

**Essays on Governance Through Disclosure: Evidence from Reporting
Outcomes in UK**

Leonor Guedes Soares

This dissertation is submitted to Lancaster University for the degree of Doctor of Philosophy
in Accounting and Finance

Department of Accounting and Finance
Lancaster University Management School

October 2025

Essays on Governance through Disclosure: Evidence from Reporting

Outcomes in UK

Abstract

In this thesis I investigate the impact of disclosure as a governance tool that shapes firm behavior on reporting outcomes of firms traded in the London Stock Exchange.

Chapter 1 introduces this thesis. Chapter 2 investigates the impact of a gender pay transparency policy implemented in the UK on antecedents of pay equality by asking whether firms respond to the mandatory disclosure of the gender pay gap ratio by adopting internal employment policies (designated as Employment Equity Actions – EE actions). Such policies are recommended by UK Government guidelines and their effectiveness in contributing to workplace gender equality is supported by research in psychology, human resources and management. Their adoption is expected to represent a key step to reducing the gender pay gap as it addresses its causes and allows me to analyze the effectiveness of the disclosure mandate through the lens of the regulator. Results show a slight increase in the adoption of EE actions and provide evidence that firms that disclose gender pay gap metrics adopt more actions than those that do not disclose the metrics. However, the effect is economically insignificant. I conclude that while the adoption rates of EE actions have increased, the policy's effect seems to have been limited.

Chapter 3 asks whether the presence of an independent board Chair affects corporate disclosure by testing whether Chair commentary is incrementally informative beyond management commentary. I leverage the UK setting where London Stock Exchange Traded firms operate under the UK Corporate Governance Code that recommends the separation of Chair and CEO positions and the appointment of a non-affiliated board Chair. High

compliance with both provisions has a direct consequence on narrative disclosure: UK annual reports not only include performance commentary authored by management but also include a letter to shareholders authored by the board Chair. I develop and test the hypothesis that Chair commentary is incrementally informative beyond management commentary by 1) testing whether the explanatory power of Chair tone is higher than that of the explanatory power of management tone on the regression of realized earnings on tone and 2) testing whether the Chair commentary carries incremental information beyond management when predicting one-year ahead earnings. Both tests confirm my hypothesis that Chair commentary is incrementally informative beyond management commentary. My hypothesis identifies two non-mutually exclusive roles that may explain incremental informativeness of Chair commentary: monitoring and information. I continue in this chapter to explore the monitoring role of the Chair by partitioning the sample using earnings losses as a proxy for management incentives for obfuscation and impression management. The monitoring hypothesis predicts that the incremental informativeness will be more pronounced where the incentives for impression management are more acute. I do not find evidence that earnings predictability is higher for loss firms; indeed, results reveal that incremental predictive ability of Chair tone is due mainly to profitable firms. This unexpected result prompts me to conduct additional tests. I find that the monitoring role of the Chair manifests in Chair tone that is more pessimistic relative to management when there are incentives for impression management. I also find that the predictability of management commentary is weaker when the Chair is more negative than management. Based on these results, I conclude that Chair commentary plays a monitoring role in reporting but it is limited to, and focuses mainly on, weak realized earnings performance. The Chair's monitoring role over corporate reporting does not appear to explain the incremental predictive ability of their commentary, nor the fact this effect proves particularly strong for profitable firms. I therefore proceed by testing whether the

predictiveness of Chair commentary among profitable firms is consistent with an information role. I find evidence consistent with the information role arising from two separate functions: confirmation and resource provision. However, my tests are unable to distinguish between information resulting from confirmation or information resulting from resource provision. I seek to distinguish between these alternative information explanations in Chapter 4.

Chapter 4 asks how the information role of the board Chair affects Chair-authored commentary by adopting a topic modeling approach to examine the content of Chair and management commentary and variation therein. Consistent with evidence that the board Chair may support the management team (Boivie et al., 2021), I predict that if the information role of the board Chair primarily derives from serving a confirmation function, then Chair-authored commentary should disclose a content that is closely aligned to that disclosed by management. This implies that there should be a substantial level of topic overlap between Chair and management commentary and that the incremental predictability of Chair commentary should be, at least partially, explained by topics that feature in management and Chair commentary. Conversely, consistent with the evidence that independent board Chairs provide resources in the form of knowledge and expertise (Krause et al., 2016), I posit that the information role of the board Chair arises from serving a resource provision function if Chair commentary largely discusses content that is not mentioned by management. This implies that the level of topic alignment should be low and that the incremental predictability of Chair commentary should be, at least partially, explained by the disclosure of topics that are exclusively discussed by the board Chair. I find consistent evidence that the information role is explained by the confirmation function of Chair commentary and modest evidence suggesting that it equally arises from both functions. Chapter 5 concludes this thesis.

Acknowledgments

The PhD has been a challenging but very rewarding journey. During this journey, I was lucky to meet people that have helped me in many different ways.

I would like to express my sincere gratitude to Steve Young for all the help, advice, encouragement and mentorship during the last five years. Completing this dissertation would not have been possible without him and I am deeply grateful for his support.

I would also like to thank Mohamed Ghaly and Sarah Kroeichert for their helpful feedback throughout the PhD. As I would not have followed a research path without his encouragement, I am very grateful to Paulo Alves for all the help before and throughout the PhD.

I also thank the Department of Accounting and Finance of Lancaster University for promoting a welcoming and supportive research environment. I am particularly grateful to Justin Chircop, Mahmoud Gad, Igor Goncharov, Argyro Panaretou, Gitae Park, Roberto Pinto, Sam Rawsthorne, Andrew Smerdon, and Dasha Smirnow for their comments and advice. I would also like to thank the PhD cohort of the Department, and particularly my colleagues from C38. Special thanks to Carmine, who started the PhD at the same time as I did, for all the talks, laughter and friendship.

I am grateful for the financial support provided by the Department of Accounting and Finance of the University, the Lancaster University Management School, and the International Centre for Research Accounting.

I would also like to thank my family and friends in Portugal for their unconditional love and support, despite all the moments I have missed during the last five years. Finally, a big thank you to Anastasios for being by my side through all the ups and downs of this journey.

Declaration of Authorship

I hereby declare that the content of my dissertation is original and the result of my own work. This dissertation has not been submitted in whole or in part for the award of any other degree. I further declare that Chapter 2 forms the basis of a solo-authored working paper, while Chapters 3 and 4 form the basis of a working paper co-authored with Professor Steven Young and Professor Paulo Alves. Both working papers are pending submission to peer-reviewed journals.

Leonor Guedes Soares

Table of Contents

1	Introduction.....	1
2	The Impact of Gender Pay Transparency on the Antecedents of Pay Equality.....	13
2.1	Introduction.....	13
2.2	Background and prior research	21
2.2.1	Gender pay gap and its antecedents	21
2.2.2	Organizational practices and the persistence of the gender pay gap.....	22
2.2.3	The impact of pay transparency on the gender pay gap.....	25
2.3	Institutional setting and research question	27
2.3.1	Gender pay transparency policy in the UK.....	27
2.3.2	Research question	29
2.4	Research design and data	31
2.4.1	Sample selection	31
2.4.2	Gender pay gap data	31
2.4.3	Employment Equity Actions	33
2.4.3.1	Identification of relevant actions	33
2.4.3.2	Manual collection of EE action adoption data.....	35
2.4.4	Descriptive statistics	38
2.5	Results.....	40
2.5.1	Univariate evidence	40
2.5.2	Main tests	42
2.5.2.1	Time trend analysis.....	42
2.5.2.2	The incremental effect of the mandatory disclosure of the gender pay gap	44
2.5.2.3	Cross-sectional tests	46
2.5.2.4	Difference-in-differences analysis.....	51
2.5.2.5	Robustness analysis	55
2.5.2.5.1	Classification of firms as GPG disclosers and non-disclosers	55
2.5.2.5.2	Gender pay gap metrics are matched to the fiscal year that were disclosed in but not the fiscal year they refer to.....	56
2.5.3	Further analyses	57
2.5.3.1	The role of cost in the adoption of EE actions.....	57
2.5.3.2	The ability of EE actions to predict future gender pay gaps.....	59
2.6	Conclusion	61
3	Tones at the Top: The Impact of Board Leadership Structure on the Quality of Performance Commentary.....	108
3.1	Introduction.....	108
3.2	Institutional setting, prior literature, research question, and prediction development	115

3.2.1	The UK Corporate Governance Code.....	115
3.2.2	UK corporate reporting.....	116
3.2.3	Narrative disclosure	117
3.2.4	The role of the Chair and board leadership structure, and prediction development .	121
3.3	Research design, key variables, and sample	124
3.3.1	Research design	124
3.3.2	Sample selection and descriptive statistics	125
3.4	Main tests	127
3.4.1	Association with realized earnings	127
3.4.2	Predictiveness for future earnings.....	129
3.5	What roles(s) explain the incremental informativeness of Chair commentary?	132
3.5.1.1	Monitoring role.....	133
3.5.1.1.1	The determinants and predictive power of Chair pessimism	134
3.5.1.1.2	Relative importance of realized earnings and future earnings	138
3.5.1.2	Information role.....	141
3.5.1.2.1	Confirmation function.....	141
3.5.1.2.2	Resource provision function	142
3.6	Conclusion	144
4	Thematic Content of Performance Commentary: A Topic Modeling Approach.....	168
4.1	Introduction.....	168
4.2	Background and predictions.....	175
4.2.1	Informativeness of narrative disclosure	175
4.2.2	Confirmation and resource provision functions, and prediction development	178
4.3	Research design and sample	179
4.3.1	Research design	179
4.3.2	Sample, corpus and pre-processing steps.....	180
4.3.3	Topic modeling	181
4.3.3.1	Model selection and LDA hyperparameters	181
4.3.3.2	Topic labelling.....	185
4.3.3.3	Topic visualization.....	186
4.3.4	Key variables	188
4.3.4.1	Topic intensity	188
4.3.4.1.1	Intensity of individual topics.....	188
4.3.4.1.2	Intensity of common topics and new topics	189
4.3.4.2	Tone of common topics and tone of new topics	190
4.3.5	Descriptive evidence.....	191
4.4	Results.....	196

4.5	Conclusion	199
5	Conclusion	233
	References.....	238

List of tables

Table 2.1: Sample Selection	66
Table 2.2: Distribution of observations by year and industry	67
Table 2.3: Descriptive Statistics	68
Table 2.4: Difference in means between firms GPG disclosing and non-disclosing firms	71
Table 2.5: Regression of EE actions on year (Probability values in parentheses).....	74
Table 2.6: Regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap (Probability values in parentheses.).....	76
Table 2.7: Regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap conditional on the proportion of female representation (Probability values in parentheses.).....	79
Table 2.8: Regression of EE actions on year conditional on the level of the gender pay gap in 2018 (Probability values in parentheses.)	81
Table 2.9: Difference in Difference regression (Probability values in parentheses.).....	82
Table 2.10: Regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap using an entropy balanced sample (Probability values in parentheses.).....	85
Table 2.11: Difference in difference regression using an entropy balanced sample (Probability values in parentheses.)	88
Table 2.12: Regression of EE actions on year testing the incremental effect of the implementation of the policy to disclose the gender pay gap (Probability values in parentheses.)	91
Table 2.13: Difference in difference regression using an alternative definition of Post based on the year of the implementation of the policy to disclose the gender pay gap (Probability values in parentheses.).....	94
Table 2.14: Regression examining the role of cost on the adoption of EE actions (Probability values in parentheses.)	97
Table 2.15: Regression of two- and three-period ahead gender pay gap on EE actions (Probability values in parentheses.)	98
Table 3.1: Sample selection.....	147
Table 3.2: Descriptive statistics.....	148
Table 3.3: Regressions of realized accounting and market performance on contemporaneous tone. (Probability values reported in parentheses.).....	150
Table 3.4: Regressions of one-period-ahead earnings on tone. (Probability values reported in parentheses.).....	151
Table 3.5: Regressions of one-period-ahead earnings on tone conditional on the sign of contemporaneous earnings. (Probability values reported in parentheses.)	153

Table 3.6: Logistic regressions for the determinants of Chair pessimism (probability values in parentheses and average marginal effects in italics)	154
Table 3.7: Regression of one-year ahead earnings on tone conditional on Chair pessimism (Probability values reported in parentheses.)	156
Table 3.8: General dominance statistics of regressing tone on contemporaneous and future earnings	157
Table 3.9: Regressions of one-period-ahead earnings on tone conditional on the level of analyst following. (Probability values reported in parentheses.)	158
Table 4.1: Evaluation metrics per LDA model.....	206
Table 4.2: Topic labels of LDA models.....	208
Table 4.3: Topic intensity ranking.....	217
Table 4.4: Descriptive statistics.....	220
Table 4.5: Mean levels of common topics.....	222
Table 4.6: Mean levels of new topics	225
Table 4.7: Regression of one-year ahead earnings on tone of performance commentary (probability values in parentheses.)	228

List of figures

Figure 2-1: Classification of GPG disclosing and non-disclosing firms.....	63
Figure 2-2: Comparative plots of cross-sectional means of EE actions.....	64
Figure 2-3: Adoption of EE actions around the mandatory disclosure of the gender pay gap	65
Figure 4-1: Inter-topic distance maps	203

List of Appendices

Appendix 2.1: Variable definitions	101
Appendix 2.2: Examples of EE actions as mentioned in annual reports	105
Appendix 2.3: Word list to support the search of EE actions.	107
Appendix 3.1: Variable definitions	159
Appendix 3.2: Regressions of one-period-ahead earnings on an alternative measure of tone. (Probability values reported in parentheses.)	160
Appendix 3.3: Regressions of one-period-ahead earnings on tone using the word list by García et al. (2023) (Probability values reported in parentheses.)	162
Appendix 3.4: Regressions of one-period-ahead earnings on tone using an alternative proxy of management commentary. (Probability values reported in parentheses.)	164
Appendix 3.5: Regressions of one-period-ahead earnings with an alternative structure of fixed effects. (Probability values reported in parentheses.)	166
Appendix 4.1: Topic labeling prompt	230

1 Introduction

The agency view of the firm justifies the need for corporate governance mechanisms by arguing that the separation of ownership and control creates agency conflicts between managers and shareholders. Governance mechanisms therefore serve as a form of monitoring and control that shapes managers' behavior and protects shareholders' interests (Shleifer and Vishny, 1997). Examples of internal governance mechanisms include the separation of the Chair and CEO positions and the appointment of an independent Chair and board. Still, the literature provides mixed results regarding the benefits of such board leadership structures and calls for further evidence that relies in new methods and approaches (Banerjee et al., 2020; Boivie et al., 2021; Krause et al., 2014; Yu, 2023).

Another form of monitoring can be accomplished through corporate disclosure mandates. One of the arguments in favor of mandating disclosure is that disclosure should be translated into important and meaningful firm actions. If firms do not comply with regulatory requirements, then they face non-compliance enforcement measures set out by regulators and, at the same time, are subject to potential market-induced consequences. In this respect, disclosure serves as a governance tool that promotes transparency and accountability through investor and overall market oversight (Georgiev, 2025). However, research finds that firms often treat disclosure regulation as a tick box exercise or do not respond in the way that is initially predicted by regulators, which contributes to unintended consequences (Bennedsen et al., 2023; Boone et al., 2024; Duchini et al., 2023b; Pan et al., 2022). Further evidence on the real effects of disclosure is therefore required.

In this thesis, I contribute to the research gaps identified above. In Chapter 2, I examine the impact of gender pay transparency on firm-level policies and practices that are a necessary condition for achieving organizational gender equity in the medium- and long-

term. Specifically, I ask whether firms respond to the mandatory disclosure of the gender pay gap by adopting employment equity actions (EE actions).

In 2017, the UK Government mandated the disclosure of gender pay gap metrics for all UK-registered firms with more than 250 employees. In this respect, since 2018, UK firms have been disclosing mean and median gender gap of hourly pay and bonus pay. In addition to these, firms are also encouraged to disclose action plans and supporting narratives explaining how they are tackling their gender pay gap. One key argument in favor of this regulation is the expectation that by having to disclose these metrics, firms will try to understand the causes of their gender pay gap and take targeted actions to mitigate their reported figures. In this respect, while prior literature relies on pay outcomes to examine the effectiveness of the disclosure mandate, I focus on the adoption of EE actions. I argue that this is a key outcome that speaks to the effectiveness of the policy and reflects the overall goal of the UK regulator in mandating gender pay gap disclosure for two reasons.

First, by relying on pay outcomes to examine the effectiveness of the disclosure mandate, research is, implicitly, assuming that pay structures may change significantly and almost immediately so that the policy's effects could be observed in the short-term. However, pay structures are complex and therefore any meaningful changes may take time and not be immediate. Conversely, the adoption of EE actions is a way for firms to respond to the regulation that is ignored if research exclusively focuses on pay outcomes. Second, EE actions are recommended by UK Government guidelines and are classified according to evidence on their effectiveness to promote workplace gender equity and equality.

Specifically, these actions are classified into three groups: effective, promising and mixed evidence. Effective actions include appointing a diversity manager; promising actions include providing flexible working conditions, and mixed evidence actions include providing diversity training. This means that their adoption speaks to the fundamental causes of the

gender pay gap and therefore reflects the view of the legislator in mandating disclosure of gender pay gap metrics. Furthermore, this approach highlights the importance of workplace practices in potentially reducing the gender pay gap.

I posit that if the disclosure requirement triggered changes in firm behavior aimed at improving pay outcomes for women, then I expect to see more pronounced adoption of EE actions supporting women in the workplace for firms that disclose their gender pay gap ratio versus those that do not. I rely on annual report disclosures of one hundred and thirty FTSE250 traded firms with year ends from 2015 to 2021 to identify adoption of EE actions. Of these, twenty-five do not report gender pay gap metrics and one hundred and five do.

Descriptive evidence suggests that the median annual report mentions two actions and that the most adopted actions are setting targets for female representation, providing leadership training and offering flexible working conditions. These are mentioned in more than 35% of annual reports analyzed. To understand whether firms that must report gender pay gap metrics adopt more EE actions than those that do not, I first test whether the average annual adoption is higher for firms disclosing gender pay gap metrics after the implementation of the policy. Results show that the annual increase in adoption rates is slightly higher for firms disclosing gender pay gap metrics. This effect is particularly pronounced for adoption of effective actions. However, the scale of the effect is economically insignificant. Cross-sectional analyses confirm that this effect is driven by firms with high female representation and those reporting a high gender pay gap in the first disclosure year. I then conduct a difference-in-differences regression to test if the overall increase in the adoption of EE actions from the pre-mandate period to post-mandate period is higher for firms disclosing gender pay gap metrics than for those that do not disclose. I find that the overall change is higher for firms disclosing gender pay gap metrics and the effect is concentrated in the adoption of effective actions. However, the effect is again economically

insignificant as it is the equivalent of adopting one third of an EE action. Collectively, these results suggest that the adoption of EE actions is limited.

This study contributes to the emerging literature on the impact of pay transparency policies on the gender pay gap (Baker et al., 2023; Bennedsen et al., 2022, 2023; Duchini et al., 2023a, 2023b; Lagaras et al., 2022; Lyons and Zhang, 2023) by focusing on EE actions as a key outcome that reflects the point of view of the regulator to examine whether the policy is effective and by questioning the assumption that pay outcomes have immediate effects. This chapter also adds to the literature examining the causes of the gender pay gap (Blau and Kahn, 2017, 2000, 1999) by highlighting how within firm policies may contribute to reduce the gender pay gap. Last, this chapter provides insights into the overall debate regarding the disclosure of other forms of pay reporting (e.g., disability and ethnicity pay gap).

In Chapter 3, I ask whether the presence of an independent board Chair affects corporate disclosure by testing whether the informativeness of Chair-authored commentary is incrementally informative beyond management commentary. I rely on a set of London Stock Exchange-traded firms that operate under the UK Corporate Governance Code. The Code includes provisions that the Chair and CEO positions should be held by separate individuals, and that the Chair should be independent at appointment (Cadurri Committee, 1992; Financial Reporting Council, 2018, 2014, 2008, 2003). Compliance with provisions of the Corporate Governance Code means that firms disclose performance commentary authored by the board Chair and by management. In this respect, I ask whether Chair-authored commentary has incremental predictive ability for future earnings beyond management commentary appearing *in the same annual report*.

There are several theory-based arguments supporting the view that Chair commentary should be incrementally informative beyond management commentary. Agency theory predicts that managers have incentives to disclose a biased view of firm performance, which

should negatively impact the informativeness of their commentary (Boudt and Thewissen, 2019; Fama and Jensen, 1983). Conversely, an independent board Chair is expected to monitor manager's behavior and report to shareholders (Dedman, 2016). As such, their commentary is expected to be more balanced and neutral. Under the agency theory perspective, therefore, Chair commentary should be incrementally informative. Meanwhile, resource provision theory states it is the role of the Chair to provide resources, to reduce uncertainty and to manage firm dependency from the environment where it operates (Hillman et al., 2000). Given that one of the arguments for appointing an independent Chair is the intangible skills they hold (e.g., experience and knowledge), the board Chair may benefit the firm through the provision of such resources (Higgs, 2003; Krause et al., 2016). These factors should be translated into Chair commentary that carries incremental informativeness. Finally, legitimacy theory predicts that Chair commentary validate the information disclosed by management (Suchman, 1995) thereby potentially contributing to legitimacy gains. This would be consistent with a confirming management information and should be reflected in Chair commentary that provides implications for future performance. Collectively, these theories support the prediction that Chair commentary carries incremental information content beyond management commentary. I examine this prediction by testing whether 1) the explanatory power of Chair commentary for realized performance is higher than that of management commentary and 2) Chair commentary carries incremental predictive ability for future earnings beyond management commentary.

My sample comprises 1,610 London Stock Exchange-traded firms with fiscal year ends between 2005 and 2019. I focus on tone as key linguistic feature, which research shows is correlated with earnings. Results reveal that Chair commentary has higher explanatory power for realized earnings than management commentary. I also find that Chair tone carries incremental predictive ability for one-year ahead earnings beyond management commentary.

The remainder of Chapter 3 examines the channels that explain the incremental predictability of Chair commentary for future earnings.

If the board Chair is primarily serving a monitoring role that is expected to mitigate managers' disclosure bias, then the incremental predictive ability of Chair commentary should be particularly pronounced for firms reporting weak performance (i.e., losses) when incentives for managers to engage in biased reporting are more pronounced. Accordingly, I test whether the incremental predictive ability of Chair commentary is conditional on the sign of reported earnings. I find limited evidence that Chair commentary in the annual reports of weak performing firms carries incremental predictive ability for future earnings. Instead, results show that profitable firms are driving the incremental predictive ability of Chair commentary. Such evidence may seem counterintuitive. To further understand this, I test whether the Chair adopts a more pessimistic tone when management has incentives to engage in impression management. I find evidence consistent with this expectation. This means that the monitoring role of the board Chair is more pronounced in weak performing firms and this role translates into the use of more pessimistic tone than management. I further show that management's ability to predict future earnings is weaker when the Chair is more pessimistic than management.

The fact that the incremental predictability of Chair commentary for future earnings is driven by profitable firms is consistent with an information role. Specifically, as predicted by legitimacy theory, the need for a board Chair that is not affiliated with management to confirm management information is particularly pronounced for good performing firms. This is because investors know that managers may adopt a favorable and positive tone that is not aligned with performance. In this respect, I therefore interpret the results as evidence that is consistent with the board Chair serving an information role that is consistent with a confirmation function.

As an independent board member, the Chair is expected to provide resources to the firm in the form of skills that arise from experience, such as knowledge and expertise (Krause et al., 2016). This is therefore expected to add predictive value to Chair commentary, particularly in environments with increased information demand by analysts. Additional analysis reveals that the incremental predictive ability of Chair commentary for future earnings is higher for firms operating in environments with high information demand. This is consistent with the board Chair serving an information role that arises from a resource provision function. I therefore conclude that the presence of an independent Chair affects corporate disclosure and generates a reporting benefit for shareholders that arises from the board Chair serving both a monitoring role and an information role. I identify two non-mutually exclusive functions of the information role: confirmation and resource provision.

