during the fiscal year plus one.	Thomson Reuters Eikon
$RET_{i,[d-90,d-15]}$	The sum of abnormal return for firm *i* over the pre-announcement windows of *d-90* to *d-15*.	Thomson Reuters Eikon
$TURN_{i,[d-90,d-15]}$	The average ratio of trading volume to shares outstanding for firm *i* over the pre-announcement windows of *d-90* to *d-15*.	Thomson Reuters Eikon
$SRV_{i,d-90}$	The standard deviation of the average daily stock return of firm *i* on day *d* for the last 90 days.	Thomson Reuters Eikon
ZERO_RET	The frequency of zero returns for firm *i* in a fiscal year.	Thomson Reuters Eikon
NIND	Natural logarithm of the number of firms in the industry to which firm *i* belongs on day *d*.	Thomson Reuters Eikon

HERFSALE	A revenue-based Herfindahl index of industry-level concentration, measured as a sum of squared terms of the proportion of a firm's revenue to total revenue in the industry.	Thomson Reuters Eikon
TONE	The number of positive words less the number of negative words divided by the total number of words. I use word dictionaries developed explicitly for financial context by Loughran and McDonald (2011) to estimate the tone for both periodic and nonperiodic announcements. I thank Tim Loughran and Bill McDonald for making sentiment word lists and Python code publicly available at https://sraf.nd.edu/textual-analysis/code/.	ASX Website