Chapter 3 makes the following contributions to literature. First, I add to the literature examining the role of an independent Chair as a key governance mechanism (Banerjee et al., 2020; Boyd, 1995; Brickley et al., 1997; Dahya et al., 1996; Krause, 2017; Krause et al., 2016, 2014; Withers and Fitza, 2017). As opposed to US-focused studies examining the role of the Chair that rely on a setting where firms choose to separate the roles of the Chair and CEO or to appoint an independent Chair, I rely on a setting where separation of roles and independence criteria are the norm. This means that my empirical strategy helps to address endogeneity and self-selection concerns. Furthermore, while prior research tests the benefits of Chair independence on firm performance or reporting quality (proxied by earnings management), I focus on examining the informativeness of performance commentary in a setting where there is variation in authorship and governance responsibilities. Specifically, I rely on a disclosure setting that allows me to observe the board Chair reporting to shareholders, which is one of their key responsibilities as listed by the Corporate Governance Code. Second, I contribute to the literature examining the linguistic properties of performance

commentary by studying variation in the informativeness of annual report sections authored by different individuals within the same report, which the literature has largely ignored despite evidence suggesting that variation in authorship should impact informativeness (Argamon et al., 2009; Ball et al., 2003). As the board Chair and management disclose their commentary in the same reporting channel (the annual report) at the same time, any variation in informativeness is more likely to derive from differences in reporting incentives or expertise.

In Chapter 3, I examine variation in *how* Chair and management discuss firm performance and conclude that monitoring and information roles explain incremental informativeness. Specifically, the information role arises from two non-mutually exclusive functions: a confirmation and a resource provision function. In Chapter 4, I extend the analysis by examining variation in *what* is discussed as a means of distinguishing between the certification and resource provision explanations.

The confirmation function of the board Chair is consistent with legitimacy theory that predicts that the board Chair generate legitimacy gains through the provision of Chair-authored commentary (Perrault and McHugh, 2015; Suchman, 1995). In the context of corporate disclosure, this means supporting management by confirming management information and therefore disclosing broadly similar content to that disclosed by management. Conversely, as an independent Chair may provide resources to the firm in the form of information skills that arise from substantial experience and knowledge, resource dependency theory predicts that the board Chair serves a resource provision function (Higgs, 2003). This should therefore be reflected in a Chair commentary displaying low content overlap with management and addressing topics that management has not mentioned. In this respect, I predict that the confirmation function explains the information role of the board Chair if the Chair's statement mainly discusses themes that are also mentioned by

management and that the resource provision function explains the information role of the board Chair if the Chair's statement consists of 'new' topics that are not discussed by management.

To analyze content discussed in Chair and management commentary, I model topics using Latent Dirichlet Allocation (LDA - Blei et al., 2003) on a corpus of annual reports. I compare results across two separate LDA models – one model that includes fifty topics that several evaluation criteria identify as the best performing model and an alternative model including twenty-five topics. To label the topics produced by both models, I follow Gad et al. (2025) and use ChatGPT4o.

I follow Huang et al. (2018) and compute the intensity level of each topic. This measures the proportion of sentences dedicated to a given topic scaled by the number of sentences within a given annual report section. Descriptive evidence from both LDA models shows that Chair commentary places more importance on governance and leadership-related topics than management, whereas management places more emphasis on financial performance related topics than the board Chair. The result helps to validate my labeling strategy as these topics are consistent with the themes identified for each annual report section as described by a 2015 ICSA report on the content of UK annual reports.

I test whether the information role of the board Chair is associated with a certification function or a resource provision function by testing if the incremental predictive ability of Chair commentary is explained by common topics to Chair and management commentary or topics that feature only in Chair commentary. In this respect, I decompose tone of Chair commentary into two separate variables: *Chair Tone Common Topics* and *Chair Tone New Topics*. *Chair Tone Common Topics* is the difference between positive sentences discussing common topics and negative sentences discussing common topics in Chair commentary, scaled by the total number of sentences discussing common topics in Chair commentary.

Meanwhile, *Chair Tone New Topics* is the difference between positive sentences discussing new topics and negative sentences discussing new topics in Chair commentary, scaled by the total number of sentences discussing new topics in Chair commentary.

Descriptive evidence shows that regardless of the difference in topic granularity, more than 70% (75%) of the topics discussed by the average (median) Chair's letter are also mentioned by management commentary. This suggests that there is a high degree of content alignment between Chair and management commentary. Descriptive evidence therefore points towards the confirmation function of the board Chair.

Results from the 25-topic model show that the incremental predictive ability of Chair commentary is entirely explained by the content that is featured in both Chair and management commentary. A test of differences in coefficients reveals that the coefficient of tone of common topics is greater than that of new topics. To understand the economic significance of tone of common topics, I compare the effect of an interquartile range change in common topics tone on future earnings with the effect on future earnings for a comparable change in contemporaneous earnings. I find that the magnitude of the effect of tone of common topics is equal to 23% of the effect of current earnings, which confirms that these common topics have a substantive impact on the informativeness of Chair commentary. Based on these findings, I conclude that the information role of Chair commentary comes mainly from its certification function.

In contrast, results from the 50-topic model show that the predictive ability of Chair commentary is explained by both the tone of common topics and the tone of new topics. The effect of an interquartile change in the tone of common (new) topics on future earnings represents 19% (20%) of the effect of current earnings on future earnings. Given the marginal difference, the incremental predictability of Chair commentary for future earnings seems to be equally shared between both. Overall, this means that the information role of the board

Chair equally arises from serving a confirmation function and a resource provision function. Collectively, this difference in results is not surprising as greater granularity is associated with greater variation in topics. On the one hand, at a more aggregate and broad level, results suggest that Chair commentary is particularly important in certifying management information. On the other hand, at a more granular level, results suggest that resource provision and certification functions are not competing explanations. Instead, both functions complement each other and form the information role of the Chair. As both models support the certification function, this provides strong and consistent evidence in its favor. By contrast, the findings offer only modest evidence supporting the resource provision function.

This chapter adds to two streams of research. First, I contribute to the literature examining the role of the board Chair by providing deeper insights on how the information role of Chair commentary affects corporate disclosure. While research focuses mainly on the monitoring role of the Chair (Banerjee et al., 2020; Boivie et al., 2021; Dedman, 2016; Krause et al., 2014), I use a disclosure setting and content analysis to explore whether the information role of the Chair arises from a certification or a resource provision function. Second, I contribute to the literature examining the informativeness of performance commentary. Specifically, I show how variation in content discussed across two sections within the same report has implications for future performance.

Overall, my work speaks to the ability of disclosure as a governance mechanism that shapes firm behavior. Chapter 2 tests the effectiveness of a mandatory disclosure policy on firm behavior by focusing on annual report disclosures. While I show that there has been a slight increase in the disclosure of EE actions mentioned in annual reports, it is unclear whether stakeholders access and rely on companies' gender-related disclosures. Future research may examine how the disclosed metrics and actions plans are used by different

stakeholders and whether the mandatory disclosure of the gender pay gap in the UK generated unintended consequences such as an increase in gender washing.

Chapter 3 examines how the presence of an independent board Chair affects the ability of narrative disclosure to predict future financial future earnings beyond management commentary. Future research could examine the predictive power of Chair commentary for market-based performance and confirm whether investors value the information provided by the board Chair.

Chapter 4 attempts to distinguish between the two non-mutually exclusive functions of the information role of the Chair (certification and resource provision) by using a Latent Dirichlet Approach to model topics. While LDA is the dominant method in accounting research, LDA requires researchers to define hyperparameters and is sensitive to changes in those parameters. Additionally, it assumes that topics are independent from each other, which is an assumption that is unlikely to be verified (Lafferty and Blei, 2005). In this respect, future research could examine performance commentary using more sophisticated methods such as Large Language Models.

Overall, the results of my work are consistent with the argument that disclosure policies affect firm behavior and may therefore serve as a governance mechanism.

2 The Impact of Gender Pay Transparency on the Antecedents of Pay Equality

2.1 Introduction

The pay differential between women and men (described as the mean or median gender pay gap) is widely documented across different professions, industries and countries (Blau and Kahn, 2017). For example, the median male pay of full-time workers in the US in 2022 was 17% higher than the median female pay of the same worker category.¹ In the same year, the Euro Area and Australia reported gender pay gaps of 13.2% and 21.7%, respectively.² Even Iceland as a world-leader on gender equality policy reports that, in some jobs, men currently earn 21% more than women.³ Given this worldwide evidence, several countries have adopted pay transparency policies in an attempt to reduce the gender pay gap (Duchini et al., 2023b). Prior work on the effectiveness of these policies focuses on pay outcomes and concludes that despite some evidence of the gender pay gap shrinking following their implementation, the magnitude of the decline is modest and more likely reflects a reduction in compensation levels for male workers rather than higher pay outcomes for women (Baker et al., 2023; Bennedsen et al., 2022, 2023; Duchini et al., 2023b). The benefits of greater pay transparency therefore remain an open question.

Relative pay outcomes for men and women are a consequence of complex interactions between multiple organizational policies, processes, and practices, many of which are structural in nature and therefore slow to change. For example, inadequate childcare provision is frequently cited as a factor limiting female career progression and hence pay

¹ See the Bureau of Labor Statistics webpage describing the highlights of women's earnings in 2023: <https://www.bls.gov/opub/reports/womens-earnings/2023/> [Accessed on February 2nd, 2025].

² See the Eurostat webpage describing gender pay gap statistics: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Gender_pay_gap_statistics [Accessed on February 2nd, 2025].

See the Workplace Gender Equality Agency webpage describing gender pay gap data in Australia: <https://www.wgea.gov.au/pay-and-gender/gender-pay-gap-data> [Accessed on February 2nd, 2025].

³ See The Guardian news article: <https://www.theguardian.com/world/2023/oct/23/icelands-first-full-day-womens-strike-in-48-years-aims-to-close-pay-gap>. [Accessed on August 8th, 2024].

(PwC, 2023). However, the time lag between offering additional childcare support and seeing the benefits of such investments in terms of more female promotions to higher paid roles is measured in years rather than months. Examining the efficacy of pay transparency mandates through the exclusive lens of short-term gender pay outcomes therefore ignores stickiness in firms' employment and pay structures, and risks overlooking fundamental shifts in organizational practice that provide the foundations for a lower pay gap in the future. I therefore examine the direct (short-term) impact of pay transparency regulations on firm-level policies and practices to support female workers that are a necessary condition for achieving organizational gender equity in the medium- and long-term. I posit that if disclosure stimulates structural changes in reporting entities' policies and practices, then mandating pay transparency can have a material positive impact on reducing the gender pay gap in the medium and longer term, even if little evidence of progressive pay outcomes for women is apparent in the immediate post-implementation period. Specifically, I test whether a 2017 requirement for large UK firms to disclose their gender pay gap annually catalyzed adoption of employment equity actions that, according to research and UK Government guidelines, should reduce the gender pay gap in the medium and long term. If the disclosure requirement triggered changes aimed at improving pay outcomes for women, then I expect to see more pronounced adoption of employment equity actions for firms disclosing their gender pay gap ratio versus those that do not.

I provide two arguments to motivate my analysis of employment equity (EE) actions. First, the adoption of EE actions is a means to understand whether firms are committed to closing the gender pay gap by taking actions that target its fundamental antecedents. Indeed, EE actions are evidence-based as their effectiveness in improving gender equality in the workplace has been previously tested (BIT, 2023). Using the adoption of EE actions as an outcome to evaluate the effectiveness of pay transparency policies is therefore consistent with

evaluating the effectiveness of pay transparency policies through the eyes of the regulator, which emphasizes the importance of targeting the fundamental causes of the gender pay gap as the solution to close it in the long run. Second, evidencing whether a pay transparency mandate promotes actions that underpin positive and sustainable pay outcomes for women is important for building a complete picture of the benefits of disclosure and determining how transparency leads to changes in firm behavior.

In 2017, the UK Government compelled UK-registered entities with more than 250 employees to disclose their gender pay gap figures under the Equality Act 2010.⁴ Entities must submit data to the Government Equalities Office's (GEO) website annually and publish a gender pay gap report, which must be available on the entity's website. In addition to the mandatory disclosure of gender pay gap metrics, firms are encouraged to design action plans to reduce the gender pay gap. The disclosure mandate applies at the level of the legal entity, meaning that entities belonging to a Group must disclose their gender pay gap metrics individually and that the parent-level entity need not disclose if its employee count is less than 250.

My sampling frame is FTSE250-traded entities (excluding investment and real estate trusts) over the period 2015 to 2021. The sample contains 910 firm-year observations for 130 firms, 105 of which disclose gender pay gap figures while the remainder do not. Since firms are expected to provide supporting narratives explaining how they are addressing their gender pay gap, I use annual report commentary as a source of information on the use of actions sponsored by the UK Government to promote gender equality and equity. Given the evidence from research in management, psychology and human resources, UK government guidelines classify these actions as effective, promising and mixed evidence based on a survey of

⁴ Gender pay gap reporting requirements are set out in <https://www.legislation.gov.uk/ukdsi/2017/9780111152010>. [Accessed on August 8th, 2024].

research assessing their effectiveness in improving workplace gender equality and equity. My analysis includes nineteen distinct EE actions. Offering flexible working arrangements, setting targets for female representation, and providing diversity training are examples of the type of EE actions on which I focus. These three actions are classified as promising, effective, and mixed evidence actions, respectively. Appendix 2.2 contains details of all 19 actions.

The UK disclosure mandate only applies to FTSE250 entities with at least 250 employees. Many FTSE250 parent entities do not meet this threshold directly because the legal reporting entity has fewer than 250 staff. I use a two-stage process to identify FTSE250 firms that disclose gender pay gap information directly at the parent level or indirectly via one or more subsidiaries. First, I identify FTSE250 firms in my sample that disclose gender pay gap details directly on the UK Government's dedicated website. Second, I collect details of all subsidiaries and check whether any of those subsidiaries disclose gender pay gap metrics. Where the parent does not disclose information but at least one subsidiary does, I use available information from all disclosing subsidiaries to construct a proxy for the parent entity's gender pay gap status. I classify an entity as a non-discloser if it does not disclose any gender pay gap information, either directly through the parent company or indirectly through its subsidiaries.⁵

Descriptive evidence highlights a key finding that the use of EE actions is very limited throughout the sample period. Analyses reveal that the median firm employs just two of the nineteen available EE actions. The three most popular actions are providing leadership training; offering mentoring, networking, and sponsoring conditions; and setting targets for female representation. All three policies are present in at least 40% of the sample.

⁵ All the entities classified as non-disclosers are firms that do not fall under the scope of the regulation. In other words, they are not required to disclose gender pay gap metrics.

Conversely, an action such as supporting an employee's return to the labor market is mentioned in less than 5% of annual reports.

While average adoption rates are low across the sample period, an increasing trend in the mean number of EE actions between 2015 and 2021 is visible and a time trend analysis confirms that the annual average increase is statistically significant. Results, which are robust to the inclusion of industry and firm fixed effects, demonstrate monotonic year-on-year growth in employability equity actions, albeit from a low baseline. Comparing the economic significance of the time trend variable with the impact of firm performance (a known determinant of firm actions) reveals that the economic significance of the time trend is almost four times larger than the performance effect. My analysis therefore provides evidence of *unconditional* growth in EE adoption from an extremely low base.

Next, I examine the conditional effect of the gender pay gap disclosure mandate by testing whether the annual increase in the adoption of EE actions following the introduction of the mandate is higher for entities that disclose gender pay gap metrics. Pooled descriptive statistics suggest that the average number of EE actions is slightly higher for entities that disclose gender pay gap metrics under the mandate. Temporal analysis confirms that, from 2018 onwards, the annual increase in the annual adoption of EE actions is statistically higher for gender pay gap disclosers. Further analysis reveals that the result reflects adoption of a specific subset of EE actions relating to effective actions. =

I continue by proposing two mechanisms that may be associated with higher adoption rates for gender pay gap disclosing firms. First, I posit that firms with high female representation should experience greater pressure to adopt policies that reduce the gender pay gap and address its fundamental causes. Consistent with this prediction, I find that the relation between the disclosure of gender pay gap metrics and the annual adoption of actions occurs primarily among firms with high female representation at the employee-level. Second,

I focus on the subset of gender pay gap disclosers and posit that those revealed as having a high gender pay gap in the first disclosure year (2018) are those exposed to higher reputational damage. Results confirm this expectation; the annual adoption of EE actions is higher for firms that disclose a high gender pay gap in 2018. Results from these two tests suggest that firms' response to the disclosure mandate is conditional on entity-specific circumstances and pressures.

To further understand whether the pay transparency mandate triggered a change in firm behavior, I conduct a difference-in-differences analysis to examine the conditional effect of the gender pay gap ratio on the adoption of EE actions. I find that the change in the adoption of actions classified as effective after the implementation of the policy is higher for gender pay gap disclosers relative to non-disclosers. Collectively, my findings suggest that the adoption of EE actions is limited. Mandatory disclosure of gender pay gap information in the UK therefore appears not to have been especially effective in driving substantive policy and behavioral change at the firm level.

My final analysis involves two further tests. First, I examine whether adoption of EE actions is associated with their relative cost. I classify the nineteen EE actions into low, moderate, and high cost categories based on a qualitative assessment of the investment required to implement each action. An example of a low-cost action is setting targets for the number of women that are shortlisted in a recruitment process, while examples of moderate and high-cost actions are offering diversity training and appointing a diversity lead/taskforce, respectively. I find evidence consistent with EE action adoption concentrating on the set of low-cost actions. Importantly, out of six actions classified as effective, three are relabeled as low-cost. Specifically, these are setting targets for female representation, removing biased language from job ads, and conducting structured interviews.

Second, I test the ability of EE actions to predict the medium horizon (i.e., three-year-ahead) gender pay gap. I focus on the subset of firms that report gender pay gaps in favor of men. I show that the adoption of EE actions is associated with a lower gender pay gap in the medium term; the adoption of effective actions predicts a 13% reduction in the three-year-ahead gender pay gap. Results highlight the importance of focusing on the adoption of real EE actions when examining the effects of reporting transparency on pay outcomes for women.

A series of recent papers study the impact of pay transparency policies on the gender pay gap (Bennedsen et al., 2022, 2023; Duchini et al., 2023a, 2023b; Gamage et al., 2024; Gulyas et al., 2023; Jones and Kaya, 2022; Lagaras et al., 2022; Lyons and Zhang, 2023; Seitz and Sinha, 2022). I contribute to this emergent literature in two ways. First, while prior work focuses on wages as a primary means of assessing the effectiveness of a gender pay transparency policy, I examine intermediate adoption of EE actions designed to reduce the gender pay gap in the medium term. My analysis considers the effectiveness of pay transparency policies through the lens of a policymaker by using EE actions as a key outcome. This approach reflects the Government Equalities Office's (2019) view that the only way to eliminate the gender pay gap is to understand and address its fundamental drivers. Second, I build a comprehensive dataset of EE actions. My work speaks to the adoption of real policies that, in the medium-to-long run, should reduce the gender pay bias by increasing female pay rates rather than by constraining pay growth of men.

An established stream of economics literature studying the determinants of gender inequality has recently turned its attention to individual preferences and employer-specific features to explain the persistence of the gender pay gap. I add to this literature by examining whether adoption of EE actions that are employer-specific and can influence an individual's choice of employer, help to reduce the gender pay gap. I therefore adopt the view that a

material gender pay gap stems from a variety of organizational practices that affect men's and women's pay differently. Accelerating the adoption of EE actions is thus part of the answer to reducing the gender pay gap. My results speak to the importance of workplace gender equity as a means to achieve broad gender equality (Chang and Milkman, 2020; Jergins, 2023; Milliken et al., 2020; Son Hing et al., 2023; Trauth et al., 2021; Wang et al., 2023).

Finally, my results offer insights into the likely effect of other pay gap reporting initiatives targeting areas such as ethnicity and disability pay biases, which are currently under consideration by the UK Government.⁶ Research shows that gender pay transparency policies lead to a reduction in gender pay gap and that this effect is mainly driven by firms that are exposed to stronger reputational damage (Jones and Kaya, 2022; Lyons and Zhang, 2023). This research further concludes that these policies do seem to be associated with an increase in women's pay (Bennedsen et al., 2023, 2022; Duchini et al., 2023a, 2023b). My paper complements this body of work by demonstrating that the adoption of actions that support women in the workplace and that target the fundamental causes of the gender pay gap is limited. While the naming and shaming effect of increased transparency is associated with firms pursuing instrumental policies that reduce the pay gap, the outcome does not guarantee improved outcomes for women. An important implication of my work is the need for policymakers to rethink the role of pay gap disclosures and in particular how they can create additional incentives for firms to adopt actions that target the underlying causes of the reported pay gaps.

The remainder of this chapter is organized as follows. Section 2.2 provides background and reviews prior research on the determinants of the gender pay gap and the impact of pay transparency policies on this gap. Section 2.3 describes the UK's institutional setting and research question. Section 2.4 presents the research design and data, outlines the sample

⁶ See BBC news article: <https://www.bbc.co.uk/news/uk-politics-68202>(Clatworthy and Jones, 2006)⁵⁴¹

selection, describes the process of manual data collection, and explains the classification of firms as gender pay gap disclosers and non-disclosers. Section 2.5 presents and discusses the results. Section 2.6 concludes.

2.2 Background and prior research

2.2.1 Gender pay gap and its antecedents

The gender pay gap refers to the difference between the remuneration earned by a man and a woman. While it is established that the gender pay gap narrowed following the second world war, evidence from the last thirty years reveals that the differential has remained stubbornly persistent and constant (Bennedsen et al., 2023; Blau and Kahn, 2017).

Research splits the determinants of the gender pay gap into explained and unexplained components. The explained component is the result of observable factors such as individual preferences and labor market characteristics that include employee- and employer-specific features. Employee-specific features include human capital factors such as experience, age, tenure, education and training, whereas employer-specific features include, among others, industry, unionization and sector (Bishu and Alkadry, 2017; Blau and Kahn, 2017, 2000, 1999; Miller, 2009).⁷ Meanwhile, the unexplained component refers to the portion of the gender pay gap that is not explained by observable employee and employer features, and is often interpreted as pay discrimination (Card et al., 2016; Cook et al., 2021; Hardies et al., 2021; Jewell et al., 2020).

The ability of employee- and employer-specific features to explain the gender pay gap has changed in recent decades (Blau and Kahn, 2017; Jewell et al., 2020). For example, in the US from 1980 to 2010, gender differences in education and experience reversed (Blau and Kahn, 2017; Olsen and Walby, 2004). While these factors were responsible for 27% of the

⁷ In this context, sector refers to the distinction between public (government) and private sector (Bishu and Alkadry, 2017).

gender pay gap in 1980, these effects had declined to 8% in 2010.⁸ Consequently, Jewell et al. (2020) conclude that the importance of individual preferences and employer-specific features in explaining the gender pay gap has increased. Using a sample of UK firms, Jewell et al. (2020) estimates that firm-specific characteristics that affect the allocation of employees across firms and have the potential to influence employee preference, are responsible for 16% of the gender pay gap. Consistent with this view, Wiswall and Zafar (2018) show that women have a preference for jobs that offer flexibility and security. Bradley et al (2022) find that women are more likely to choose to work for low pay universities (as they are less sensitive to pay-for-performance) and less likely than men to quit if they are underpaid. Collectively, the evidence hints at the ability of organizational practices to influence employee's choice of employers and therefore to perpetuate or reduce the gender pay gap.

2.2.2 Organizational practices and the persistence of the gender pay gap

The Cambridge Dictionary defines equality as “the right of different groups of people to have similar social position and receive the same treatment”. The key element of this definition is “same treatment” – equality involves providing the same treatment to different groups while ignoring any pre-existent differences. Conversely, equity is defined as “the situation in which everyone is treated fairly according to their needs and no group of people is given special treatment”. In other words, as stated by the Employment Equity Act from Canada “equity means more than treating persons in the same way but also requires special measures and the accommodation of differences”.⁹

In a workplace context, gender equity involves understanding the organizational factors that may be perpetuating the gender pay gap. Recently, work examining the determinants of the gender pay gap has turned its attention to sociology and psychology

⁸ While this result is reported for the US, similar trends are seen in other developed countries (e.g., UK).

⁹ See the Employment Equity Act: <https://laws-lois.justice.gc.ca/eng/acts/e-5.401/page-1.html>.

research. Duchini et al., (2023b) split this stream of the literature into three groups. First, they discuss the impact of different social norms attributed to men and women. Roethlisberger et al. (2023) state that despite having an active role in the workforce, women are expected to be the primary caretaker and are therefore more likely than men to be responsible for household chores and childcare. As expected, this affects a woman's career preference and job position, which ultimately manifests itself in pay realizations. As the primary caretakers, women are more likely to take a career break. Consistent with this evidence, a 2024 article in *The Economist* featuring the work by Kleven et al. (2024) reports that the employment gap between men and women in the UK, Canada, Sweden and Iceland is entirely explained by motherhood. This gap hampers career progression and, in the long term, pay. This highlights a major obstacle to workplace gender equity in the form of work-life conflict (Son Hing et al., 2023). To mitigate this effect and attract more women, firms may advertise jobs offering flexible working conditions, incentivize workers to share parental responsibilities with their partners through paternity leave or shared parental leave, and create a returners' policy that specifically supports individuals coming back from a career break (Atkinson, 2017; Cook et al., 2021; Fuller and Hirsh, 2019; Women Returners and Timewise, 2018).

Second, Duchini et al. (2023b) highlight the role of different personality traits and noncognitive skills, and how these lead to different levels of pay. When compared to men, women are more likely to underestimate their performance and attribute their success to external factors. Conversely, men are more likely to overstate their performance (Beyer, 1990; Fletcher, 1999). Accordingly, a man or a woman with the same performance will evaluate themselves differently. Hence, a company that relies on self-assessments for performance appraisal or promotion decisions will disadvantage a female candidate and that may hamper her ability to receive a pay increase or be promoted. In addition, women are less likely than men to negotiate higher wages (Finley et al., 2022; Leibbrandt and List, 2015).

Further, where women do request a pay increase, research shows that they face a social cost as this behavior is not consistent with gender stereotypes (Bowles and Babcock, 2013). To mitigate this effect, firms may take initiatives such as the approach introduced by Chang and Milkman (2020). The paper describes a company that understood that during promotions windows, self-nominations were higher for men than for women. Considering this information, all workers received an email communicating research describing how women understate their performance and informing that the applications for promotions had started. This initiative led to an increase in self-nominations by women. Additional initiatives include advertising jobs with a salary range or stating that the salary is negotiable (BIT, 2021a).

Third, Duchini et al. (2023b) discuss the role of gender stereotypes and unconscious bias in perpetuating the gender pay gap. Research shows that between equally qualified men and women, men are more likely to be hired when the job's stereotype favors males (Coffman et al., 2021). Such evidence implies that in the CV screening stage for a position that is typically male dominated, all else equal, call back rates of female candidates are lower than they could be due to the presence of unconscious bias. To mitigate this effect, research recommends the use of blind CVs. This is expected to reduce gender bias as it does not allow the recruiter to know if the applicant is male or female (Rinne, 2018). Hence, decision making should be strongly motivated by experience and qualifications. In the interview stage, research warns against the use of unstructured interviews. Unstructured interviews provide flexibility to the recruiter as they do not involve a pre-defined set of questions and a set of "correct" answers. This means that the recruiter may ask different questions to different candidates and that harms comparability between candidates (BIT, 2021a; Kausel et al., 2016; Levashina et al., 2014). Importantly, lack of comparability implies that decision making may be partially driven by bias rather than by the criteria that define a "good" candidate. To

prevent this, the use of structured set of questions is the recommended interview method (BIT, 2023, 2021b, 2021a).

One important conclusion arising from the discussion in this subsection is that correcting behaviors that disadvantage women (or men) and affect their likelihood of being hired or promoted (despite presenting similar abilities and qualifications) is a key step to cultivating female talent and reducing the gender pay gap (Chang and Milkman, 2020; Son Hing et al., 2023; Stamarski and Son Hing, 2015).

2.2.3 The impact of pay transparency on the gender pay gap

With the aim of reducing the gender pay gap and its causes, several countries have adopted different types of pay transparency policies. These typically involve disclosing remuneration information based on gender, eliminating pay secrecy clauses, and implementing pay audits or other actions that prevent growth of the gender pay gap. The key argument in favor of greater transparency is that it facilitates more informed decisions, both for employers and employees (Bennedsen et al., 2023). Greater pay transparency allows employees to learn their peers' wages and their own firm's level of gender pay gap. This information is expected to change employees' bargaining power in the sense that, all else equal, lesser paid employees can either demand higher salaries or choose to work for higher-paying firms. In addition, by forcing the collection of gender disaggregated salary information, greater transparency increases firms' awareness of their own gender pay gap. Such awareness should lead to changes that improve workplace gender equity (Bennedsen et al., 2023; Duchini et al., 2023b). Through disclosing salary-related information, firms may also experience external pressure from shareholders, customers, and media to reduce their gender pay gap (Lyons and Zhang, 2023).

Conversely, Cullen (2024) warns about the unintended consequences of pay transparency policies. The paper argues that such policies lead to a decline in overall wages. Specifically, to avoid future salary renegotiation, firms respond to pay transparency policies by refusing to pay higher wages. In addition, she contends that pay transparency policies may affect employees' morale and effort negatively; by revealing the level of gender pay inequality in the organization, lesser paid employees might reduce their effort and productivity. Consistent with Cullen's (2024) arguments that pay transparency policies may have unintended consequences, several papers examining the adoption of these policies in the UK, Canada, and Denmark report similar results: while they lead to a reduction in the gender pay gap, this reduction is partially driven by a decrease in men's wage growth (Bennedsen et al., 2022; Duchini et al., 2023a). This result implies that (male) employees are worse off with the adoption of pay transparency policies. For example, Duchini et al., (2023a) study the impact of the UK's pay transparency policy on gender pay differences and document a 19 percent reduction in the gender pay gap of treated firms. While this suggests the policy has been effective in closing the gender pay gap, the paper also concludes that the decrease in the gender pay differential is driven by a reduction in men's wage growth rather than improved outcomes for women. Similarly, Bennedsen et al. (2022) focus on the Danish setting and examine whether disclosing gender disaggregated salary information affects the gender pay gap. While this gap reduced by 13% relative to the period before the pay transparency policy, further analysis reveals the effect was driven by a cut in the growth of male wages. Using a policy change in Canada, Baker et al., (2023) exploit the staggered adoption of a pay transparency policy across different provinces, times, and salary thresholds in Canada. The paper examines the policy's impact on the gender pay gap of university faculty members. Results show that during the period 1990-2018, there was a 20-30 percent gender pay gap reduction. Results suggest that this effect is partially driven by a cut in men's wage growth.

Two conclusions emerge from this body of work. First, while the evidence suggests that pay transparency policies may close the gender pay gap, employees are worse off overall; women do not seem to experience improved wage outcomes and men experience a slower wage growth. Second, research studying the impact of pay transparency policies focuses on wages as a primary outcome. Wages are the natural focal point given the objective of closing the gender pay gap. However, concentrating exclusively on pay outcomes in the immediate post-regulation period ignores general wage stickiness in the short run, as well as the need for structural employment practices that disadvantage women to change before any systematic improvements in pay outcomes for women can feed through.

2.3 Institutional setting and research question

2.3.1 Gender pay transparency policy in the UK

In 2017 the UK Government established (under the Equality Act 2010) that all UK-registered entities with at least 250 employees must disclose gender pay gap statistics on an annual basis.¹⁰ Entities must publish the required information on their website and also submit details to the UK Government's dedicated gender pay archive managed by the Government Equalities Office.

Public (private) firms must provide snapshot statistics for the gender pay gap as of March 31 (April 5). Firms have 12 months to submit their data, and the majority submit close to the deadline. Accordingly, comprehensive data for the first snapshot in April 2017 was not available until April 2018 and the one-year reporting lag has continued thereafter. Mandatory reporting was suspended for the March 2020 snapshot due to COVID-19, and the submission deadline for the 2021 snapshot was extended to October 2021. To comply with the gender

¹⁰ Gender pay gap reporting requirements are set out in <https://www.legislation.gov.uk/ukdsi/2017/9780111152010>. [Accessed on February 15th, 2023].

pay gap reporting requirements, entities must (a) disclose a gender pay gap report that should be available on the entity's website, and (b) provide the mean and median gender pay gap and bonus gap between female and male workers, and the proportion of women and men receiving a bonus. These metrics are unconditional averages and do not therefore adjust for differences in factors such as level of experience, education levels, or other individual features that might account for observable pay differentials. In addition to disclosing gender pay gap metrics, the UK Government encourages firms to understand the determinants of their gender pay gap figures. This process involves analyzing each stage of the recruitment and selection process to identify potential barriers that affect women's progression and retention in the organization. Armed with this information, firms are encouraged to develop an action plan aimed at addressing the causes of the gender pay gap. The UK Government's approach therefore involves a combination of mandatory gender pay gap disclosures supplemented by voluntary narratives.¹¹

A key feature of the regulation is that the mandatory disclosure of the gender pay gap data applies to all entities with at least 250 employees. Specifically, the mandate applies to the legal entity level, and this may not be same as the parent-level in corporate group structures. Indeed, an entity that belongs to a group must report its gender pay gap metrics individually. For example, JD Sports Fashion PLC is a FTSE250 parent company that discloses the gender pay gap individually because it employs more than 250 staff. Further, in 2021, the seven subsidiaries that JD Sports Fashion PLC owns also disclose their entity-level gender pay gap metrics individually.¹² In this case the FTSE250 company discloses gender pay gap metrics along with seven subsidiaries. Conversely, AstraZeneca PLC is a FTSE100 traded company. In 2021, as shown by their gender pay gap report, AstraZeneca discloses

¹¹ See <https://www.gov.uk/government/publications/gender-pay-gap-reporting-guidance-for-employers/closing-your-gender-pay-gap#how-to-understand-your-gender-pay-data> [Accessed on March 5th, 2024]

¹² See the 2021 gender pay gap reports published in JD Sports Fashion PLC website: <https://www.jdplc.com/esg/governance/gender-gap-pay-reports/default.aspx> [Accessed on July 7th, 2025]

gender pay gap metrics in the UK through three of its subsidiaries employing more than 250 workers each (pages 5 and 7 of the report).¹³

There are no legal or regulatory consequences associated with high gender pay disparity or failing to narrow the gap over time, although the Equality and Human Rights Commission (EHRC) does hold litigation and enforcement powers under the Equalities Act 2010 to take legal action against an entity that fails to comply with gender pay gap reporting requirements (e.g., not submitting gender pay gap metrics or failing to meet the deadline). Firms nevertheless face reputational risk from reporting high gender pay gap ratios. For example, media outlets name and shame firms for their reported figures.¹⁴ Additionally, the EHRC names firms that do not comply with gender pay gap reporting requirements on its website.¹⁵ Additionally, reputational risk may also arise from internal sources (within the firm) from decreased employee satisfaction and productivity. This is due to increased awareness of within firm inequality may negatively impact employees' morale (Bennedsen et al., 2022; Duchini et al., 2023b).

2.3.2 Research question

The UK's gender pay transparency policy mandates that entities must collect gender disaggregated data and report gender pay gap metrics. At the same time, the policy encourages entities to construct a plan to address their gender pay gap. The goal of this policy

¹³ See 2021 gender pay gap report published in Astrazeneca PLC website: <https://www.astrazeneca.co.uk/careers> [Accessed on July 7th, 2025]

¹⁴ The Guardian newspaper listed the ten firms with the highest gender pay gap ratio in 2018. See <https://www.theguardian.com/society/2018/apr/05/the-uk-firms-reporting-the-biggest-gender-pay-gaps>. [Accessed on February 15th, 2023]

Also in 2018, The New York Times shared a similar news article disclosing the fashion brands with highest gender pay gap ratios: <https://www.nytimes.com/2018/04/05/fashion/uk-fashion-firms-gender-pay-gap.html> In 2024, the Guardian published a news article discussing the evolution of the gender pay gap at Goldman Sachs: <https://www.theguardian.com/business/2024/apr/04/gender-pay-gap-at-uk-arm-of-goldman-sachs-at-highest-level-in-six-years>

¹⁵ See <https://www.equalityhumanrights.com/our-work/gender-pay-gap-our-enforcement-action> for the list of firms that did not report their gender pay gap metrics in 2022 and 2023. For example, in 2022, 28 entities did not report their gender pay gap. [Accessed on April 18th, 2024]

is for each organization to understand the causes of the reported gender pay gap, and with this information to take the necessary steps to close the gender pay gap.¹⁶ Still, despite the emphasis on understanding the causes of the gender pay gap, prior research examining the impact of the UK's pay transparency policy has focused exclusively on testing for reductions in the magnitude of the gender pay gap (Duchini et al., 2023a; Gamage et al., 2024; Jones and Kaya, 2022). Such focus builds on the assumption that the policy has an immediate effect on pay outcomes. However, testing the effectiveness of pay transparency policies using wage outcomes ignores the long-term nature of a material change in pay practices due in part to structural factors that affect women and men differently and perpetuate pay inequality.

Shrinking the gender pay gap in a way that benefits women, rather than disadvantaging men (by restricting their pay growth), requires entities to adopt organizational policies and practices that promote pay growth for women. Accordingly, I investigate whether mandatory gender pay gap ratio reporting in the UK is associated with a change in firm behavior that translates into the adoption of employment equity (EE) actions. Research confirms that the gender pay gap narrows in response to pay transparency policies, and that the reduction is larger for firms subject to transparency rules (Bennedsen et al., 2022, 2023; Duchini et al., 2023a, 2023b; Lagaras et al., 2022). Building on this evidence, I test whether *adoption of EE actions is higher for firms that are mandated to disclose the gender pay gap relative to those that do not.*

¹⁶ The UK Government's website states: "If you find that your organization has a gender pay gap, you should first try to understand why. If you know the factors that are causing your gap, you can take the most effective actions to close it." This statement is presented on the page: <https://www.gov.uk/government/publications/gender-pay-gap-reporting-guidance-for-employers/closing-your-gender-pay-gap> [Accessed on September 5th, 2024]

2.4 Research design and data

2.4.1 Sample selection

My sample frame consists of firms traded in the FTSE250 index for at least four years between 2015 and 2021. I focus on the FTSE250 index for two reasons. First, while the FTSE100 includes large international firms, the FTSE250 index includes more domestic and UK-focused firms. Since mandatory disclosure of the gender pay gap falls on UK-registered firms, the FTSE250 includes more firms that are under the scope of the disclosure mandate. Second, the FTSE250 comprises firms that are more diversified in terms of size. This ensures variation in the number of employees and therefore allows me to observe differences in the adoption of EE actions between firms that are under the scope of the gender pay gap disclosure mandate because they have at least 250 employees, and those that are not.

The consultation process on the introduction of the UK's transparency policy started in 2015 and therefore my sample window starts in 2015. Two years later, in 2017, the UK Government introduced mandatory gender pay gap ratio reporting. From the set of firms that are traded in the FTSE250 index for at least four years, I remove entities that go private or have at least one missing annual report. The sample selection process is described in Table 2.1. My final sample comprises 910 firm-year observations between 2015 and 2021 relating to 130 firms. The distribution of observations by year and industry is presented in Table 2.2.

2.4.2 Gender pay gap data

Gender pay gap data is obtained from the UK Government's gender pay website.¹⁷ As part of the gender pay gap ratio disclosure mandate, UK-registered firms with at least 250 employees are required to submit their gender pay gap metrics to the UK Government's

¹⁷ An important limitation of the gender pay gap data is that the number of observations and the gender pay gap metrics disclosed by entities can vary with the date when the data was initially downloaded. This is because the UK Government allows firms to restate their figures if necessary. I downloaded the gender pay gap data on February 17th, 2024.

dedicated website. This requirement applies at the entity level and the threshold may not always be reached at the parent-level. Accordingly, firms that belong to a group and meet the disclosure threshold must disclose gender pay gap metrics individually. This means that a FTSE250 (parent) company can disclose gender pay gap information directly or indirectly via its subsidiaries, while parents and subsidiaries with fewer than 250 employees do not disclose directly. To identify the subsidiaries of the firms included in the sample, I collect subsidiaries data from FAME. After identifying the subsidiaries that are owned by each company included in my FTSE250 sample, I proceed to identify which firms and respective subsidiaries disclose gender pay gap metrics.

Gender pay gap data as provided by the Government Equalities Office's (GEO) website includes the company's registration number as a firm identifier. However, this number is missing for a subset of firms. I therefore merge gender pay gap data from the GEO website with my FTSE250 sample and their respective subsidiaries using name matching. This process involves a combination of fuzzy matching augmented by manual checking. Out of the one hundred and thirty firms in my sample, nineteen parent firms report gender pay gap (GPG) metrics directly, ninety one report GPG metrics through their subsidiaries, and twenty-five do not disclose gender GPG metrics. Non-disclosers do not report gender pay gap information because they do not meet the GPG disclosure threshold of 250 employees. When a parent company reports gender pay gap metrics and it owns subsidiaries that also report, I focus on the metrics as disclosed by the parent company. Where a parent company does not disclose GPG figures but has at least one subsidiary that does disclose, I follow prior literature and compute the average gender pay gap of the subsidiaries (Raghunandan and Rajgopal, 2021). I classify a FTSE250 sample company as a gender pay gap discloser if at least one of the two following conditions holds: either a) the parent company discloses GPG

metrics or b) the parent company does not disclose GPG metrics, but it owns at least one subsidiary that does disclose. Figure 2-1 visualizes the disclosure classification process.

After identifying firms that disclose gender pay gap information, I then match mandatory gender pay gap disclosures at April each year to the entity's corresponding reporting period. Note that gender pay gap data is only available for the period after the introduction of the mandate. Additionally, although the first snapshot date is 5 April 2017, figures as of this date were disclosed until April 2018 due to the 12-month filing window. I merge gender pay gap data with company-level data from Datastream and EE action data that is manually collected from annual reports using a) the year in which the gender pay gap metrics are *disclosed* and b) the company's fiscal year. Accordingly, gender pay gap metrics *disclosed* in year t are matched with fiscal year t . Fiscal year t is defined as including company reporting periods ending between 6 April t and 5 April $t + 1$. A company whose reporting period ends 31 December 2018 is therefore matched with the gender pay gap metrics disclosed in April 2018, as is a company whose reporting period ends 31 March 2019.

As there is variation in the availability of gender pay gap metrics across the sample period, I create the variable *D_GPG_Metrics*. This variable captures the *reporting* of gender pay gap metrics; it takes the value one from 2018 onwards if the company discloses the gender pay gap figures at least once between 2018 and 2021 and zero otherwise. In 2015, 2016, and 2017, this variable is equal to zero for all observations.

2.4.3 Employment Equity Actions

2.4.3.1 Identification of relevant actions

To examine adoption of actions that improve gender equity following the UK's mandate to disclose the gender pay gap ratio, I focus on evidence-based actions that firms can implement to improve pay outcomes for women. I rely on actions documented in research

reports published by the Behavioral Insights Team (BIT) (2018), (2021a), and (2023). This work was conducted under the Gender and Behavioral Insights (GABI) research program, which was a collaboration between the Government Equalities Office and the Behavioral Insights Team.¹⁸ Two factors support this approach. First, BIT is a social-oriented organization that was founded by the UK Government in 2010.¹⁹ Also known as the Nudge Unit, the BIT was created to support public policy through behavioral science research.²⁰ Until 2021, the UK Government fully owned BIT. Their work on gender equity and equality is sponsored by the UK Government and is recommended for employers seeking to reduce the gender pay gap. BIT's (2018) report is provided as guidance for employers on the UK Government's website.²¹ Second, BIT reports build on research and evidence from UK-based case studies and randomized control trials. Indeed, BIT (2021a: 2) states "this evidence-based guide is an important step towards helping employers know what works."

I identify all actions referenced at least once in the BIT (2018), (2021a) and (2023) reports that firms can adopt to improve workplace gender equity. The pooled list comprises thirty-eight actions. From these, I remove three actions due to their lack of specificity (e.g., "Request advice for actionable ways to improve instead of feedback on past performance" (BIT, 2021a)). Additionally, I remove four actions that are present only in the BIT 2023 report where the goal is to improve overall equity as opposed to being focused on gender equity (e.g., "Make workplace or role adjustments available for everyone" (BIT, 2023)). I

¹⁸ The Government and Equalities Office (GEO) "leads the work on policy relating to women" and is responsible for "improving equality", "(...) taking the lead on the Equality Act 2010 and being the lead department on gender", and "(...) supporting and implementing international equality measures in the UK". These citations were extracted from the GEO's website (<https://www.gov.uk/government/organisations/government-equalities-office/about>). [Accessed on August 8th, 2024].

¹⁹ See BIT's website: <https://www.bi.team/about-us-2/who-we-are/> [Accessed on August 8th, 2024].

²⁰ See the web page: <https://www.instituteforgovernment.org.uk/article/explainer/nudge-unit> [Accessed on August 8th, 2024].

²¹ See the UK Government's webpage: <https://gender-pay-gap.service.gov.uk/actions-to-close-the-gap> [Accessed on August 8th, 2024]

also remove two duplicate actions that are nested in other actions.²² I consolidate four actions into two broader categories due to their similar nature. Specifically, I combine unconscious bias training and diversity training into a single category because unconscious bias training represents a form of diversity training. I also combine the offer of mentoring and sponsorship and the offer of networking programs into one single category. Finally, I augment the consolidated list of twenty-two BIT actions with the presence of childcare arrangements, as support for childcare is widely recognized as a factor contributing to the persistence of the gender pay gap.²³ My preliminary list of positive actions supporting equitable pay outcomes for women therefore consists of twenty-three EE actions.

2.4.3.2 Manual collection of EE action adoption data

I rely on firms' annual reports to collect data on EE actions. To find the actions in the annual reports, I build a comprehensive word list that combines general words such as "gender" and "diversity" with specific words that are directly related to the actions such as "returner" (for returners' program) and "leadership" (for leadership training). I use this wordlist purely as a filtering mechanism to guide my manual search and therefore I favor a more inclusive list (i.e., higher recall) over a less inclusive list (i.e., higher precision). My word list is presented in Appendix 2.3. I collect annual reports from entities' respective investor relations website, or from the www.annualreports.com repository.

²² I remove "Shared local support for parental leave and flexible working" (BIT, 2021a) as this action is captured by the two following actions that are manually collected: offer of flexible working conditions and offer of shared parental leave. The second duplicate I remove is "Use specialized outreach to increase applications from underrepresented groups" (BIT, 2023)). This policy is captured by the use of targeted referral schemes, which is manually collected.

²³ I follow prior evidence documented by the PwC Report (2023) which focuses on the role of the motherhood penalty as a driver of the gender pay gap ratio and highlights the role of childcare policies in mitigating its effect. Simintzi et al. (2022) exploit a policy change in Canada and study the effects of subsidized childcare on women's careers. The paper finds that access to childcare reduces women's unemployment and increases their productivity. With these results, it concludes that women's career and their allocation across firms is conditional on their access to childcare.

I remove four EE actions from the preliminary list of 23 actions on conclusion of the manual data collection task because no firm in the sample makes any mention of them. The four actions that I remove are: a) making recruitment and selection decisions using batches of applicants; b) disclosing job advertisements with the information that salary is negotiable; c) encouraging CVs to present information in terms of years of experience rather than years in a job position; and d) offering flexible working conditions in job ads. The final set of EE actions therefore comprises 19 actively applied policies and practices that theory and evidence predict can help to improve pay outcomes for women and thereby mitigate the gender pay gap.

The BIT reports build on prior evidence regarding the effectiveness of each action in contributing to gender equity and classify each recommended action as effective, promising, or mixed evidence. An effective action is one where “...there is strong evidence that shows that these actions are effective, and worth implementing.” (page 4: BIT, 2021). For example, appointing a diversity lead or taskforce is categorized as an effective action. See Dobbin and Kalev (2014) for review of the features that render the appointment of a diversity lead/taskforce an effective action in improving workplace gender equality. Promising actions are those which may be effective but that “... still need further research to improve the evidence of their effectiveness and how to best implement them.” (page 4: BIT, 2021). Provision of targeted referral schemes is an example of a promising action. Nicks et al. (2021) summarize evidence on the application of targeted referral schemes. Mixed evidence actions are those which report mixed results; “...actions [that] have been shown sometimes to have a positive impact and other times a negative impact. This might be due to how they are implemented or other factors that we do not fully understand yet.” (page 4: BIT, 2021). Provision of a diversity statement is an example of a mixed evidence action. See Windscheid et al. (2016) for a study on the provision of diversity statements.

I follow BIT's classification and group EE actions according to these categories in some of my tests aimed at understanding which actions matter most. The variable *Effective Actions* includes the following six actions: a) setting targets of female representation, b) appointing a diversity lead/taskforce, c) removing biased language, d) adopting skill-based/assessment center recruitment, e) offering pay, promotion and reward sessions, and f) conducting structured interviews. By construction, this variable has a maximum score of six, which indicates a company that adopts all six actions included. The variable *Promising Actions* includes the following eight actions: a) using blind CVs, b) setting a target of shortlisted women, c) implementing a returner program d) offering mentoring, networking and sponsorship programs, e) offering flexible working conditions, f) offering shared parental leave, g) providing a childcare policy, and h) having a referrals scheme. By construction, this variable has a maximum score of eight, which indicates a company that adopts all actions in the category. The variable *Mixed Evidence Actions* includes the following five actions: a) using a diverse interview panel, b) issuing a diversity statement, c) relying on self-assessment for performance reviews, d) providing diversity statements, and e) offering female leadership. By construction, this variable has a maximum score of five, which indicates a company that adopts all actions in the category. The variable *All Actions* comprises all actions categorized as effective, promising, and mixed evidence. By construction, this variable has a maximum score of 19. Appendix 2.2 lists all the actions collected and presents examples extracted from firms' annual reports.

The disclosure of EE actions is voluntary. Firms are strongly encouraged to disclose action plans to explain how they aim to reduce the gender pay gap, but such information is not mandated. Examples of different actions and how they are mentioned by firms are provided in Appendix 2.2. A key assumption of my analysis is that the policy mandate changes the propensity for firms to adopt actions but does not change the propensity to

disclose actions. My empirical strategy is therefore based on the joint hypothesis that firms adopt EE actions, *and* they disclose details of these actions. Type 1 errors are mitigated by the fact that the actions being collected are specific and so is the way firms mention them. For example, considering the presence of a diversity lead/taskforce, a company either appoints someone (or a task force) responsible for diversity issues or it does not. I assume it is highly unlikely that a company discloses that it has a diversity lead without having one.

The key concern with the assumption that disclosure represents actions lies with the possibility of type 2 errors; the possibility that a company implements an EE action but does not disclose such information, or a company that already adopted EE actions before the mandate only starts disclosing after the implementation of the mandate. I provide two arguments to mitigate this concern. First, jointly with the disclosure of gender pay gap metrics, the regulation encourages firms to provide supporting narratives and action plans. As such, firms are incentivized to disclose any actions that they implement to address their gender pay gap. Second, I posit that the incentive to adopt and therefore disclose EE actions should be strengthened in the first reporting year when gender pay gap figures are reported for the first time and therefore public pressure to address the gender pay gap increases as companies experience strong media scrutiny (Duchini et al., 2023a).

2.4.4 Descriptive statistics

Table 2.3 presents the descriptive statistics for gender pay gap metrics in Panel A, employment equity actions in panel B and control variables, which capture different firm characteristics, in Panel C. Panel A shows that the median company reports that average male hourly pay is 17% higher than average female hourly pay. While this unconditional difference does not account for differences in individual characteristics that may drive the gender pay gap, it suggests that women are not well represented in well paid positions.

Descriptive statistics for EE actions are provided in Panel B of Table 2.3. Results at the aggregate level reveal that the adoption of EE actions is very limited throughout the sample period. The median firm applies only one promising action and one mixed evidence action across the sample period.

Within the *Effective Actions* category, setting targets for female representation and appointing a diversity lead or a taskforce are the most widely adopted actions. Nearly 40% of the sample sets targets for female representation, of which 32% report a numerical target and 25% report a time frame to achieve this target. The remaining *Effective Actions* are reported by less than 3% of the sample.

Adoption patterns for *Promising Actions* display a similar pattern. Out of a total of eight promising actions, only three are adopted in more than 10% of firm-years. These three actions are offering mentoring, networking, and sponsoring programs; offering flexible working conditions; and committing to increase the number of shortlisted women. Key policies such as providing a returner program or shared parental leave are offered in only 4% of firm-years.

The *Mixed Evidence Actions* category includes the most widely adopted actions. For example, more than 50% of the sample offers leadership training. In addition to being a mixed evidence action, however, leadership training is an example of an action that can apply to the entire workforce rather than targeted to reverse the gender pay gap. Collectively, results in Table 2.3 provide evidence that UK firms' commitment to improving workplace gender equity through the adoption of EE actions is limited and that substantial room for improvement exists. Whether or not regulatory action to increase pay transparency has had a material impact on adoption rates of EE actions is an important but overlooked question that the remainder of my analysis seeks to examine.

2.5 Results

2.5.1 Univariate evidence

After establishing that the adoption of EE actions appears to be limited, I test if there is any difference between firms that disclose gender pay gap metrics (GPG disclosers) in response to the reporting mandate versus those that do not (GPG non-disclosers). A GPG discloser is a company that between 2018 and 2021 discloses gender pay gap metrics at least once, and zero otherwise. Panel A of Table 2.4 compares the adoption of EE actions between GPG disclosers and GPG non-disclosers in two separate periods: 2015-2017 when reporting of gender pay gap metrics was not required, and 2018-2021 when gender pay gap disclosures are mandatory and publicly available. The panel “Difference in means for sample period between 2015 and 2017”, compares the adoption of EE actions between GPG disclosers and GPG non-disclosers between 2015 and 2017. A t-test confirms that the adoption of effective and mixed evidence actions is higher for firms that are subsequently caught by the gender pay gap reporting mandate. This result is driven by three specific EE actions: the appointment of a diversity lead or taskforce, the provision of diversity statements, and the provision of leadership training. Overall, the adoption of actions between disclosers and non-disclosers in the pre-mandate period only differs for a limited subset of actions. The panel “Difference in means for sample period between 2018-2021” in Table 2.4 reveals a similar pattern. The differences primarily relate to the adoption of targets for female representation and provision of mentoring, networking, and sponsorship programs. In addition to the initiatives mentioned in the previous analysis, these actions are also associated with higher average values among GPG disclosers. Overall, panel A in Table 2.4 provides weak evidence that the adoption of actions is higher for GPG disclosers in both the pre-mandate and the mandate periods. In Panel B, I compare the differences in firm characteristics between the two groups of firms and across the two sample periods. Between 2015-2017 and 2018-2021, GPG disclosers and

GPG non-disclosers do not differ in terms of size, R&D intensity, or firm performance (proxied by ROA and sales growth). However, in the period before the policy is implemented the two groups do differ in terms of female representation. A GPG discloser reports a higher percentage of female representation at the employee level than a GPG non-discloser whereas a GPG discloser reports a lower percentage of female representation at the board than a GPG non-disclosers. The difference in the level of female representation at the employee-level across the two groups is no longer significant in the period between 2018-2021. In this period, the level of female representation is higher for GPG disclosers than non-disclosers.

In Figure 2-2, I plot cross sectional means of *All Actions*, *Effective Actions*, *Promising Actions*, and *Mixed Evidence Actions* over the seven years of the sample. I provide a separate graph for each category of action. Figure 2-2 provides graphical evidence indicating an upward trend in the adoption of EE actions. The split between GPG disclosers and non-disclosers highlights a clear wedge between the two groups. This wedge is particularly large for *Effective Actions* following mandatory disclosure of the gender pay gap. An analysis of Figure 2-2 suggests that the increase in the adoption of actions seems constant for the GPG discloser group across the sample period, showing a slight uptick from 2018-19. Conversely, adoption rates for non-disclosers are less pronounced for GPG non-disclosers during the pre-mandate period but appear to gain pace in the post-mandate period. Overall, this figure provides weak evidence that the rate of EE action adoption increased materially following the disclosure mandate and suggests the rate of EE adoption increased among non-disclosers following the mandate. This may suggest that the policy had spillover effects and affected firms that are not required to disclose the pay gap. Importantly, conclusions from this figure should be interpreted with caution as the analysis does not control for possible confounding effects (e.g., firm size).

A t-test confirms that the difference in the number of adopted actions for GPG disclosers versus non-disclosers is not statistically significant for any year before 2018. The adoption of effective actions is higher for GPG disclosers on an annual basis between 2018 and 2021. Further, the adoption of promising actions is also higher for firms disclosing gender pay gap metrics in 2018. In the following section, I confirm the documented trend in Figure 2-2 by conducting a time trend analysis.

2.5.2 Main tests

2.5.2.1 Time trend analysis

This subsection reports results from a time trend analysis where I regress the aggregate score including all the EE actions on a time trend variable and controls using the following model:

$$All\ Actions_{it} = \beta_0 + \beta_1 Year_{it} + \sum_{n=1}^N \theta_n Controls_{it} + \varepsilon_{it}. \quad (2.1)$$

Equation (2.1) presents a OLS regression of *All Actions* on the time trend variable *Year* and a set of control variables. *All Actions* is the aggregate score that includes *Effective Actions*, *Promising Actions*, and *Mixed Evidence Actions*, and is equal to the sum of the 19 separate EE actions. *Year* takes the value one if fiscal year is 2015, two if fiscal year is 2016, three if fiscal year is 2017, four if fiscal year is 2018, five if fiscal year is 2019, six if fiscal year is 2020, and seven if fiscal year is 2021. β_1 is the main coefficient of interest as it captures the average annual (linear) increase in the adoption of EE actions. Consistent with graphical evidence from Figure 2-2 , which shows an upward trend in the adoption of EE actions, I expect $\hat{\beta}_1 > 0$. *Controls* is a vector of variables that is based on the prior literature and includes firm size, growth opportunities, R&D, leverage, sales growth, ROA, percentage of female employees, and percentage of female board members (Raghunandan and Rajgopal, 2021).

Table 2.5 presents the results for Equation (2.1). I also estimate the regression separately for each category of actions. From Panels A to D, the dependent variable is *All Actions*, *Effective Actions*, *Promising Actions* and *Mixed Evidence Actions*, respectively. Model 1 in Table 2.5 regresses *All Actions* on *Year* without including control variables. Models 2, 3, and 4 regress *All Actions* on *Year* and the vector of control variables. To understand the impact of time-invariant industry and firm effects, I explore different fixed effect structures. Models 1 and 2 do not include fixed effects; model 3 includes industry fixed effects and model 4 includes firm fixed effects. Models are estimated using heteroscedasticity-consistent standard errors. Results show that the adoption of EE actions is positively associated with firm size and performance (models 2 and 3). Results from each panel of Table 2.5 show that *Year* loads positively at the one percent level of significance across all specifications and category of actions. Results from Panel A reveal that estimates of β_1 vary between 0.517 and 0.479 in models 1 and 4, respectively. To gauge economic significance, the coefficient estimate for *Year* in model 4 implies an annual increase of approximately 17% in the adoption of EE actions. A one standard deviation change in *Year* in Model 4 implies a 33.7% increase in the adoption of EE actions.²⁴ By way of comparison, a one standard deviation change in ROA implies an 8.6% increase in the adoption of EE actions.²⁵ The economic significance of the time trend is almost four times larger than the economic impact of performance measured using ROA (0.337/0.086). Findings therefore confirm that the adoption of EE actions increased monotonically over the sample period and the magnitude of this time effect is important when benchmarked against other established determinants of EE adoption.

²⁴ Economic significance is calculated as follows: (coefficient x standard deviation of the explanatory variable) / sample mean of the explained variable. As so, the economic significance of year is $(0.479 \times 1.987) / 2.821 = 0.337$.

²⁵ Economic significance of ROA is $(1.016 \times 0.240) / 2.821 = 0.086$.

2.5.2.2 The incremental effect of the mandatory disclosure of the gender pay gap

In this section I test for evidence of an incremental effect from the gender pay gap disclosure mandate. Specifically, I test whether the average annual increase of the adoption of EE actions is higher for firms reporting gender pay gap metrics than non-disclosing firms in the post-mandate period.

$$\begin{aligned} All\ Actions_{it} = & \alpha_0 + \alpha_1 D_GPG_Metrics_{it} \times Year_t + \alpha_2 D_GPG_Metrics_{it} \\ & + \alpha_3 Year_t + \sum_{n=1}^N \theta_n Controls_{it} + \varepsilon_{it} \end{aligned} \quad (2.2)$$

Equation (2.2) presents the regression of *All Actions* on *D_GPG_Metrics*, *Year*, the interaction variable of *D_GPG_Metrics* and *Year*, and the vector of control variables as described above. Consistent with Equation (2.2), *All Actions* is the aggregate score that includes *Effective Actions*, *Promising Actions*, and *Mixed Evidence Actions*. *D_GPG_Metrics* takes the value of one from 2018 onwards if the company reports gender pay gap metrics at least once between 2018 and 2021, and zero otherwise. For fiscal years 2015-2017, this variable takes the value zero for all observations. *Year* has the same interpretation as in Equation (2.2); the interaction $D_GPG_Metrics \times Year$ is the key coefficient of interest in Equation (2.2); α_1 reflects the average annual difference in the adoption of actions between GPG disclosers and non-disclosers and by construction it only captures differences for the period 2018-2021. If the GPG disclosure mandate triggered incremental adoption of EE actions among treated firms then I expect to observe $\hat{\alpha}_1 > 0$.

Results of estimating Equation (2.2) are presented in Table 2.6. In addition to estimating the effect using *All Actions* (Panel A), I also report results separately for *Effective Actions* (Panel B), *Promising Actions* (Panel C), and *Mixed Evidence Actions* (Panel D). Models 2-4 in each panel include control variables. Models 1 and 2 do not include fixed effects, while model 3 includes industry fixed effects and model 4 includes firm fixed effects. Regressions are estimated using robust standard errors. Model 1 in Panel A regresses *All*

Actions on the indicator variable *D_GPG_Metrics*. Results show that α_1 loads positive ($p<0.01$), indicating that the number of adopted actions is higher for firms that report gender pay gap metrics from the fiscal year 2018 onwards. Model 2 regresses *All Actions* on the indicator variable *D_GPG_Metrics*, the time trend variable *Year*, the interaction variable of *D_GPG_Metrics* and *Year*, and the vector of control variables. The estimate for α_3 loads positive ($p<0.01$). The coefficient of 0.348 reflects the average annual increase in the adoption of actions in the pre-2018 period.

The main coefficient of interest Panel A is α_1 , which loads positively ($p<0.05$) in model 2. The coefficient estimate implies that GPG disclosers experience a 0.217 higher increase in average annual increase in EE adoption compared with non-disclosers. This result is robust to the inclusion of industry fixed effects in model 3 but not firm fixed effects in model 4. This means that time-invariant firm characteristics absorb the incremental effect of the policy on the adoption of EE actions. Results for model 2 imply that firms reporting gender pay gap metrics from 2018 onwards adopt approximately 7.6% more actions per year on average than non-disclosers.²⁶

Results in panels B, C, and D suggest that the effect of the disclosure mandate on EE action adoption documented in Panel A is driven by adoption of *Effective Actions* and *Mixed Evidence Actions*. Specifically, α_1 loads positive ($p<0.01$) across all model specifications in Panel B for *Effective Actions*. The coefficient estimate varies between 0.108 in model 2 and 0.099 in model 4. Results for model 4 imply that firms reporting gender pay gap metrics from 2018 onwards adopt approximately 16% more actions per year on average than non-disclosers.²⁷ Regarding the adoption of mixed evidence actions, results from Model 3 in Panel

²⁶ Economic significance is calculated as follows: $(0.217 \times 1.985) / 2.820 = 15.27$. Since the standard deviation of *Year* is 1.985, this result can be interpreted as follows: on average, from 2018 onwards, a GPG discloser adopts approximately 7.6% more actions per year than a non-discloser.

²⁷ Economic significance is calculated as follows: $(0.099 \times 1.987) / 0.625 = 0.3147$. Since the standard deviation of *Year* is 1.987, this result can be interpreted as follows: on average, from 2018 onwards, a GPG discloser adopts approximately 16% more actions per year than a non-discloser.

D imply that firms reporting gender pay gap metrics from 2018 onwards adopt approximately 9.26% more actions per year on average than non-disclosers.²⁸

While the results in Table 2.6 collectively provide some evidence that the mandatory disclosure of the gender pay gap ratio is effective in triggering changes in firm behavior, particularly through the adoption of effective actions. Given a coefficient of 0.099 and an average of 0.625 effective actions per annual report, the effect, however, translates into less than half an action per year. Findings therefore suggest that the economic impact of the disclosure mandate appears to be limited.

2.5.2.3 Cross-sectional tests

I next investigate mechanisms that I expect to impact the magnitude of the average annual increase of the adoption of EE actions for firms that disclose the gender pay gap. I focus on two such mechanisms; female representation and the size of the pay gap in the first disclosure year (2018).

Female representation

Research examining the consequences of the adoption of gender pay transparency policies examines its impact on both wage and non-wage outcomes. Bennedsen et al. (2022) find that firms targeted by these regulations are more likely to hire women than their peers that are not affected by the regulation. Despite this effect, the paper does not find that female employees experience a wage increase following the adoption of a gender pay transparency policy. Card et al. (2012) show that pay transparency policies may affect employees' perception of fair pay and increase their intentions to quit. Consistent with this, Gamage et al.

²⁸ Economic significance is calculated as follows: $(0.104 \times 1.985) / 1.114 = 18.53$. Since the standard deviation of *Year* is 1.985, this result can be interpreted as follows: on average, from 2018 onwards, a GPG discloser adopts approximately 9.2% more actions per year than a non-discloser.

(2024) show that, while female employees with strong bargaining power may negotiate higher salaries, others may change employers and choose those with lower gender pay gap. Given the evidence presented above, I posit that firms with higher female representation at the employee level face increased pressure to demonstrate they are taking meaningful steps to address workplace gender inequality that will be exposed following disclosure of gender pay gap metrics. I therefore test whether the annual average increase in the adoption of EE actions is more pronounced for firms with a higher female representation in the years prior to the GPG disclosure mandate.

To identify a company with high female representation, I compute the median level of the percentage of female representation at the employee-level by fiscal year. This variable is measured as the number of female employees of the company scaled by the total number of employees as disclosed by firms in their annual report. I classify a company as having high female representation if, in the period prior to the GPG disclosure, it reports female representation above the cross-sectional median level in any pre-mandate year. I classify seventy firms out of one hundred and thirty as having high female representation. Six firms report levels of female representation above the median in one year, 11 report high levels in two years, and 53 firms are classified as having high levels of female representation in all three years before 2018.

Panel A of Table 2.7 presents the results of estimating Equation (2.2) separately for firms with high female representation (models 1, 3 and 5) and low female representation (models 2, 4 and 6). Models 1 and 2 do not include fixed effects. Models 3 and 4 include industry fixed effects. Models 5 and 6 include firm fixed effects. The coefficient estimate of interest is for the interaction variable $D_GPG_Metrics \times Year$. I test whether this coefficient is larger for the subset of firms with high female representation. Results from Table 2.6 suggest that the average annual increase of EE actions is higher for firms that must disclose the

gender pay gap. Results from Panel A of Table 2.7 confirm that this effect is more pronounced for firms with high female representation. While the coefficient estimate on *D_GPG_Metrics x Year* loads positive across all model specifications for the high female representation subsample, the estimate is statistically indistinguishable from zero for the subset of firms with low female representation. Tests on the equality of coefficients presented in the final three columns of Panel A confirms that the coefficient is significantly larger for firms with high female representation for specifications 3 and 4 including industry fixed effects, and 5 and 6 including firm fixed effects. In untabulated results, I find that this effect is driven by the adoption of effective and mixed evidence actions. I therefore conclude that higher female employee representation triggers a stronger reaction to the GPG disclosure mandate with respect to EE action adoption.

I also test whether the annual average increase in the adoption of EE actions is more pronounced for firms that have high female representation on the board of directors. It is unclear whether increased board gender diversity is associated with increased adoption of EE actions. On the one hand, prior research finds that the presence of female representation on the board is positively associated with the adoption and disclosure of ESG-related matters (Alkhawaja et al., 2023). This therefore would mean that the adoption of EE actions should be higher for firms with high female representation in the board. On the other hand, it is also possible that increased female representation on the board is not associated with adoption of EE actions. This would be consistent with evidence suggesting that female employees in top executive positions may behave differently from the average female employee and, when compared to their male peers, may behave in a similar manner and therefore not incentivize the adoption of ESG-related actions (Adams and Funk, 2012). This would therefore imply that there should be no difference between the adoption of EE actions for firms with high or low female representation in the board of directors.

Panel B of Table 2.7 presents the results of estimating Equation (2.2) separately for firms with high female board representation (models 1, 3 and 5) and low female board representation (models 2, 4 and 6). Models 1 and 2 do not include fixed effects. Models 3 and 4 include industry fixed effects. Models 5 and 6 include firm fixed effects. The coefficient estimate of interest is for the interaction variable $D_GPG_Metrics \times Year$. I test whether this coefficient is larger for the subset of firms with high female representation. Results are consistent with the work by Adams and Funk (2012) as I do not find evidence that high board gender diversity is associated with increased adoption of EE actions.

Magnitude of the gender pay gap in in the first disclosure year

The predicted effectiveness of the GPG disclosure mandate in the UK lies in the transparency of the information disclosed and the additional scrutiny that it produces. Gender pay gap figures are available in a centralized and public manner on the Government Equalities Office dedicated website and this allows anyone to access and compare gender pay gap outcomes across firms. Additionally, evidence shows that the annual disclosure of the gender pay gap figures is closely monitored by the business media. Consistent with this, Duchini et al (2023) show that a search for the term “gender pay gap” on Google peaked in the first disclosure year (2018). Consistent with significant public attention and external pressure to reduce the gender pay gap, Jones and Kaya (2022) find that firms with high initial gender pay gaps (revealed publicly in 2018) experienced the greatest reduction in future reported gender pay gaps. Accordingly, I test whether firms with high gender pay gaps in the first disclosure year report a higher average annual increase in the adoption of EE actions. Since gender pay gap figures are only available for firms that are under the scope of the

regulation, I estimate Equation (2.1) for two separate groups within the subset of GPG disclosers: one group with high gender pay gap in 2018 and a second group with low gender pay gap in 2018.

I rely on two gender pay gap features to identify firms that report a high gender pay gap in 2018: the difference in mean hourly pay and the difference in median hourly pay between men's and women's wages (variables: *Mean GPG_Hourly Pay* and *Median GPG_Hourly Pay*). For each measure I compute the 75th percentile in fiscal year 2018. If a company's *Mean GPG_Hourly Pay* or *Median GPG_Hourly Pay* (or both) is at or above the 75th percentile in 2018, then the company is allocated to the high gender pay gap group. Otherwise, it is allocated to the low gender pay gap group. This yields a total of thirty-one (seventy-one) firms that report a high (low) gender pay gap in 2018. Importantly, this variable is missing for firms that do not disclose gender pay metrics.

Table 2.8 presents the results of estimating Equation (2.1) separately for firms with a high gender pay gap in 2018 (Models 1, 3, 5) and those with a low gender pay gap in 2018 (Models 2, 4 and 6). This is a modified version of Equation (2.2) that includes only gender pay gap disclosing firms. Models 1 and 2 do not include fixed effects. Models 3 and 4 include industry fixed effects, while models 5 and 6 include firm fixed effects. The time trend variable *Year* is positive in all specifications. A test of differences in coefficient estimates reported in the final three columns reveals that the coefficient on *Year* is significantly larger where Equation (2.1) is estimated using subset of firms with high GPG in 2018. The result is robust to different fixed effect structures. Untabulated results indicate that the difference is due primarily to the adoption of promising actions, and to a lesser extent to the adoption mixed evidence actions.

2.5.2.4 Difference-in-differences analysis

Graphical evidence in Figure 2-2 suggests that the adoption of EE actions has been increasing since 2015. Further analysis confirms that the annual increase is slightly larger for firms that are mandated to report gender pay gap metrics from 2018 onwards, and for firms with high female representation and more pronounced pay gaps in the period before the GPG disclosure. Nonetheless, the evidence shows that these effects tend to be limited to adoption of effective actions and mixed evidence actions.

The analyses in the previous subsection focus on the period after the implementation of the gender pay gap disclosure mandate and tests whether the average annual increase in the adoption of EE actions is higher for firms that disclose gender pay gap metrics (than those that do not) during this period. I complement these analyses in this section by testing whether the change in the adoption of EE adoption between the pre- and post-disclosure mandate is higher for firms that disclose gender pay gap metrics. This test is important for a complete picture of the impact of the disclosure mandate. Specifically, analyses to date do not compare the overall change between the pre- and post-disclosure mandate period. It is possible that the annual adoption of EE actions is higher for firms disclosing gender pay gap metrics after the implementation of the policy but that the overall difference between the pre- and post-mandate is not higher for firms disclosing gender pay gap metrics. I therefore compare the change in the adoption of effective, promising, and mixed evidence actions between GPG disclosers and non-disclosers before and after the mandatory disclosure of the gender pay gap using the following model:

$$\begin{aligned} All\ Actions_{it} = & \rho_0 + \rho_1 D_GPG_Disclosure_{it} Post_t + \rho_2 D_GPG_Disclosure_{it} \quad (2.3) \\ & + \rho_3 Post_t + \sum_{n=1}^N \theta_n Controls_{it} + \varepsilon_{it} \end{aligned}$$

Equation (2.3) presents a quasi-difference-in-differences specification that regresses *All Actions* on *D_GPG_Disclosure*, *Post*, the interaction between *D_GPG_Disclosure* and *Post*,

and a set of control variables. This is a quasi-difference-in-difference regression as the assignment of companies to the group of GPG discloser and non-discloser is not random and as companies that are affected by the policy were able to anticipate this during the policy's consultation period. I distinguish between GPG disclosers and GPG non-disclosers with the variable $D_GPG_Disclosure$, which takes the value one if the company discloses gender pay gap metrics (either through the parent or the subsidiary) at least once between 2018 and 2021, and zero otherwise. This variable also takes the value one in the pre-mandate years 2015-2017 if a company discloses gender pay metrics at least once from 2018 onwards. $Post$ is the indicator variable that takes the value one if the company's fiscal year is from 2018 onwards and zero otherwise. My set of control variables includes size, growth opportunities, R&D, leverage, sales growth, ROA, percentage of female employees, and percentage of female board members. The coefficient of interest is ρ_1 , which captures the interaction between $D_GPG_Disclosure$ and $Post$. The interaction between $D_GPG_Disclosure$ and $Post$ tests if overall change between the pre- and post-disclosure for gender pay gap reporting firms is higher than the same change from non-disclosing firms. It is therefore the key coefficient of interest. A positive and significant estimate for ρ_1 confirms that the change in the adoption of effective, promising, and mixed evidence actions before and after the mandatory disclosure of the gender pay gap is larger for firms that are under the disclosure mandate.

Results from estimating Equation (2.3) must be interpreted with caution, however. A traditional difference-in-differences regression is used to estimate the *causal effect* of the passage of a policy. To establish a reliable causal effect, several assumptions regarding the treatment and control group are necessary. In my case, treated firms would be those that disclose gender pay gap metrics and control firms would be those that do not disclose gender pay gap metrics. One assumption is that there are no trends in the period before the policy is implemented in the adoption of EE actions between the group of treated and control firms

(Baker et al., 2025; Roth et al., 2023). As a preliminary test of the parallel trends assumption, I compare the annual means of *All Actions*, *Effective Actions*, *Promising Actions* and *Mixed Evidence Actions* between GPG disclosing and non-disclosing firms before and after the mandatory disclosure of the gender pay gap ratio. A t-test confirms that, before 2018, there is no difference in the adoption of these actions. I interpret this as preliminary evidence suggesting that there are no trends in the adoption of EE actions before the implementation of the UK's pay transparency regulations. I provide additional and more formal evidence in Figure 2-3. Specifically, I estimate Equation (2.3) and replace the *Post* with separate event-time dummies. These variables represent the observations in years -3, -2, -1, 0, 1, 2 and 3, relative to 2018. I omit year -1 (2017) from the model to serve as the baseline for evaluating other years. Figure 2-3 suggests that there is no pre-trend in adoption of EE actions from GPG disclosing firms relative to GPG non-disclosing firms. Once gender pay gap metrics are first disclosed, the adoption of effective actions is higher for firms disclosing gender pay gap metrics.

The second assumption is that there is no anticipation of the mandate and that the treatment group is only affected by the policy once the policy is implemented (Baker et al., 2025; Roth et al., 2023). In this respect, it is important to acknowledge that there was a consultation period and policy discussion at least two years before the disclosure mandate was implemented. In addition to these two assumptions, it also unclear whether and how control firms are affected by the policy. In technical terms, it is possible to argue that firms coded as control firms are not affected by the policy as they do not have to disclose gender pay gap metrics. Nonetheless, the disclosure of the gender pay gap in the UK receives extensive media attention. Whether employers from control firms reacted or not to discussion is therefore subject to question. Graphical evidence from Figure 2-2 seems to show an increasing trend in adoption of EE actions by firms that disclose gender pay gap metrics that

is particularly pronounced after 2018 when the mandate had its first reporting year.

Collectively, this means findings must be interpreted with caution as ρ_1 is unlikely to provide a reliable point estimate of the average treatment effect.

Results are presented in Table 2.9. I also estimate the regression separately for the three categories of actions. Accordingly, Panels A to D present results where the dependent variable is *All Actions*, *Effective Actions*, *Promising Actions* and *Mixed Evidence Actions*, respectively. Models 2-4 include control variables. Models 1-2 do not include any fixed effects; model 3 includes industry fixed effects; and model 4 includes firm fixed effects. The regression is estimated using heteroscedasticity-consistent standard errors. Results presented in Panels A, C and D reveal that $\hat{\rho}_1$ is not statistically significant in any of the specifications. Results presented in Panel B show that $\hat{\rho}_3$ loads positive ($p < 0.05$) in all model specifications. However, the treatment effect estimate in model 4 is 0.295 is economically insignificant as it implies adopting less than a third of an effective EE action.

In sum, my quasi-difference-in-difference results confirm that the overall change in the adoption of EE actions is higher for firms reporting gender pay gap metrics. However, this result is economically insignificant. In addition, apart from *Effective Actions*, results also show that there is no significant difference in the adoption of *Promising Actions* and *Mixed Evidence Actions* by GPG disclosers versus non-disclosers. This result provides further evidence confirming the results that the average annual increase in the adoption of effective actions is statistically higher for firms that report gender pay gap metrics from 2018 onwards. Collectively, tests conducted to this point imply that the UK's mandatory disclosure of the gender pay gap ratio may have positively contributed to the trend towards adopting of effective EE actions between 2015 and 2021. Overall, however, the 2017 gender pay transparency mandate does not appear to have been particularly effective in delivering structural changes in firm behavior through the adoption of EE actions.

2.5.2.5 Robustness analysis

2.5.2.5.1 Classification of firms as GPG disclosers and non-disclosers

Any UK-registered company must disclose the gender pay gap if its legal entity has at least 250 employees on the snapshot date. In this study, a company is classified as GPG discloser if it discloses gender pay gap metrics (either through the parent or the subsidiary) at least once between 2018 and 2021 and zero otherwise. Importantly, firms that are classified as non-GPG disclosers are firms that do not fall under the scope of the regulation because they do not meet the threshold for disclosure of 250 employees. This non-random assignment between treatment and control groups is a source of potential endogeneity bias: *ex-ante* it is possible that larger firms adopt more EE actions.

To address this endogeneity concern, I re-estimate Equations (2.2) and (2.3) using entropy balanced samples (Hainmueller, 2012). I match the first moment (mean) of the determinants of the adoption of EE actions: size, growth opportunities, R&D, leverage, sales growth, ROA, percentage of female employees, and percentage of female board members. Table 2.10 presents the results of re-estimating Equation (2.2). Consistent with previous analyses, Panels A to D contain results where the dependent variables are *All Actions*, *Effective Actions*, *Promising Actions*, and *Mixed Evidence Actions*, respectively. Results for model 1 in Panel A show that $D_GPG_Metrics \times Year$ loads positive ($p < 0.05$) and this result is robust to the inclusion of industry fixed effects in model 2. However, the treatment effect is not robust to inclusion of firm fixed effects in model 3. Results in Panel B of Table 2.10 show that the interaction term is positive in all model specifications for *Effective Actions*. In contrast, results in Panels C and D suggest that there is no difference in the average annual increase of the adoption of promising and mixed evidence actions between GPG disclosers and non-disclosers. Overall, results in Table 2.10 are consistent with those reported in Table

2.6: the average annual increase in the adoption of EE actions is statistically higher for firms that disclose the gender pay gap relative to those that do not, and the effect seems to center on the adoption of *Effective Actions*.

Table 2.11 presents the results of re-estimating Equation (2.3) using entropy balanced samples (Hainmueller, 2012). Results from Panels A, C and D show that the interaction term $D_GPG_Disclosure \times Post$ is not significant. Results from Panel B show that the change in the adoption of effective actions after the mandatory disclosure of the gender pay gap is larger for firms that are under the disclosure mandate. This result is robust to the inclusion of firm fixed effects. Results from Table 2.11 confirm that the change in adoption of EE actions is marginally higher for firms disclosing the gender pay gap and limited to a subset of policies: effective actions. Overall, these results are in-line with those reported in Table 2.6 and Table 2.9.

2.5.2.5.2 Gender pay gap metrics are matched to the fiscal year that were disclosed in but not the fiscal year they refer to

Implementation of the UK's mandatory disclosure of the gender pay gap took place in 2017. However, the first disclosure year occurs one year later in 2018 and so the data capture pay gap characteristics at the 2017's snapshot date. This creates a mismatch between the period that the gender pay gap metrics refer to and the year in which they were disclosed. Specifically, $D_GPG_Metrics$ and $Post$ are constructed for the disclosure year and not the period to which the gender pay gap metrics relate. I therefore re-estimate Equations (2.2) and 3 with alternative definitions of $D_GPG_Metrics$ and $Post$ in an attempt to address this mismatching problem. The variable $D_GPG_Metrics$ takes the value of one from 2017 fiscal year onwards if the company reports gender pay gap metrics at least once between 2017 and 2021, and zero otherwise. In 2015 and 2016, this variable takes the value zero for all

observations. *Post* is an indicator variable that takes the value one if the company's fiscal year is from 2017 onwards, and zero otherwise. Table 2.12 presents the results of re-estimating Equation (2.2) using this alternative definition of *D_GPG_Metrics*. The dependent variables in Panel A to D are *All Actions*, *Effective Actions*, *Promising Actions* and *Mixed Evidence Actions*, respectively. Results are consistent with those reported in Table 2.6: the average annual increase in the adoption of EE actions is marginally higher for firms that disclose the gender pay gap relatively to those that do not. This effect is limited to the adoption of effective actions and partially mixed evidence actions.

Table 2.13 presents the results of re-estimating Equation (2.3) using the alternative definition of *Post*. Results from Panels A, C and D show that the interaction term *D_GPG_Disclosure x Post* is not significant. Results from Panel B show that the change in the adoption of effective actions after the mandatory disclosure of the gender pay gap is statistically larger for firms that are under the disclosure mandate. Overall, the results and conclusions are similar to those reported in Table 2.6 and Table 2.9, and as such help to discount the possibility that the findings are due to biases resulting from mismatching gender pay gap data and EE action adoption data.

2.5.3 Further analyses

2.5.3.1 The role of cost in the adoption of EE actions

Panel B of Table 2.3 shows that the most adopted actions are those labeled as effective and mixed evidence; for example, setting targets for female representation and offering leadership and diversity training. Nevertheless, a promising action like appointing a diversity manager is a potentially costly action when compared to targets of female representation. The same argument can be made when comparing referral schemes (which often involve financial compensation) with an action such as removing biased language (which can be done using

software tools). In this respect, I propose a reclassification of EE actions at low, moderate and high cost. My classification reflects an expectation about the initial investment that is necessary for the adoption of each EE action and assumes that firms implement EE actions in the recommended and expected manner as described in the literature.

I group EE actions according to their expected implementation costs using a subjective approach. Setting targets for female representation, setting targets of shortlisted women, disclosing a diversity statement, removing biased language from job ads, selecting a diverse interview panel, adopting structured interviews, and offering flexible working conditions are labeled as low-cost actions. Anonymizing CVs, recruiting using skill-based assessments, promoting mentoring, networking and sponsoring schemes, offering diversity training, providing leadership training and offering pay, promotion and reward sessions are labeled as moderate cost actions. Appointing a diversity lead, creating a returner's program, promoting shared parental leave, having a childcare policy and having a referral scheme in place are labeled as high-cost actions. I proceed by examining whether the effect of the gender pay gap disclosure on the adoption of EE actions is conditioned by the actions' cost.

$$\begin{aligned}
 EE\ Actions_{it} = & \alpha_0 + \alpha_1 D_GPG_Metrics_{it} + \alpha_2 Year_t \\
 & + \alpha_3 D_GPG_Metrics_{it} \times Year_t + \sum_{n=1}^N \theta_n Controls_{it} + \varepsilon_{it}
 \end{aligned} \tag{2.4}$$

Equation (2.4) presents the regression of *EE Actions* on *D_GPG_Metrics*, *Year*, the interaction variable of *D_GPG_Metrics* and *Year* and include the vector of control variables as described above. *EE Actions* is captured by the variables *Low-cost Actions*, *Moderate-cost Actions* and *High-cost Actions*. Actions are labeled as low-cost, moderate cost and high cost as described before. *D_GPG_Metrics Year* and the interaction variable of *D_GPG_Metrics* and *Year* keep the same interpretation as described in Table 2.5.

Results are presented in Table 2.14. The dependent variable is *Low-cost Actions* in models 1-3, *Moderate-cost Actions* in models 4-6 and *High-cost Actions* in Models 7-9. Models 1-9 include control variables. Models 1,4 and 7 do not include any fixed effects, models 2, 5, and 7 include industry fixed effects, and models 3, 6 and 9 include firm fixed effects. Regressions are estimated using heteroscedasticity-consistent standard errors. Results show that α_3 in model 3 is positive and significant, varying between 0.110 in model 1 and 0.094 across cost groups. Importantly, this coefficient is only significant for the subset of *Low-cost Actions*, while it remains consistently insignificant for the subset of *Moderate-cost Actions* and *High-cost Actions*.²⁹ Results suggest that, even though some firms respond to the mandatory disclosure of the gender pay gap by adopting EE actions, they tend to focus on the actions that are easier and less costly to implement.

2.5.3.2 The ability of EE actions to predict future gender pay gaps

My analysis to date documents evidence of growth in the adoption of EE actions aimed at reducing the gender pay gap across the sample period, and also a (weak) uptick in adoption rates in response to the pay gap reporting mandate. Additionally, I provide evidence showing that the adoption of effective actions is more pronounced for firms disclosing the gender pay gap. However, I have not tested whether the presence of EE actions reduces the gender pay gap in the medium or long run. I address this question in this section by testing whether the adoption of EE actions predicts a lower gender pay gap in the future. Based on prior evidence, I posit that effective and promising actions should be negatively associated with future gender pay gaps. Due to their nature, the ability of mixed evidence actions to predict future gender pay gap is unclear. I test the link between EE action adoption and the magnitude of the future pay gap using the following regression:

²⁹ Aggregating moderate and low-cost actions into a single group leads to similar conclusions.

$$GPG_level_{it+n} = \delta_0 + \delta_1 All\ Actions_{it} + \sum_{n=1}^N \theta_n Controls_{it} + \varepsilon_{it} \quad (2.5)$$

Equation (2.5) regresses *GPG_level* on *All Actions* and a set of control variables. *GPG_level* is captured by the variables *Mean GPG_Hourly Pay* in Panel A and *Median GPG_Hourly Pay* in Panel B. δ_1 is the main coefficient of interest, showing the ability of EE actions at time t to predict the $t + n$ -period gender pay gap. *Controls* is a vector of variables that includes size, growth opportunities, R&D, leverage, sales growth, ROA, percentage of female employees, and percentage of female board members.

Results are presented in Table 2.15. Models 1 to 4 (5 to 8) in Panel A use as dependent variable the *Mean GPG_Hourly Pay* _{$t+2$} (*Mean GPG_Hourly Pay* _{$t+3$}). In Panel B, models 1 to 4 (5 to 8) use as dependent variable the *Median GPG_Hourly Pay* _{$t+2$} (*Median GPG_Hourly Pay* _{$t+3$}). All model specifications include industry and year fixed effects. The regression is estimated using heteroscedasticity-consistent standard errors. The key explanatory variables in models 1 and 5, 2 and 6, 3 and 7, 4 and 8 are *All Actions*, *Effective Actions*, *Promising Actions* and *Mixed Evidence Actions*, respectively. Results show that the ability of EE actions to predict two- and three-year ahead gender pay gap is limited to *Effective Actions* (models 2 and 6). The coefficient estimate on *Effective Actions* is negative and significant at the $p < 0.06$, which is consistent with the view that adoption of effective actions helps to address the pay gap in the medium term. The coefficient on *Effective Actions* is -1.800 and -3.482 in models 2 and 6, respectively. This implies that, on average, the adoption of effective actions is associated with a 7% and 13% reduction of the gender pay gap on the two- and three-year horizon, respectively.³⁰ Importantly, this effect is limited to the gender pay gap level that is captured by the variable *Mean GPG_Hourly Pay* but not *Median GPG_Hourly Pay*. The

³⁰ Economic significance is calculated as follows: (coefficient x standard deviation of the explanatory variable) / sample mean of the explained variable. As so, the economic significance of *Mean GPG_Hourly Pay* _{$t+2$} (*Mean GPG_Hourly Pay* _{$t+3$}) is $(-1.800 \times 0.761) / 19.173 = -0.071$ $((-3.482 \times 0.756) / 20.151 = -0.1306)$.

evidence is consistent with EE actions reducing more extreme instances of the gender pay gap firms in the right tail of the distribution. The lack of significance for promising and mixed evidence actions should be interpreted with caution as I can only estimate the ability of EE actions to predict gender pay gap levels on two- and three-year horizons, whereas the impact of a policy such as shared parental leave is expected to be quantified only in the long-term and is therefore difficult to capture in Equation (2.5).

2.6 Conclusion

Several countries have recently implemented gender pay transparency policies to address a persistent pay differential between male and female employees. Prior literature tests the effectiveness of such policies by focusing on wage outcomes and examines whether the gender pay gap declined after their introduction. In this chapter, I examine whether the adoption of EE actions increase following the mandatory disclosure of the gender pay gap. I find that the adoption of these actions is low across the sample period. Additionally, while the growth in the adoption of a subset of actions is larger for gender pay gap disclosing firms relative to non-disclosing firms, this effect is economically negligible. I conduct a battery of tests and report consistent evidence that while there is an increase in the adoption of EE actions, this increase is not economically meaningful. Collectively, this chapter concludes that pay transparency policies may not be particularly effective in changing firm behavior.

This paper makes two contributions to the literature. First, to the research examining the effectiveness of pay transparency policies by relying on EE actions as a key outcome to measure firms' response to the disclosure of the gender pay gap. This approach allows me to understand whether firms took actions to target the drivers of the gender pay gap, which reflects one of the goals of regulators in mandating the disclosure of gender pay gap metrics.

Additionally, this approach reflects the view that organizational practices may reduce the gender pay gap.

Importantly, the results presented in this chapter should be considered in light of the limitations of my analysis. First, I collect EE actions from firms' annual reports. In this respect, it is possible that companies have disclosed EE actions on alternative reporting channels such as ESG reports or diversity statement. Additionally, my results must be interpreted considering the paper's key assumption that it is highly unlikely that firms adopt actions without disclosing them. Second, the sample period that follows the disclosure of gender pay gap metrics includes the COVID-19 period when firms may have potentially deviated their attention from non-financial matters and focused on other priorities. Third, my sample period is short as it includes only two years of data before the policy is implemented, the year of the policy and four years that follow the implementation of the policy. Fourth, the fact that companies have in place EE actions does not necessarily mean that employees take on these actions. For example, even if a company encourages the uptake of shared parental leave, the expected reduction of the pay gap that arises from such measure is conditional on employees taking on shared parental leave. Fifth, I collect EE actions from the annual reports of the FTSE250 traded companies. However, for a subset of companies I rely on the gender pay gap disclosure of the subsidiary. This means that I cannot show that the company that adopts EE actions is necessarily the legal entity that discloses gender pay gap metrics.

Future research could test whether firms engage in gender washing. This involves studying if the mandatory disclosure of the gender pay gap is associated with an increase of gender-related commentary that is not accompanied by the adoption of EE actions. Such an analysis would shed light on the unintended consequences of mandatory disclosure of the gender pay gap.

Figure 2-1: Classification of GPG disclosing and non-disclosing firms

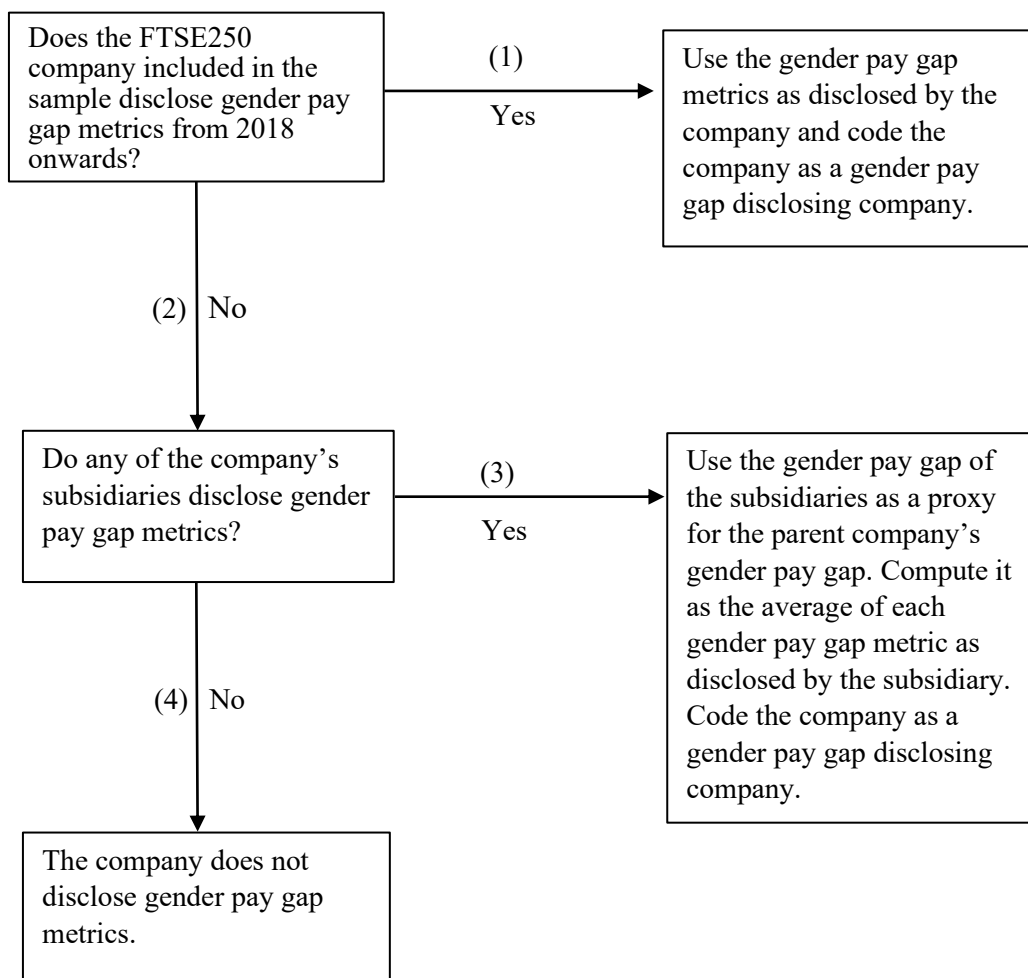
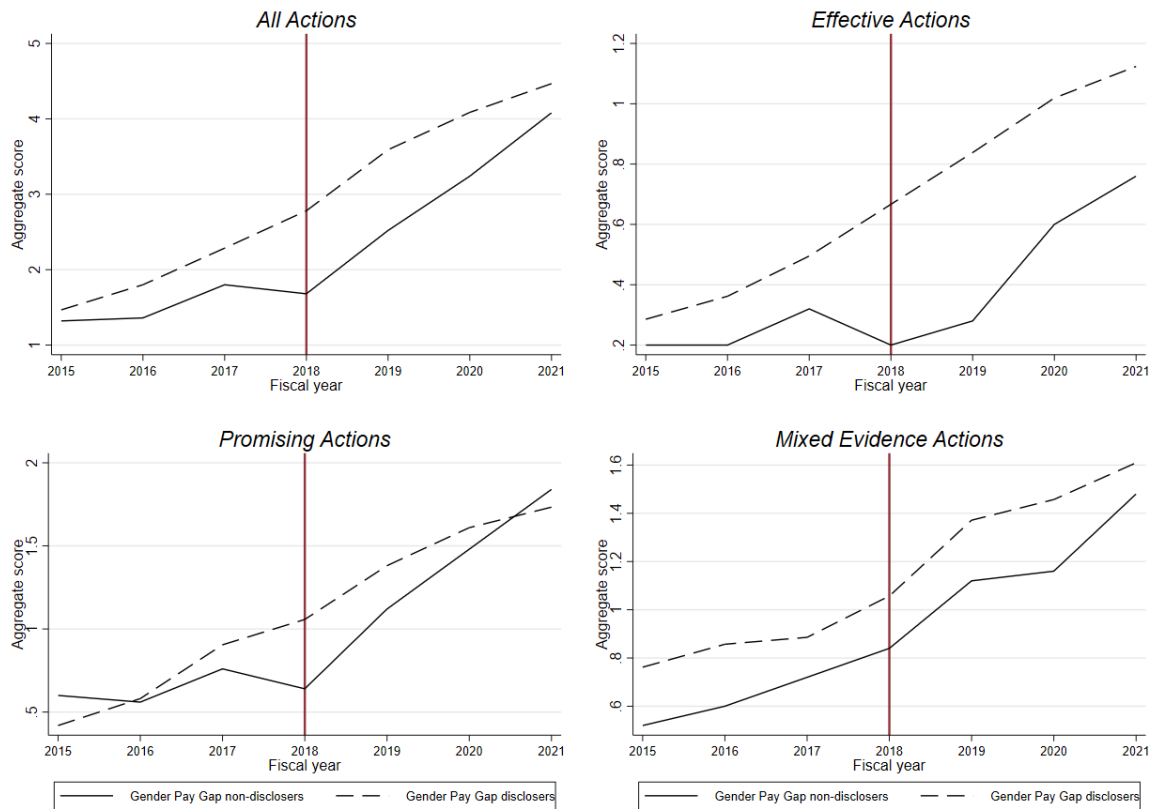
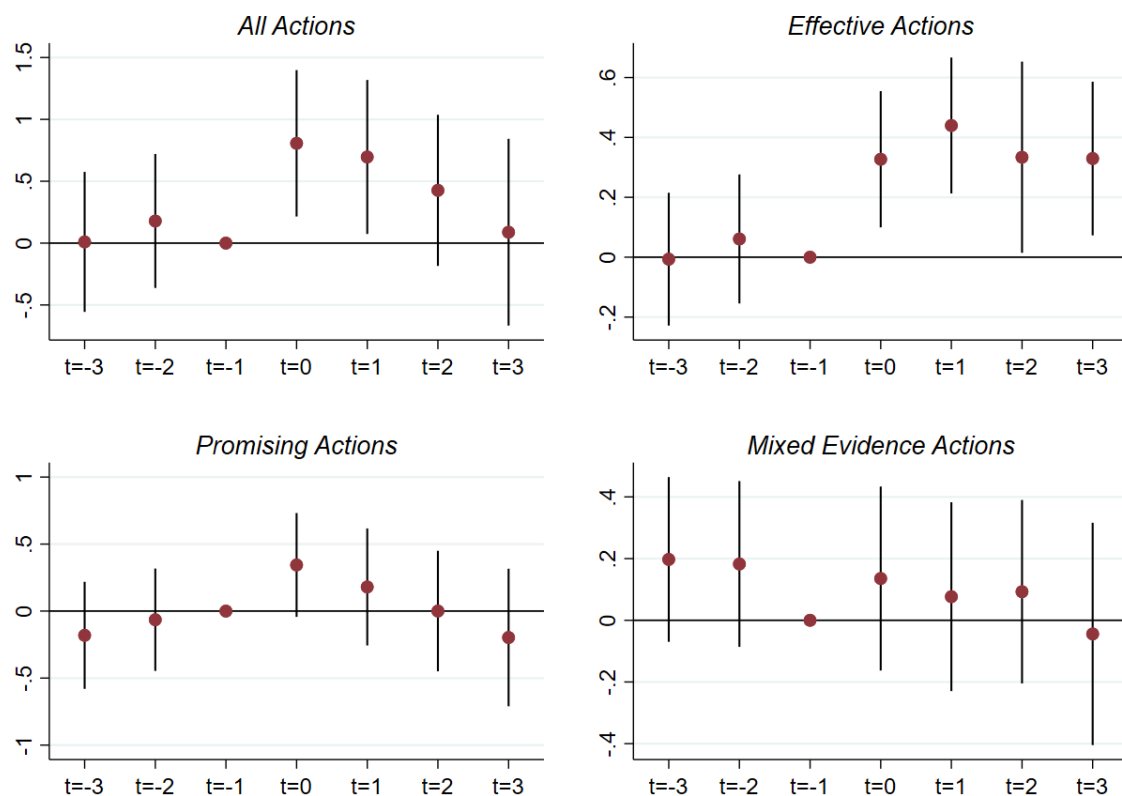


Figure 2-2: Comparative plots of cross-sectional means of EE actions



This figure presents the comparative plots of cross-sectional means of *All Actions*, *Effective Actions*, *Promising Actions*, and *Mixed Evidence Actions*. *All Actions* is the aggregate score of *Effective Actions*, *Promising Actions*, and *Mixed Evidence Actions* – in total it is the sum of nineteen actions that were collected from annual reports. *Effective Actions* is the aggregate score that includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. *Promising Actions* is the aggregate score that includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy and employing employee referral schemes. *Mixed Evidence Actions* is the aggregate score that includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training.

Figure 2-3: Adoption of EE actions around the mandatory disclosure of the gender pay gap



This figure plots the estimated coefficients of the regression that tests the effect of the mandatory gender pay gap disclosure on the adoption of EE actions. I estimate Equation (2.3) but replace the dummy variable *POST* with separate event-time dummies that represent the observations in time periods -3, -2, -1, 0, 1, 2 and 3 years relative to fiscal year when gender pay gap figures are disclosed for the first time. To do so, I omit the year -1 and use it as the baseline. This is the fiscal year 2017 when the gender pay gap regulation becomes mandatory. The error bars represent 90% confidence intervals.

Table 2.1: Sample Selection

Observations of LSE-traded firms with at least one year of non-missing total assets 2015-2021		13,727
<i>Less:</i>		
Observations of investment trust	(2,317)	
Observations with missing total assets	(1,762)	
Observations with missing fiscal year-end date	(11)	
Observations with missing price at fiscal year end	(2,558)	
Observations with price of zero	(55)	
Observations with zero employees	(44)	
Observations from firms in years they were not traded in LSE	(16)	
Observations from a company went from Main to AIM or AIM to Main	(20)	
Observations from firms that never traded in FTSE250	(5,433)	
Observations from firms that traded in FTSE250 between 1 and 3 years	(400)	
Observations per company is below 7	(201)	
Final sample (130 firms)		910
Final sample after removing missing observations from control variables		813

Table 2.2: Distribution of observations by year and industry

Panel A: Full sample		Full sample		GPG reporters:				N GPG missing
Year		N Obs		N Obs	N Parent	N Subsidiary	N Both	
Pre-mandatory pay gap reporting								
2015		130						
2016		130						
2017		130						
Disclosure of Gender Pay Gap Metrics		130						
2018		130		103	7	89	7	2
2019		130		103	5	89	9	2
2020		130		90	4	79	7	15
2021		130		103	6	86	11	2
Total		910		399	22	343	34	21

Panel B		Full sample		GPG reporters:				N GPG missing
Industry		N Obs	%	N Obs	%	N Parent	N Subsidiary	
Basic Materials		63	7	12	3		12	
Consumer Discretion		196	22	101	25	4	89	8
Consumer Staples		63	7	27	8	8	17	2
Energy		42	5	16	4		12	4
Financials		112	12	50	12		49	1
Health Care		21	2	8	2		8	
Industrials		266	29	136	34	5	115	16
Real Estate		91	10	22	6	4	15	3
Technology		28	3	16	4		16	
Telecommunications		14	2	3	1	1	2	
Utilities		14	2	8	2		8	
Total		910	100	399	100			

Table 2.3: Descriptive Statistics

Panel A: Gender Pay Gap Metrics (Source: UK Government website)										
Variable	Obs	Mean	Stdev	Min	p1	p25	p50	p75	p99	Max
<i>Mean GPG_Hourly Pay</i>	399	18.32	11.90	-20.00	-6.30	9.80	17.40	26.00	49.60	61.80
<i>Median GPG_Hourly Pay</i>	399	15.97	13.29	-20.20	-13.00	6.00	14.60	24.40	49.00	53.20

Panel B: Employment Equity Actions (aggregated and disaggregated variables - Source: manual collection)										
Variable	Obs	Mean	Stdev	Min	p1	p25	p50	p75	p99	Max
<i>All Actions (max = 19)</i>	910	2.80	1.98	0.00	0.00	1.00	2.00	4.00	8.00	9.00
<i>Effective Actions (max. = 6)</i>	910	0.62	0.72	0.00	0.00	0.00	0.00	1.00	2.00	3.00
<i>Targets of female representation:</i>	910	0.40	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00
<i>(Targets of female representation - numerical)</i>	910	0.33	0.47	0.00	0.00	0.00	0.00	1.00	1.00	1.00
<i>(Targets of female representation - time)</i>	910	0.26	0.44	0.00	0.00	0.00	0.00	1.00	1.00	1.00
<i>Diversity lead/task force</i>	910	0.19	0.40	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Removing biased language</i>	910	0.02	0.15	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Assessment center recruitment</i>	910	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	1.00
<i>Pay, promotion and reward sessions</i>	910	0.01	0.09	0.00	0.00	0.00	0.00	0.00	0.00	1.00
<i>Structured interviews</i>	910	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	1.00
<i>Promising Actions (max. = 8)</i>	910	1.08	1.10	0.00	0.00	0.00	1.00	2.00	4.00	6.00
<i>Blind CVs</i>	910	0.01	0.11	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Shortlisted women:</i>	910	0.14	0.35	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>(Shortlisted women - numerical target)</i>	910	0.04	0.21	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Returner program:</i>	910	0.05	0.21	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>(Returner program - long term career break)</i>	910	0.02	0.14	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>(Returner program - parental leave)</i>	910	0.02	0.14	0.00	0.00	0.00	0.00	0.00	1.00	1.00

Table 2.3: Descriptive Statistics

Panel B: continued										
Variable	Obs	Mean	Stdev	Min	p1	p25	p50	p75	p99	Max
<i>Mentoring, networking and sponsoring programs</i>	910	0.42	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00
<i>Flexible working conditions:</i>	910	0.36	0.48	0.00	0.00	0.00	0.00	1.00	1.00	1.00
<i>(Flexible working conditions - schedule)</i>	910	0.03	0.16	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>(Flexible working conditions - location)</i>	910	0.08	0.27	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>(Flexible working conditions - number of hours)</i>	910	0.04	0.20	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Shared parental leave:</i>	910	0.04	0.21	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>(Shared parental leave - enhanced)</i>	910	0.02	0.14	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Childcare policy:</i>	910	0.02	0.15	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>(Childcare policy - nursery)</i>	910	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	1.00
<i>(Childcare policy - financial support)</i>	910	0.01	0.07	0.00	0.00	0.00	0.00	0.00	0.00	1.00
<i>Referral schemes</i>	910	0.04	0.19	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Mixed Evidence Actions (max. = 5)</i>	910	1.10	0.87	0.00	0.00	0.00	1.00	2.00	3.00	4.00
<i>Diverse interview panel</i>	910	0.02	0.13	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Diversity statement</i>	910	0.15	0.36	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Self-assessment</i>	910	0.05	0.23	0.00	0.00	0.00	0.00	0.00	1.00	1.00
<i>Diversity training</i>	910	0.26	0.44	0.00	0.00	0.00	0.00	1.00	1.00	1.00
<i>Leadership training:</i>	910	0.61	0.49	0.00	0.00	0.00	1.00	1.00	1.00	1.00
<i>(Leadership training - female focused)</i>	910	0.06	0.24	0.00	0.00	0.00	0.00	0.00	1.00	1.00

Table 2.3: Descriptive Statistics

Panel C: Control variables (Source: Refinitiv Eikon Datastream and manual collection)

Variable	Obs	Mean	Stdev	Min	p1	p25	p50	p75	p99	Max
<i>Size</i>	813	14.30	1.11	10.68	11.57	13.58	14.24	14.97	17.87	19.62
<i>Tobin's Q</i>	813	1.94	3.24	0.37	0.55	1.07	1.41	1.99	5.33	52.45
<i>R&D</i>	813	3.06	4.49	0.00	0.00	0.00	0.00	7.82	12.09	13.32
<i>Leverage</i>	813	0.23	0.18	0.00	0.00	0.08	0.22	0.32	0.76	0.92
<i>Sales growth</i>	813	0.09	0.40	-0.92	-0.57	-0.02	0.06	0.14	1.95	6.68
<i>ROA</i>	813	0.09	0.24	-0.32	-0.17	0.02	0.05	0.11	0.65	2.97
<i>% Female Employees</i>	813	35.24	14.88	2.00	8.02	23.00	32.10	47.00	69.62	73.41
<i>% Female Board Members</i>	813	27.81	10.79	0.00	9.00	20.00	28.57	33.33	50.00	67.00

This table presents descriptive statistics for all variables. Panel A provides the gender pay gap variables. Panel B includes manually collected variables. Panel C provides the control variables. Variable definitions are as follows. *Mean GPG_Hourly Pay* is the mean percentage difference between male and female hourly pay. *Median GPG_Hourly Pay* is the median percentage difference between male and female hourly pay. *All Actions* is the aggregate score of *Effective Actions*, *Promising Actions*, and *Mixed Evidence Actions* – in total it is the sum of nineteen actions that were collected from annual reports. *Effective Actions* is the aggregate score that includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. *Promising Actions* is the aggregate score that includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy and employing employee referral schemes. *Mixed Evidence Actions* is the aggregate score that includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is defined as the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees. Source: Manual collection from firms' annual reports. *% Female Board Members* is the percentage of female board members. Source: Manual collection from firms' annual reports.

Table 2.4: Difference in means between firms GPG disclosing and non-disclosing firms

Panel A: Employment Equity (aggregated and disaggregated variables - Source: manual collection)

	Difference in means for sample period between 2015-2017						Difference in means for sample period between 2018-2021					
	Non-discloser		Discloser		Difference		Non-discloser		Discloser		Difference	
	N(0)	Mean(0)	N(1)	Mean(1)	(1)-(0)	p	N(0)	Mean(0)	N(1)	Mean(1)	(1)-(0)	p
All Actions (max = 19)	75	1.49	315	1.85	0.36	0.05	100	2.88	420	3.73	0.85	0.00
Effective Actions (max. = 6)	75	0.24	315	0.38	0.14	0.04	100	0.46	420	0.91	0.45	0.00
Targets of female representation:	75	0.24	315	0.29	0.05	0.40	100	0.28	420	0.53	0.25	0.00
(Targets of female representation - numerical)	75	0.20	315	0.21	0.01	0.90	100	0.26	420	0.46	0.20	0.00
(Targets of female representation - time)	75	0.19	315	0.14	-0.05	0.31	100	0.20	420	0.38	0.18	0.00
Diversity lead/task force	75	0.00	315	0.09	0.09	0.01	100	0.16	420	0.32	0.16	0.00
Removing biased language	75	0.00	315	0.00	0.00	0.63	100	0.02	420	0.04	0.02	0.29
Assessment center recruitment	75	0.00	315	0.00	0.00	.	100	0.00	420	0.00	0.00	0.63
Pay, promotion and reward sessions	75	0.00	315	0.00	0.00	.	100	0.00	420	0.02	0.02	0.19
Structured interviews	75	0.00	315	0.00	0.00	0.63	100	0.00	420	0.00	0.00	0.63
Promising Actions (max. = 8)	75	0.64	315	0.63	-0.01	0.96	100	1.27	420	1.45	0.18	0.17
Blind CVs	75	0.00	315	0.01	0.01	0.49	100	0.03	420	0.01	-0.02	0.28
Shortlisted women:	75	0.15	315	0.06	-0.09	0.02	100	0.21	420	0.18	-0.03	0.54
(Shortlisted women - numerical target)	75	0.04	315	0.02	-0.02	0.28	100	0.10	420	0.05	-0.05	0.06
Returner program:	75	0.00	315	0.03	0.03	0.14	100	0.07	420	0.07	0.00	0.91
(Returner program - long term career break)	75	0.00	315	0.02	0.02	0.27	100	0.01	420	0.03	0.02	0.33
(Returner program - parental leave)	75	0.00	315	0.01	0.01	0.49	100	0.05	420	0.03	-0.02	0.28
Mentoring, networking and sponsoring programs	75	0.20	315	0.28	0.08	0.18	100	0.38	420	0.57	0.19	0.00

Table 2.4: Difference in means between firms GPG disclosing and non-disclosing

Panel A

	Difference in means for sample period between 2015-2017						Difference in means for sample period between 2018-2021					
	Non-discloser		Discloser		Difference		Non-discloser		Discloser		Difference	
	N(0)	Mean(0)	N(1)	Mean(1)	(1)-(0)	p	N(0)	Mean(0)	N(1)	Mean(1)	(1)-(0)	p
<i>Flexible working conditions:</i>	75	0.24	315	0.21	-0.03	0.52	100	0.43	420	0.47	0.04	0.46
<i>(Flexible working conditions - schedule)</i>	75	0.03	315	0.01	-0.02	0.24	100	0.02	420	0.04	0.02	0.37
<i>(Flexible working conditions - location)</i>	75	0.03	315	0.03	0.00	0.82	100	0.12	420	0.11	-0.01	0.77
<i>(Flexible working conditions - number of hours)</i>	75	0.00	315	0.03	0.03	0.16	100	0.05	420	0.06	0.01	0.78
<i>Shared parental leave:</i>	75	0.00	315	0.02	0.02	0.27	100	0.06	420	0.07	0.01	0.75
<i>(Shared parental leave - enhanced)</i>	75	0.00	315	0.01	0.01	0.49	100	0.02	420	0.03	0.01	0.49
<i>Childcare policy:</i>	75	0.01	315	0.01	0.00	0.97	100	0.04	420	0.03	-0.01	0.46
<i>(Childcare policy - nursery)</i>	75	0.00	315	0.00	0.00	.	100	0.01	420	0.00	-0.01	0.27
<i>(Childcare policy - financial support)</i>	75	0.01	315	0.01	0.00	0.77	100	0.01	420	0.00	-0.01	0.04
<i>Referral schemes</i>	75	0.04	315	0.03	-0.01	0.49	100	0.05	420	0.04	-0.01	0.76
<i>Mixed evidence actions (max. = 5)</i>	75	0.61	315	0.83	0.22	0.02	100	1.15	420	1.37	0.22	0.02
<i>Diverse interview panel</i>	75	0.00	315	0.00	0.00	0.63	100	0.03	420	0.03	0.00	0.83
<i>Diversity statement</i>	75	0.01	315	0.08	0.07	0.05	100	0.16	420	0.23	0.07	0.11
<i>Self-assessment</i>	75	0.04	315	0.04	0.00	0.96	100	0.12	420	0.05	-0.07	0.01
<i>Diversity training</i>	75	0.12	315	0.11	-0.01	0.83	100	0.27	420	0.40	0.13	0.02
<i>Leadership training:</i>	75	0.44	315	0.60	0.16	0.01	100	0.57	420	0.66	0.09	0.08
<i>(Leadership training - female focused)</i>	75	0.03	315	0.03	0.00	0.93	100	0.09	420	0.08	-0.01	0.83

Table 2.4: Difference in means between firms GPG disclosing and non-disclosing

Panel B: Control variables (Source: Refinitiv Eikon Datastream and manual collection)

		Difference in means for sample period between 2015-2017						Difference in means for sample period between 2018-2021					
		Non-discloser		Discloser		Difference		Non-discloser		Discloser		Difference	
		N(0)	Mean(0)	N(1)	Mean(1)	(1)-(0)	p	N(0)	Mean(0)	N(1)	Mean(1)	(1)-(0)	p
<i>Size</i>	62	14.12	287	14.14	0.02	0.90		87	14.29	377	14.45	0.16	0.22
<i>Tobin's Q</i>	62	1.49	287	2.29	0.80	0.15		87	1.30	377	1.90	0.60	0.05
<i>R&D</i>	62	3.06	287	3.15	0.09	0.89		87	2.92	377	3.03	0.11	0.84
<i>Leverage</i>	62	0.24	287	0.20	-0.04	0.18		87	0.22	377	0.25	0.03	0.18
<i>Sales growth</i>	62	0.13	287	0.14	0.01	0.92		87	0.02	377	0.06	0.04	0.23
<i>ROA</i>	62	0.06	287	0.11	0.05	0.21		87	0.07	377	0.07	0.00	1.00
<i>% Female Employees</i>	62	38.03	287	34.06	-3.97	0.06		87	37.56	377	35.14	-2.42	0.17
<i>% Female Board Members</i>	62	20.16	287	22.27	2.11	0.09		87	30.38	377	32.68	2.30	0.05

This table provides a t-test on difference in means of two groups of firms: those disclosing the GPG (discloser) vs not disclosing it (non-discloser). Panel A includes manually collected variables. Panel B includes firm characteristics. Variable definitions are as follows. *All Actions* is the aggregate score of *Effective Actions*, *Promising Actions*, and *Mixed Evidence Actions* – in total it is the sum of nineteen actions that were collected from annual reports. *Effective Actions* is the aggregate score that includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. *Promising Actions* is the aggregate score that includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy and employing employee referral schemes. *Mixed Evidence Actions* is the aggregate score that includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is defined as the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees. Source: Manual collection from firms' annual reports. *% Female Board Members* is the percentage of female board members. Source: Manual collection from firms' annual reports.

Table 2.5: Regression of EE actions on year (Probability values in parentheses)

Panel A				
	(1)	(2)	(3)	(4)
VARIABLES	<i>All Actions</i>			
<i>Year</i>	0.517 (0.01)	0.487 (0.01)	0.503 (0.01)	0.479 (0.01)
<i>Size</i>		0.437 (0.01)	0.259 (0.01)	0.042 (0.83)
<i>Tobin's Q</i>		0.032 (0.35)	0.014 (0.67)	-0.041 (0.30)
<i>R&D</i>		0.005 (0.70)	0.010 (0.52)	-0.001 (0.96)
<i>Leverage</i>		-0.281 (0.41)	0.104 (0.75)	0.292 (0.65)
<i>Sales Growth</i>		-0.154 (0.35)	-0.180 (0.18)	-0.102 (0.34)
<i>ROA</i>		0.978 (0.04)	0.954 (0.04)	1.016 (0.02)
<i>% Female Employees</i>		-0.005 (0.22)	-0.007 (0.14)	-0.002 (0.87)
<i>% Female Board Members</i>		0.004 (0.53)	0.001 (0.89)	0.015 (0.03)
<i>Intercept</i>	0.735 (0.01)	-5.403 (0.01)	-2.814 (0.01)	-0.098 (0.97)
Observations	910	813	813	811
Adjusted R-squared	0.271	0.317	0.353	0.630
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes
Panel B				
	(1)	(2)	(3)	(4)
VARIABLES	<i>Effective Actions</i>			
<i>Year</i>	0.137 (0.01)	0.129 (0.01)	0.136 (0.01)	0.140 (0.01)
Observations	910	813	813	811
Adjusted R-squared	0.146	0.182	0.206	0.539
Control variables	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

Table 2.5: Regression of EE actions on year

Panel C				
VARIABLES	(1)	(2)	(3)	(4)
	<i>Promising Actions</i>			
<i>Year</i>	0.227 (0.01)	0.217 (0.01)	0.225 (0.01)	0.207 (0.01)
Observations	910	813	813	811
Control variables	No	Yes	Yes	Yes
Adjusted R-squared	0.172	0.217	0.266	0.528
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

Panel D				
VARIABLES	(1)	(2)	(3)	(4)
	<i>Mixed Evidence Actions</i>			
<i>Year</i>	0.152 (0.01)	0.141 (0.01)	0.143 (0.01)	0.132 (0.01)
Observations	910	813	813	811
Control variables	No	Yes	Yes	Yes
Adjusted R-squared	0.122	0.153	0.161	0.419
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

This table presents the regression of EE actions on year. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. In Panel A the dependent variable is *All Actions* which is the aggregate score of effective actions, promising actions, and mixed evidence actions – in total it is the sum of nineteen actions that were collected from annual reports. In Panel B the dependent variable for is the aggregate score *Effective Actions*, which includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. In Panel C the dependent variable is the aggregate score of *Promising Actions*, which includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy and employing employee referral schemes. In Panel D the dependent variable is the aggregate score of *Mixed Evidence Actions*, which includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training. *Year* takes the value one if fiscal year is 2015, two if fiscal year is 2016, three if fiscal year is 2017, four if fiscal year is 2018, five if fiscal year is 2019, six if fiscal year is 2020, and seven if fiscal year is 2021. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is defined as the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.6: Regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap (Probability values in parentheses.)

Panel A				
VARIABLES	(1)	(2)	(3)	(4)
	<i>All Actions</i>			
<i>D_GPG_Metrics x Year</i>		0.217 (0.03)	0.208 (0.03)	0.115 (0.14)
<i>D_GPG_Metrics</i>	1.725 (0.01)	-0.529 (0.27)	-0.405 (0.39)	-0.328 (0.37)
<i>Year</i>		0.348 (0.01)	0.350 (0.01)	0.414 (0.01)
<i>Size</i>		0.430 (0.01)	0.247 (0.01)	0.041 (0.83)
<i>Tobin's Q</i>		0.010 (0.76)	-0.004 (0.90)	-0.047 (0.23)
<i>R&D</i>		0.005 (0.70)	0.014 (0.35)	0.001 (0.98)
<i>Leverage</i>		-0.330 (0.33)	-0.012 (0.97)	0.172 (0.79)
<i>Sales Growth</i>		-0.156 (0.36)	-0.182 (0.20)	-0.093 (0.39)
<i>ROA</i>		1.236 (0.01)	1.104 (0.02)	1.107 (0.01)
<i>% Female Employees</i>		-0.004 (0.31)	-0.005 (0.25)	-0.003 (0.85)
<i>% Female Board Members</i>		0.002 (0.78)	-0.001 (0.91)	0.014 (0.04)
<i>Intercept</i>	2.006 (0.01)	-4.985 (0.01)	-2.354 (0.02)	0.105 (0.97)
Observations	910	813	813	811
Adjusted R-squared	0.187	0.328	0.365	0.630
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

Table 2.6: Regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap

Panel B				
VARIABLES	(1)	(2)	(3)	(4)
		<i>Effective Actions</i>		
<i>D_GPG_Metrics x Year</i>		0.108 (0.01)	0.098 (0.01)	0.099 (0.01)
<i>D_GPG_Metrics</i>	0.536 (0.01)	-0.251 (0.20)	-0.214 (0.27)	-0.281 (0.05)
<i>Year</i>		0.058 (0.01)	0.069 (0.01)	0.084 (0.01)
Observations	910	813	813	811
Adjusted R-squared	0.139	0.206	0.224	0.548
Control variables	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

Panel C				
VARIABLES	(1)	(2)	(3)	(4)
		<i>Promising Actions</i>		
<i>D_GPG_Metrics x Year</i>		0.018 (0.77)	0.007 (0.91)	-0.024 (0.63)
<i>D_GPG_Metrics</i>	0.680 (0.01)	0.023 (0.94)	0.101 (0.73)	0.156 (0.49)
<i>Year</i>		0.195 (0.01)	0.200 (0.01)	0.207 (0.01)
Observations	910	813	813	811
Adjusted R-squared	0.095	0.216	0.266	0.527
Control variables	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

Panel D

VARIABLES	(1)	(2)	(3)	(4)
		<i>Mixed Evidence Actions</i>		
<i>D_GPG_Metrics x Year</i>		0.091 (0.05)	0.104 (0.02)	0.040 (0.33)
<i>D_GPG_Metrics</i>	0.509 (0.01)	-0.301 (0.18)	-0.292 (0.20)	-0.203 (0.30)
<i>Year</i>		0.096 (0.01)	0.081 (0.01)	0.124 (0.01)
Observations	910	813	813	811
Adjusted R-squared	0.084	0.158	0.170	0.418
Control variables	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

This table presents the regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. In Panel A the dependent variable is *All Actions* which is the aggregate score of effective actions, promising actions, and mixed evidence actions – in total it is the sum of nineteen actions that were collected from annual reports. In Panel B the dependent variable for is the aggregate score *Effective Actions*, which includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. In Panel C the dependent variable is the aggregate score of *Promising Actions*, which includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy and employing employee referral schemes. In Panel D the dependent variable is the aggregate score of *Mixed Evidence Actions*, which includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training. *D_GPG_Metrics* takes the value one from 2018 onwards and if the company reports the gender pay gap figures at least once between 2018 and 2021 and zero otherwise. In 2015, 2016, and 2017 this variable takes the value zero for all observations. *Year* takes the value one if fiscal year is 2015, two if fiscal year is 2016, three if fiscal year is 2017, four if fiscal year is 2018, five if fiscal year is 2019, six if fiscal year is 2020, and seven if fiscal year is 2021. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is defined as the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.7: Regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap conditional on the proportion of female representation (Probability values in parentheses.)

Panel A: Dependent variable is *All Actions*

	(1)	(2)	(3)	(4)	(5)	(6)			
	Partitions based on % Female Employees:						Difference in partition coefficients:		
VARIABLES	High	Low	High	Low	High	Low	(1)-(2)	(3)-(4)	(5)-(6)
<i>D_GPG_Metrics x Year</i>	0.291 (0.03)	0.138 (0.31)	0.312 (0.02)	0.046 (0.73)	0.107 (0.01)	-0.022 (0.71)	0.153 (0.23)	0.266 (0.07)	0.129 (0.03)
<i>D_GPG_Metrics</i>	-0.633 (0.35)	-0.547 (0.40)	-0.515 (0.42)	-0.313 (0.62)					
<i>Year</i>	0.262 (0.01)	0.493 (0.01)	0.253 (0.01)	0.547 (0.01)	0.391 (0.01)	0.507 (0.01)			
Observations	439	374	439	374	437	374			
Adjusted R-squared	0.338	0.358	0.385	0.405	0.649	0.626			
Control variables	Yes	Yes	Yes	Yes	Yes	Yes			
Industry FE	No	No	Yes	Yes	No	No			
Firm FE	No	No	No	No	Yes	Yes			

Panel B: Dependent variable is *All Actions*

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	Difference in partition coefficients:		
	Partitions based on % Female Board members						(1)-(2)	(3)-(4)	(5)-(6)
	High	Low	High	Low	High	Low			
<i>D_GPG_Metrics x Year</i>	0.224	0.255	0.192	0.283	0.060	0.048	-0.031	-0.091	0.012
	(0.06)	(0.16)	(0.11)	(0.11)	(0.16)	(0.39)	(0.45)	(0.33)	(0.44)
<i>D_GPG_Metrics</i>	-0.429	-1.006	-0.296	-0.901					
	(0.44)	(0.31)	(0.59)	(0.32)					
<i>Year</i>	0.352	0.314	0.369	0.283	0.482	0.382			
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)			
Observations	584	229	584	229	582	229			
Adjusted R-squared	0.349	0.296	0.380	0.368	0.599	0.711			
Control variables	Yes	Yes	Yes	Yes	Yes	Yes			
Industry FE	No	No	Yes	Yes	No	No			
Firm FE	No	No	No	No	Yes	Yes			

This table presents the regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap conditional on the proportion of female representation at the employee-level. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. The dependent variable is *All Actions* which is the aggregate score of effective actions, promising actions, and mixed evidence actions – in total it is the sum of nineteen actions that were collected from annual reports. *D_GPG_Metrics* takes the value one from 2018 onwards and if the company reports the gender pay gap figures at least once between 2018 and 2021 and zero otherwise. In 2015, 2016, and 2017 this variable takes the value zero for all observations. *Year* takes the value one if fiscal year is 2015, two if fiscal year is 2016, three if fiscal year is 2017, four if fiscal year is 2018, five if fiscal year is 2019, six if fiscal year is 2020, and seven if fiscal year is 2021. Control variables included in the regressions are defined as follows: *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.8: Regression of EE actions on year conditional on the level of the gender pay gap in 2018 (Probability values in parentheses.)

	(1)	(2)	(3)	(4)	(5)	(6)			
	Partitioning by GPG in 2018:						Difference in coefficients:		
VARIABLES	High	Low	High	Low	High	Low	(1)-(2)	(3)-(4)	(5)-(6)
<i>Year</i>	0.766 (0.01)	0.460 (0.01)	0.755 (0.01)	0.503 (0.01)	1.009 (0.01)	0.550 (0.01)	0.306 (0.07)	0.252 (0.097)	0.459 (0.02)
Observations	104	254	104	254	103	251			
Adjusted R-squared	0.230	0.145	0.313	0.223	0.618	0.597			
Control variables	Yes	Yes	Yes	Yes	Yes	Yes			
Industry FE	No	No	Yes	Yes	No	No			
Firm FE	No	No	No	No	Yes	Yes			

This table presents the regression of EE actions on year conditional on level of reported gender pay gap in 2018. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. The dependent variable is *All Actions* which is the aggregate score of effective actions, promising actions, and mixed evidence – in total it is the sum of nineteen actions that collected from annual reports. *Year* takes the value one if fiscal year is 2015, two if fiscal year is 2016, three if fiscal year is 2017, four if fiscal year is 2018, five if fiscal year is 2019, six if fiscal year is 2020, and seven if fiscal year is 2021. Control variables included in the regressions are defined as follows: *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.9: Difference in Difference regression (Probability values in parentheses.)

Panel A				
VARIABLES	(1)	(2)	(3)	(4)
	<i>All Actions</i>			
<i>D_GPG_Disclosure x Post</i>		0.384 (0.19)	0.322 (0.29)	0.320 (0.17)
<i>D_GPG_Disclosure</i>	0.639 (0.01)	0.324 (0.07)	0.609 (0.01)	
<i>Post</i>		1.209 (0.01)	1.301 (0.01)	0.921 (0.01)
<i>Size</i>		0.441 (0.01)	0.262 (0.01)	0.443 (0.02)
<i>Tobin's Q</i>		0.019 (0.60)	0.005 (0.88)	-0.020 (0.65)
<i>R&D</i>		0.005 (0.71)	0.017 (0.29)	-0.045 (0.18)
<i>Leverage</i>		-0.230 (0.51)	0.053 (0.88)	0.311 (0.66)
<i>Sales Growth</i>		-0.134 (0.46)	-0.171 (0.26)	-0.116 (0.35)
<i>ROA</i>		0.964 (0.05)	0.756 (0.13)	0.666 (0.16)
<i>% Female Employees</i>		-0.004 (0.39)	-0.004 (0.43)	0.011 (0.46)
<i>% Female Board Members</i>		0.019 (0.01)	0.017 (0.01)	0.044 (0.01)
<i>Intercept</i>	2.286 (0.01)	-5.079 (0.01)	-2.758 (0.01)	-5.743 (0.03)
Observations	910	813	813	811
Adjusted R-squared	0.015	0.270	0.309	0.575
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

Table 2.9: Difference in Difference regression (Probability values in parentheses.)

Panel B				
VARIABLES	(1)	(2)	(3)	(4)
		<i>Effective Actions</i>		
<i>D_GPG_Disclosure x Post</i>		0.255 (0.01)	0.238 (0.02)	0.295 (0.01)
<i>D_GPG_Disclosure</i>	0.319 (0.01)	0.136 (0.03)	0.161 (0.03)	
<i>Post</i>		0.195 (0.03)	0.224 (0.01)	0.101 (0.24)
Observations	910	813	813	811
Adjusted R-squared	0.030	0.175	0.191	0.508
Control variables	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

Panel C				
VARIABLES	(1)	(2)	(3)	(4)
		<i>Promising Actions</i>		
<i>D_GPG_Disclosure x Post</i>		0.161 (0.32)	0.117 (0.50)	0.114 (0.43)
<i>D_GPG_Disclosure</i>	0.098 (0.27)	-0.014 (0.89)	0.091 (0.48)	
<i>Post</i>		0.540 (0.01)	0.600 (0.01)	0.421 (0.01)
Observations	910	813	813	811
Adjusted R-squared	0.000	0.179	0.228	0.495
Control variables	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

Table 2.9: Difference in Difference regression

Panel D				
VARIABLES	(1)	(2)	(3)	(4)
		<i>Mixed Evidence Actions</i>		
<i>D_GPG_Disclosure x Post</i>		-0.032	-0.033	-0.090
		(0.82)	(0.82)	(0.39)
<i>D_GPG_Disclosure</i>	0.223	0.202	0.357	
	(0.01)	(0.04)	(0.01)	
<i>Post</i>		0.474	0.478	0.399
		(0.01)	(0.01)	(0.01)
Observations	910	813	813	811
Adjusted R-squared	0.009	0.134	0.151	0.397
Control variables	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No
Firm FE	No	No	No	Yes

This table presents a difference in difference analysis. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. In Panel A the dependent variable is *All Actions* which is the aggregate score of effective actions, promising actions, and mixed evidence – in total it is the sum of nineteen actions that collected from annual reports. In Panel B the dependent variable for is the aggregate score *Effective Actions*, which includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. In Panel C the dependent variable is the aggregate score of *Promising Actions*, which includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy, and employing employee referral schemes. In Panel D the dependent variable is the aggregate score of *Mixed Evidence Actions*, which includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training. *D_GPG_Disclosure* takes the value one if the company discloses gender pay gap metrics (either through the parent or the subsidiary) at least once between 2018 and 2021 and zero otherwise. In 2015, 2016, and 2017 this variable also takes the value one if from 2018 onwards a company discloses gender pay metrics at least once. *Post* is the indicator variable that takes the value one from the 2018 fiscal year onwards and zero otherwise. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.10: Regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap using an entropy balanced sample (Probability values in parentheses.)

Panel A			
VARIABLES	(1)	(2)	(3)
	<i>All Actions</i>		
<i>D_GPG_Metrics x Year</i>	0.228 (0.04)	0.246 (0.02)	0.022 (0.52)
<i>D_GPG_Metrics</i>	-0.810 (0.15)	-0.710 (0.20)	
<i>Year</i>	0.420 (0.01)	0.413 (0.01)	0.436 (0.01)
<i>Size</i>	0.684 (0.01)	0.667 (0.01)	0.428 (0.13)
<i>Tobin's Q</i>	-0.102 (0.43)	0.012 (0.94)	0.345 (0.15)
<i>R&D</i>	0.021 (0.18)	0.043 (0.02)	0.000 (1.00)
<i>Leverage</i>	-0.937 (0.03)	-1.073 (0.01)	-0.809 (0.27)
<i>Sales Growth</i>	-0.030 (0.90)	-0.022 (0.92)	-0.041 (0.77)
<i>ROA</i>	1.477 (0.04)	1.421 (0.04)	0.905 (0.25)
<i>% Female Employees</i>	-0.004 (0.38)	0.000 (1.00)	-0.005 (0.72)
<i>% Female Board Members</i>	-0.016 (0.04)	-0.018 (0.02)	0.015 (0.06)
<i>Intercept</i>	-8.262 (0.01)	-7.949 (0.01)	-4.954 (0.26)
Observations	813	813	813
R-squared	0.333	0.350	0.686
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Table 2.10: Regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap using an entropy balanced sample

Panel B			
VARIABLES	(1)	(2)	(3)
	<i>Effective Actions</i>		
<i>D_GPG_Metrics x Year</i>	0.121 (0.01)	0.124 (0.01)	0.038 (0.01)
<i>D_GPG_Metrics</i>	-0.382 (0.09)	-0.376 (0.09)	
<i>Year</i>	0.082 (0.01)	0.079 (0.01)	0.094 (0.01)
Observations	813	813	813
R-squared	0.199	0.208	0.576
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Panel C			
VARIABLES	(1)	(2)	(3)
	<i>Promising Actions</i>		
<i>D_GPG_Metrics x Year</i>	0.041 (0.53)	0.048 (0.46)	-0.009 (0.68)
<i>D_GPG_Metrics</i>	-0.240 (0.46)	-0.175 (0.59)	
<i>Year</i>	0.202 (0.01)	0.198 (0.01)	0.180 (0.01)
Observations	813	813	813
R-squared	0.228	0.247	0.578
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Table 2.10: Regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap using an entropy balanced sample

Panel D			
VARIABLES	(1)	(2)	(3)
	<i>Mixed Evidence Actions</i>		
<i>D_GPG_Metrics x Year</i>	0.066 (0.24)	0.074 (0.18)	-0.008 (0.65)
<i>D_GPG_Metrics</i>	-0.188 (0.51)	-0.159 (0.58)	
<i>Year</i>	0.136 (0.01)	0.136 (0.01)	0.162 (0.01)
Observations	813	813	813
R-squared	0.188	0.218	0.597
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

This table presents the regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap using an entropy balancing method. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. In Panel A the dependent variable for is *All Actions* which is the aggregate score of effective actions, promising actions, and mixed evidence – in total it is the sum of nineteen actions that collected from annual reports. In Panel B the dependent variable for is the aggregate score *Effective Actions*, which includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. In Panel C the dependent variable is the aggregate score of *Promising Actions*, which includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy and employing employee referral schemes. In Panel D the dependent variable is the aggregate score of *Mixed Evidence Actions*, which includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training. *D_GPG_Metrics* takes the value one from 2018 onwards and if the company reports the gender pay gap figures at least once between 2018 and 2021 and zero otherwise. In 2015, 2016, and 2017 this variable takes the value zero for all observations. *Year* takes the value one if fiscal year is 2015, two if fiscal year is 2016, three if fiscal year is 2017, four if fiscal year is 2018, five if fiscal year is 2019, six if fiscal year is 2020, and seven if fiscal year is 2021. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.11: Difference in difference regression using an entropy balanced sample (Probability values in parentheses.)

Panel A			
VARIABLES	(1)	(2)	(3)
		<i>All Actions</i>	
<i>D_GPG_Disclosure x Post</i>	-0.105 (0.73)	-0.092 (0.76)	-0.107 (0.64)
<i>D_GPG_Disclosure</i>	0.492 (0.01)	0.804 (0.01)	
<i>Post</i>	1.776 (0.01)	1.820 (0.01)	1.357 (0.01)
<i>Size</i>	0.705 (0.01)	0.689 (0.01)	0.912 (0.01)
<i>Tobin's Q</i>	-0.135 (0.27)	0.010 (0.94)	0.177 (0.46)
<i>R&D</i>	0.021 (0.20)	0.047 (0.01)	-0.036 (0.21)
<i>Leverage</i>	-1.012 (0.02)	-1.181 (0.01)	-1.446 (0.05)
<i>Sales Growth</i>	0.028 (0.92)	0.043 (0.87)	-0.090 (0.51)
<i>ROA</i>	1.651 (0.02)	1.543 (0.03)	0.704 (0.42)
<i>% Female Employees</i>	-0.005 (0.33)	0.001 (0.89)	0.001 (0.91)
<i>% Female Board Members</i>	-0.008 (0.31)	-0.009 (0.24)	0.032 (0.01)
<i>Intercept</i>	-7.906 (0.01)	-8.080 (0.01)	-11.420 (0.01)
Observations	813	813	813
R-squared	0.311	0.334	0.662
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Table 2.11: Difference in difference regression using an entropy balanced sample

Panel B			
	(1)	(2)	(3)
VARIABLES	<i>Effective Actions</i>		
<i>D_GPG_Disclosure x Post</i>	0.114 (0.32)	0.119 (0.30)	0.190 (0.06)
<i>D_GPG_Disclosure</i>	0.185 (0.01)	0.239 (0.01)	
<i>Post</i>	0.353 (0.01)	0.350 (0.01)	0.257 (0.01)
Observations	813	813	813
R-squared	0.181	0.194	0.562
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Panel C			
	(1)	(2)	(3)
VARIABLES	<i>Promising Actions</i>		
<i>D_GPG_Disclosure x Post</i>	-0.141 (0.41)	-0.148 (0.39)	-0.175 (0.21)
<i>D_GPG_Disclosure</i>	0.078 (0.37)	0.222 (0.03)	
<i>Post</i>	0.790 (0.01)	0.818 (0.01)	0.568 (0.01)
Observations	813	813	813
R-squared	0.212	0.232	0.564
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Table 2.11: Difference in difference regression using an entropy balanced sample

Panel D			
VARIABLES	(1)	(2)	(3)
	<i>Mixed Evidence Actions</i>		
<i>D_GPG_Disclosure x Post</i>	-0.079 (0.59)	-0.063 (0.67)	-0.122 (0.26)
<i>D_GPG_Disclosure</i>	0.229 (0.01)	0.343 (0.01)	
<i>Post</i>	0.633 (0.01)	0.653 (0.01)	0.533 (0.01)
Observations	813	813	813
R-squared	0.187	0.221	0.586
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

This table presents a difference in difference analysis using an entropy balanced sample. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. In Panel A the dependent variable is *All Actions* which is the aggregate score of effective actions, promising actions, and mixed evidence – in total it is the sum of nineteen actions that collected from annual reports. In Panel B the dependent variable for is the aggregate score *Effective Actions*, which includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. In Panel C the dependent variable is the aggregate score of *Promising Actions*, which includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy, and employing employee referral schemes. In Panel D the dependent variable is the aggregate score of *Mixed Evidence Actions*, which includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training. *D_GPG_Disclosure* takes the value one if the company discloses gender pay gap metrics (either through the parent or the subsidiary) at least once between 2018 and 2021 and zero otherwise. In 2015, 2016, and 2017 this variable also takes the value one if from 2018 onwards a company discloses gender pay metrics at least once. *Post* is the indicator variable that takes the value one from the 2018 fiscal year onwards and zero otherwise. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the Percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.12: Regression of EE actions on year testing the incremental effect of the implementation of the policy to disclose the gender pay gap (Probability values in parentheses.)

Panel A			
VARIABLES	(1)	(2)	(3)
		<i>All Actions</i>	
<i>D_GPG_Metrics x Year</i>	0.232 (0.01)	0.234 (0.01)	0.117 (0.08)
<i>D_GPG_Metrics</i>	-0.592 (0.06)	-0.498 (0.10)	-0.439 (0.08)
<i>Year</i>	0.346 (0.01)	0.343 (0.01)	0.428 (0.01)
<i>Size</i>	0.429 (0.01)	0.246 (0.01)	0.050 (0.80)
<i>Tobin's Q</i>	0.010 (0.77)	-0.004 (0.90)	-0.050 (0.20)
<i>R&D</i>	0.005 (0.70)	0.015 (0.33)	0.000 (0.99)
<i>Leverage</i>	-0.329 (0.33)	-0.020 (0.95)	0.166 (0.80)
<i>Sales Growth</i>	-0.164 (0.34)	-0.198 (0.16)	-0.089 (0.42)
<i>ROA</i>	1.236 (0.01)	1.086 (0.02)	1.113 (0.01)
<i>% Female Employees</i>	-0.004 (0.32)	-0.005 (0.27)	-0.002 (0.87)
<i>% Female Board Members</i>	0.002 (0.78)	-0.001 (0.93)	0.014 (0.04)
<i>Intercept</i>	-4.990 (0.01)	-2.360 (0.02)	-0.028 (0.99)
Observations	813	813	811
Adjusted R-squared	0.328	0.365	0.631
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Table 2.12: Regression of EE actions on year testing the incremental effect of the implementation of the policy to disclose the gender pay gap

Panel B			
VARIABLES	(1)	(2)	(3)
	<i>Effective Actions</i>		
<i>D_GPG_Metrics x Year</i>	0.111 (0.01)	0.103 (0.01)	0.102 (0.01)
<i>D_GPG_Metrics</i>	-0.234 (0.06)	-0.213 (0.08)	-0.300 (0.01)
<i>Year</i>	0.055 (0.01)	0.065 (0.01)	0.084 (0.01)
Observations	813	813	811
Adjusted R-squared	0.207	0.225	0.548
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Panel C			
VARIABLES	(1)	(2)	(3)
	<i>Promising Actions</i>		
<i>D_GPG_Metrics x Year</i>	0.025 (0.58)	0.021 (0.64)	-0.006 (0.89)
<i>D_GPG_Metrics</i>	-0.005 (0.98)	0.050 (0.78)	0.111 (0.47)
<i>Year</i>	0.194 (0.01)	0.196 (0.01)	0.198 (0.01)
Observations	813	813	811
Adjusted R-squared	0.217	0.266	0.528
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Table 2.12: Regression of EE actions on year testing the incremental effect of the implementation of the policy to disclose the gender pay gap

Panel D			
VARIABLES	(1)	(2)	(3)
	<i>Mixed Evidence Actions</i>		
<i>D_GPG_Metrics x Year</i>	0.096 (0.01)	0.110 (0.01)	0.022 (0.53)
<i>D_GPG_Metrics</i>	-0.352 (0.02)	-0.336 (0.03)	-0.250 (0.07)
<i>Year</i>	0.097 (0.01)	0.082 (0.01)	0.147 (0.01)
Observations	813	813	811
Adjusted R-squared	0.159	0.170	0.422
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

This table presents the regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. In Panel A the dependent variable is *All Actions* which is the aggregate score of effective actions, promising actions, and mixed evidence actions – in total it is the sum of nineteen actions that were collected from annual reports. In Panel B the dependent variable for is the aggregate score *Effective Actions*, which includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. In Panel C the dependent variable is the aggregate score of *Promising Actions*, which includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy and employing employee referral schemes. In Panel D the dependent variable is the aggregate score of *Mixed Evidence Actions*, which includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training. *D_GPG_Metrics* takes the value one from 2017 onwards and if the company reports the gender pay gap figures at least once between 2018 and 2021 and zero otherwise. In 2015 and 2016 this variable takes the value zero for all observations. *Year* takes the value one if fiscal year is 2015, two if fiscal year is 2016, three if fiscal year is 2017, four if fiscal year is 2018, five if fiscal year is 2019, six if fiscal year is 2020, and seven if fiscal year is 2021. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is defined as the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.13: Difference in difference regression using an alternative definition of *Post* based on the year of the implementation of the policy to disclose the gender pay gap (Probability values in parentheses.)

Panel A			
VARIABLES	(1)	(2)	(3)
	<i>All Actions</i>		
<i>D_GPG_Disclosure x Post</i>	0.207 (0.47)	0.156 (0.60)	0.132 (0.57)
<i>D_GPG_Disclosure</i>	0.360 (0.08)	0.660 (0.01)	
<i>Post</i>	1.149 (0.01)	1.234 (0.01)	0.823 (0.01)
<i>Size</i>	0.455 (0.01)	0.285 (0.01)	0.631 (0.01)
<i>Tobin's Q</i>	0.032 (0.36)	0.020 (0.56)	0.005 (0.92)
<i>R&D</i>	0.005 (0.69)	0.017 (0.31)	-0.061 (0.07)
<i>Leverage</i>	-0.181 (0.62)	0.099 (0.78)	0.520 (0.47)
<i>Sales Growth</i>	-0.296 (0.07)	-0.340 (0.01)	-0.277 (0.03)
<i>ROA</i>	0.722 (0.15)	0.505 (0.32)	0.425 (0.37)
<i>% Female Employees</i>	-0.004 (0.33)	-0.004 (0.43)	0.014 (0.37)
<i>% Female Board Members</i>	0.030 (0.01)	0.028 (0.01)	0.057 (0.01)
<i>Intercept</i>	-5.673 (0.01)	-3.533 (0.01)	-8.885 (0.01)
Observations	813	813	811
Adjusted R-squared	0.234	0.273	0.554
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Table 2.13: Difference in difference regression using an alternative definition of Post based on the year of the implementation of the policy to disclose the gender pay gap

Panel B			
VARIABLES	(1)	(2)	(3)
	<i>Effective Actions</i>		
<i>D_GPG_Disclosure x Post</i>	0.175 (0.08)	0.160 (0.11)	0.195 (0.04)
<i>D_GPG_Disclosure</i>	0.147 (0.04)	0.177 (0.03)	
<i>Post</i>	0.213 (0.01)	0.239 (0.01)	0.089 (0.30)
Observations	813	813	811
Adjusted R-squared	0.155	0.171	0.489
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Panel C			
VARIABLES	(1)	(2)	(3)
	<i>Promising Actions</i>		
<i>D_GPG_Disclosure x Post</i>	0.172 (0.27)	0.132 (0.43)	0.123 (0.38)
<i>D_GPG_Disclosure</i>	-0.059 (0.59)	0.055 (0.68)	
<i>Post</i>	0.494 (0.01)	0.552 (0.01)	0.389 (0.01)
Observations	813	813	811
Adjusted R-squared	0.166	0.215	0.492
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

Table 2.13: Difference in difference regression using an alternative definition of *Post* based on the year of the implementation of the policy to disclose the gender pay gap

Panel D			
VARIABLES	(1)	(2)	(3)
	<i>Mixed Evidence Actions</i>		
<i>D_GPG_Disclosure x Post</i>	-0.140 (0.35)	-0.136 (0.37)	-0.186 (0.08)
<i>D_GPG_Disclosure</i>	0.272 (0.02)	0.428 (0.01)	
<i>Post</i>	0.442 (0.01)	0.444 (0.01)	0.345 (0.01)
Observations	813	813	811
Adjusted R-squared	0.109	0.127	0.384
Control variables	Yes	Yes	Yes
Industry FE	No	Yes	No
Firm FE	No	No	Yes

This table presents a difference in difference analysis. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. In Panel A the dependent variable is *All Actions* which is the aggregate score of effective actions, promising actions, and mixed evidence – in total it is the sum of nineteen actions that collected from annual reports. In Panel B the dependent variable for is the aggregate score *Effective Actions*, which includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews. In Panel C the dependent variable is the aggregate score of *Promising Actions*, which includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy, and employing employee referral schemes. In Panel D the dependent variable is the aggregate score of *Mixed Evidence Actions*, which includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training. *D_GPG_Disclosure* takes the value one if the company discloses gender pay gap metrics (either through the parent or the subsidiary) at least once between 2017 and 2021 and zero otherwise. In 2015, 2016, and 2017 this variable also takes the value one if from 2018 onwards a company discloses gender pay metrics at least once. *Post* is the indicator variable that takes the value one from the 2018 fiscal year onwards and zero otherwise. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.14: Regression examining the role of cost on the adoption of EE actions (Probability values in parentheses.)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	<i>Low-cost Actions</i>			<i>Moderate-cost actions</i>			<i>High-cost Actions</i>		
<i>D_GPG_Metrics x Year</i>	0.110	0.127	0.094	0.061	0.052	0.005	0.046	0.030	0.015
	(0.05)	(0.02)	(0.05)	(0.22)	(0.30)	(0.91)	(0.21)	(0.41)	(0.63)
<i>D_GPG_Metrics</i>	-0.348	-0.298	-0.295	-0.079	-0.049	0.001	-0.102	-0.058	-0.034
	(0.22)	(0.27)	(0.17)	(0.74)	(0.84)	(1.00)	(0.57)	(0.74)	(0.82)
<i>Year</i>	0.182	0.164	0.192	0.093	0.101	0.130	0.073	0.085	0.092
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	813	813	811	813	813	811	813	813	811
Adjusted R-squared	0.221	0.285	0.536	0.180	0.183	0.460	0.160	0.185	0.401
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes

This table presents the regression of EE actions on year testing the incremental effect of the mandatory disclosure of the gender pay gap. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. The dependent variables are *Low-cost actions* in models 1-3, *Moderate-cost actions* in models 4-6 and *High-cost actions* in models 7-9. *Low-cost actions* includes the following actions Setting targets of female representation, setting targets of shortlisted women, disclosing a diversity statement, removing biased language from job ads, selecting a diverse interview panel, adopting structured interviews and offering flexible working conditions. *Moderate-cost actions* includes the following actions anonymizing CVs, recruiting using skill-based assessments, promoting mentoring, networking and sponsoring schemes, offering diversity training, providing leadership training and offering pay, promotion and reward sessions. *High-cost Actions* includes the following actions appointing a diversity lead, creating a returner's program, promoting shared parental leave, having a childcare policy and having a referral scheme in place are labeled as high-cost actions. *D_GPG_Metrics* takes the value one from 2018 onwards and if the company reports the gender pay gap figures at least once between 2018 and 2021 and zero otherwise. In 2015, 2016, and 2017 this variable takes the value zero for all observations. *Year* takes the value one if fiscal year is 2015, two if fiscal year is 2016, three if fiscal year is 2017, four if fiscal year is 2018, five if fiscal year is 2019, six if fiscal year is 2020, and seven if fiscal year is 2021. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is defined as the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Table 2.15: Regression of two- and three-period ahead gender pay gap on EE actions (Probability values in parentheses.)

Panel A								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Mean GPG Hourly Pay_{t+2}</i>				<i>Mean GPG Hourly Pay_{t+3}</i>			
<i>All Actions</i>	-0.103 (0.76)				-0.480 (0.52)			
<i>Effective Actions</i>		-1.800 (0.06)				-3.482 (0.05)		
<i>Promising Actions</i>			0.309 (0.64)				0.139 (0.93)	
<i>Mixed Evidence Actions</i>				0.301 (0.70)				0.472 (0.76)
<i>Size</i>	0.356 (0.68)	0.400 (0.64)	0.291 (0.73)	0.284 (0.75)	-0.157 (0.92)	-0.227 (0.87)	-0.435 (0.77)	-0.487 (0.75)
<i>Tobin's Q</i>	0.061 (0.89)	0.200 (0.63)	0.066 (0.88)	0.064 (0.88)	-0.712 (0.64)	-0.164 (0.92)	-0.612 (0.70)	-0.538 (0.74)
<i>R&D</i>	0.435 (0.02)	0.428 (0.02)	0.442 (0.02)	0.424 (0.03)	0.544 (0.13)	0.537 (0.12)	0.515 (0.15)	0.503 (0.16)
<i>Leverage</i>	0.475 (0.92)	0.724 (0.88)	0.591 (0.90)	0.523 (0.91)	-0.495 (0.94)	-0.315 (0.96)	-1.028 (0.88)	-1.206 (0.86)
<i>Sales Growth</i>	-3.413 (0.02)	-3.939 (0.01)	-3.206 (0.04)	-3.306 (0.03)	-0.687 (0.77)	-1.836 (0.50)	-0.070 (0.98)	-0.146 (0.95)
<i>ROA</i>	-0.850 (0.86)	-2.371 (0.61)	-1.514 (0.75)	-1.025 (0.83)	6.488 (0.78)	-2.228 (0.93)	3.706 (0.88)	2.825 (0.91)
<i>% Female Employees</i>	0.190 (0.01)	0.184 (0.01)	0.191 (0.01)	0.195 (0.01)	0.151 (0.16)	0.163 (0.14)	0.148 (0.17)	0.152 (0.15)
<i>% Female Board Members</i>	-0.104 (0.15)	-0.101 (0.15)	-0.103 (0.15)	-0.102 (0.16)	0.017 (0.91)	0.045 (0.77)	0.014 (0.93)	0.013 (0.93)
<i>Intercept</i>	9.732 (0.45)	10.146 (0.44)	9.845 (0.44)	9.883 (0.44)	17.349 (0.44)	18.145 (0.39)	20.175 (0.38)	20.518 (0.38)
Observations	157	157	157	157	80	80	80	80
Adjusted R-squared	0.357	0.370	0.358	0.357	0.165	0.208	0.160	0.161
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.15: Regression of two- and three-period ahead gender pay gap on EE actions

Panel B								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Median GPG Hourly Pay_{t+2}</i>				<i>Median GPG Hourly Pay_{t+3}</i>			
<i>All Actions</i>	-0.162 (0.70)				-0.497 (0.55)			
<i>Effective Actions</i>		-1.575 (0.15)				-2.373 (0.31)		
<i>Promising Actions</i>			0.695 (0.34)				0.290 (0.85)	
<i>Mixed Evidence Actions</i>				-0.803 (0.36)				-0.876 (0.61)
<i>Size</i>	0.371 (0.68)	0.389 (0.67)	0.247 (0.79)	0.436 (0.62)	-0.263 (0.88)	-0.395 (0.81)	-0.589 (0.74)	-0.348 (0.84)
<i>Tobin's Q</i>	0.721 (0.08)	0.840 (0.04)	0.734 (0.08)	0.699 (0.09)	-0.016 (0.99)	0.387 (0.85)	0.104 (0.96)	-0.097 (0.96)
<i>R&D</i>	0.497 (0.01)	0.490 (0.01)	0.514 (0.01)	0.525 (0.01)	0.564 (0.17)	0.550 (0.16)	0.531 (0.19)	0.564 (0.18)
<i>Leverage</i>	-7.487 (0.13)	-7.251 (0.15)	-7.243 (0.14)	-7.507 (0.13)	-8.787 (0.26)	-8.836 (0.27)	-9.388 (0.22)	-8.870 (0.25)
<i>Sales Growth</i>	-3.585 (0.03)	-3.986 (0.01)	-3.176 (0.07)	-3.515 (0.04)	-3.721 (0.17)	-4.316 (0.13)	-2.993 (0.27)	-3.185 (0.23)
<i>ROA</i>	-2.383 (0.60)	-3.798 (0.43)	-3.795 (0.41)	-2.425 (0.60)	2.698 (0.93)	-4.048 (0.89)	-0.714 (0.98)	2.919 (0.92)
<i>% Female Employees</i>	0.100 (0.20)	0.096 (0.22)	0.102 (0.19)	0.094 (0.22)	0.008 (0.95)	0.016 (0.90)	0.005 (0.97)	0.001 (1.00)
<i>% Female Board Members</i>	-0.107 (0.19)	-0.103 (0.19)	-0.105 (0.19)	-0.109 (0.18)	0.004 (0.98)	0.021 (0.90)	0.001 (1.00)	0.001 (0.99)
<i>Intercept</i>	12.508 (0.38)	12.898 (0.37)	12.735 (0.37)	12.278 (0.39)	24.705 (0.35)	26.101 (0.30)	28.063 (0.30)	25.803 (0.33)
Observations	157	157	157	157	80	80	80	80
Adjusted R-squared	0.379	0.387	0.383	0.382	0.142	0.156	0.138	0.141
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents regressions two- and three – period ahead gender pay gap on EE actions. Probability values reported in parentheses are computed using heteroscedasticity-consistent standard errors. In Panel A the dependent variable is *Mean GPG_Hourly Pay_{t+2}* in models 1 to 4 and *Mean GPG_Hourly Pay_{t+3}* in models 5 to 8. In Panel B the dependent variable is *Median GPG_Hourly Pay_{t+2}* in models 1 to 4 and *Median GPG_Hourly Pay_{t+3}* in models 5 to 8. *Mean (Median) GPG_Hourly Pay_{t+n}* is the mean (median) percentage difference between male and female hourly pay measured in the n-fiscal-year ahead. *All Actions* is the aggregate score of effective actions, promising actions, and mixed evidence – in total it is the sum of nineteen actions that were collected from annual reports. *Size* is the logarithm function of total assets (code: WC02999). Source: Datastream. *Tobin's Q* is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream. *R&D* is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream. *Leverage* is the ratio between long-term debt (code: WC03251) scaled by total assets (code:

Table 2.15: Regression of two- and three-period ahead gender pay gap on EE actions (Probability values in parentheses.)

WC02999). Source: Datastream. *Sales Growth* is the ratio of sales scaled by lagged sales minus one. Source: Datastream. *ROA* is the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream. *% Female Employees* is the Percentage of female employees of the company as collected from the annual reports. *% Female Board Members* is the percentage of female board members of the company as collected from the annual reports.

Appendix 2.1: Variable definitions

Panel A: EE actions (aggregated and disaggregated variables - Source: manual collection)

Variable	Variable definition
All Actions	Aggregate score including actions classified as effective, promising, and mixed evidence.
Effective Actions	Aggregate score that includes setting targets of female representation, appointing a diversity lead/task-force, removing biased language, conducting recruitment using assessment centers, offering pay, promotion, and reward sessions, and conducting structured interviews.
<i>Targets of female representation</i>	Dummy variable that takes the value one if the company states it sets a target of female representation or zero otherwise. Following the BIT report this measure is classified as an effective measure. Source: manual collection.
<i>(Targets of female representation - numerical)</i>	Dummy variable that takes the value one if the company states it sets a numerical target of female representation or zero otherwise. Source: manual collection.
<i>(Targets of female representation - time)</i>	Dummy variable that takes the value one if the company states it sets a target of female representation and a timeline to achieve it or zero otherwise. Source: manual collection.
<i>Diversity lead/task force</i>	Dummy variable that takes the value one if the company appoints a diversity lead or task force or zero otherwise. Following the BIT reports this action is classified as an effective action. Source: manual collection.
<i>Removing biased language</i>	Dummy variable that takes the value if the company states that it removes biased/gendered language from job ads and zero otherwise. Following the BIT reports, this action is classified as effective. Source: manual collection.
<i>Assessment center recruitment</i>	Dummy variable that takes the value one if the company states it conducts skill-based recruitment by for example using assessment centers for recruitment and selection and zero otherwise. Following the BIT reports this action is classified as effective. Source: manual collection.
<i>Pay, promotion and reward sessions</i>	Dummy variable that takes the value one if the company states it offers pay, promotion and reward sessions and zero otherwise. Following the BIT report this action is classified as effective. Source: manual collection.
<i>Structured interviews</i>	Dummy variable that takes the value one if the company states it conducts structured interviews during recruitment and selection and zero otherwise. Following the BIT reports, this action is classified as promising. Source: manual collection.
Promising Actions	Aggregate score of promising actions, which includes anonymizing CVs, shortlisting women, offering a returners' program, offering mentoring, networking, and sponsoring programs, offering flexible working conditions, offering shared parental leave, having in place a childcare policy, and employing employee referral schemes.
<i>Blind CVs</i>	Dummy variable that takes the value one if the company states it anonymizes CVs and zero otherwise. Following the BIT report this variable is classified as promising. Source: manual collection.
<i>Shortlisted women</i>	Dummy variable that takes the value one if the company states it sets targets or increases the number/ proportion of shortlisted women and zero otherwise. Following the BIT report this variable is classified as promising. Source: manual collection.
<i>(Shortlisted women – numerical target)</i>	Dummy variable that takes the value one if the company states it sets a numerical targets or increases the number/ proportion of shortlisted women and zero otherwise. Source: manual collection.
<i>Returner program</i>	Dummy variable that takes the value one if the company states it offers a returner's program and zero otherwise. Following the BIT report this variable is classified as promising. Source: manual collection.

<i>(Returner program – long term career break)</i>	Dummy variable that takes the value one if the company states it offers a returner's program aimed at recruiting individuals who took a career break and zero otherwise. Source: manual collection.
<i>(Returner program – parental leave)</i>	Dummy variable that takes the value one if the company states it offers a returner's program aimed at supporting individuals during and after parental leave and zero otherwise. Source: manual collection.
<i>Mentoring, networking, and sponsoring programs</i>	Dummy variable that takes the value one if the company states it offers mentoring, networking, and sponsoring programs or zero otherwise. Following the BIT report this variable is classified as promising. Source: manual collection.
<i>Flexible working conditions:</i>	Dummy variable that takes the value one if the company states it offers flexible working conditions or zero otherwise. Following the BIT report this variable is classified as promising. Source: manual collection.
<i>(Flexible working conditions - schedule)</i>	Dummy variable that takes the value one if the company states it offers flexible working conditions, which involves the possibility of choosing the schedule or zero otherwise. Source: manual collection.
<i>(Flexible working conditions - location)</i>	Dummy variable that takes the value one if the company states it offers flexible working conditions, which involves the possibility of working remotely or zero otherwise. Source: manual collection.
<i>(Flexible working conditions - number of hours)</i>	Dummy variable that takes the value one if the company states it offers flexible working conditions, which involves the possibility of working part-time or zero otherwise. Source: manual collection.
<i>Shared parental leave</i>	Dummy variable that takes the value one if the company states it offers shared parental leave or zero otherwise. Following the BIT report this variable is classified as promising. Source: manual collection.
<i>(Shared parental leave - enhanced)</i>	Dummy variable that takes the value one if the company states it offers a childcare policy or zero otherwise. This action was not included in the BIT reports. However, there is evidence supporting its importance in improving gender equality. So, this variable is classified as promising. Source: manual collection.
<i>Childcare policy</i>	Dummy variable that takes the value one if the company states it offers a childcare policy or zero otherwise. This action was not included in the BIT reports. However, there is evidence supporting its importance in improving gender equality. Source: manual collection.
<i>(Childcare policy - nursery)</i>	Dummy variable that takes the value one if the company states it offers a childcare policy namely workplace nursery or zero otherwise. Source: manual collection.
<i>(Childcare policy - financial support)</i>	Dummy variable that takes the value one if the company states it offers a childcare policy namely financial support or zero otherwise. Source: manual collection.
<i>Referral schemes</i>	Dummy variable that takes the value one if the company states it has a employee referral scheme zero otherwise. Following the BIT report this variable is classified as promising. Source: manual collection.
Mixed Evidence Actions	Aggregate score of mixed evidence actions, which includes conducting recruitment using a diverse interview panel, disclosing a separate diversity statement, using self-assessment for performance review, offering diversity training, and offering leadership training.
<i>Diverse interview panel</i>	Dummy variable that takes the value one if the company states it conducts interviews using diverse panels and zero otherwise. Following the BIT report this variable is classified as a mixed evidence action. Source: manual collection.
<i>Diversity statement</i>	Dummy variable that takes the value one if the company states it externally discloses a diversity statement and zero otherwise. Following the BIT report this variable is classified as a mixed evidence action. Source: manual collection.

<i>Self-assessment</i>	Dummy variable that takes the value one if the company states it uses self-assessment / 360-degree feedback for performance review and zero otherwise. Following the BIT report this variable is classified as a mixed evidence action. Source: manual collection.
<i>Diversity training</i>	Dummy variable that takes the value one if the company states it offers diversity / unconscious bias training and zero otherwise. Following the BIT report this variable is classified as a mixed evidence action. Source: manual collection.
<i>Leadership training:</i>	Dummy variable that takes the value one if the company states it offers leadership training/programs and zero otherwise. Source: manual collection.
<i>(Leadership training - female focused)</i>	Dummy variable that takes the value one if the company states it offers leadership training/programs specifically target at women and zero otherwise. Following the BIT report this variable is classified as a mixed evidence action. Source: manual collection.

Panel B: Gender Pay Gap Metrics

Variable	Variable definition
<i>D_GPG_Metrics</i>	Variable that takes the value one from 2018 onwards and if the company reports the gender pay gap figures at least once between 2018 and 2021 and zero otherwise. In 2015, 2016, and 2017 this variable takes the value zero for all observations.
<i>D_GPG_Disclosure</i>	Variable that takes the value one if the company discloses gender pay gap metrics (either through the parent or the subsidiary) at least once between 2018 and 2021 and zero otherwise. In 2015, 2016, and 2017 this variable also takes the value one if from 2018 onwards a company discloses gender pay metrics at least once.

Panel C: Gender Pay Gap Metrics (Source: UK Government website³¹)

Variable	Variable definition
<i>Mean GPG: Hourly Pay</i>	Mean percentage difference between male and female hourly pay.
<i>Median GPG: Hourly Pay</i>	Median percentage difference between male and female hourly pay
<i>Mean GPG: Hourly Pay_{t+n}</i>	Mean percentage difference between male and female hourly pay measured in the n-fiscal-year ahead.
<i>Median GPG: Hourly Pay_{t+n}</i>	Median percentage difference between male and female hourly pay measured in the n-fiscal-year ahead.

Panel D: Control variables (Source: Refinitiv Eikon Datastream and manual collection)

Variable	Variable definition
<i>Size</i>	Size is the logarithm function of total assets (code: WC02999). Source: Datastream.
<i>Tobin's Q</i>	Tobin's Q is the market value of the company at fiscal-year end (code: MV) plus the total assets minus the book value of equity (code: WC03995) scaled by total assets. Source: Datastream.
<i>R&D</i>	R&D is the logarithm function of R&D (WC01201). R&D expenses are coded as zero if missing. Source: Datastream.

³¹ Gender pay gap data is available in the link: <https://gender-pay-gap.service.gov.uk/viewing/download>

<i>Leverage</i>	Leverage is defined as the ratio between long-term debt (code: WC03251) scaled by total assets (code: WC02999). Source: Datastream.
<i>Sales growth</i>	Sales growth is the ratio of sales scaled by lagged sales minus one. Source: Datastream.
<i>ROA</i>	Return on assets is defined as the net income before extraordinary items and preferred dividends (code: WC01551) scaled by lagged total assets. Source: Datastream.
<i>% Female Employees</i>	Percentage of female employees. Source: Manual collection from firms' annual reports.
<i>% Female Board Members</i>	Percentage of female board members. Source: Manual collection from firms' annual reports.

Appendix 2.2: Examples of EE actions as mentioned in annual reports

EE Actions	Examples
<i>Effective Actions</i>	
Set internal targets for gender representation and equality	“The Board aims to meet industry targets and recommendations wherever possible. This includes our objective of meeting the diversity targets recommended by the Hampton-Alexander and Parker Reviews: • 33% female share of Board Directors by 2020;” (p. 64: Keller Group PLC – Annual Report 2020)
Appoint diversity leads and/or diversity taskforces	“The Board dedicates significant time to adequately consider culture and engagement matters. It holds sessions at the half year, and at the end of the year, where it invites the Chief People Officer and Global Diversity & Inclusion Director to come to the Board to discuss cultural considerations.” (p. 33 – PageGroup – Annual Report 2020)
Remove biased language from job adverts	“(…) we ensure that all of our job descriptions and job adverts use gender neutral language and use accessible language” (p. 36: Dignity PLC – Annual Report 2021)
Use skill-based assessment tasks in recruitment	“Assessment centers are a fairer process which complements our diversity and inclusion agenda by ensuring that people are selected on the basis of merit alone.” (p. 36: Dignity PLC – Annual Report 2021)
Increase transparency to promotion, pay and reward processes	“Also responding to employee feedback we introduced Pay and Progression panels in FY20 in order to make our process more agile and transparent.” (p. 43: Qinetiq Group – Annual Report 2020)
Use structured interviews for recruitment and promotions	“Transforming the way we recruit, to promote diversity in all forms, focusing on flexible working and standardised interview formats” (p.34 – Capita PLC – Annual Report 2019)
<i>Promising Actions</i>	
Blind CVs	“Our application process (…) does not solicit information on age, date of birth, gender or a photo of the candidates” (p. 114 – Bank of Georgia Group – Annual Report 2020)
Include more women in shortlists for recruitment and promotions	“The appointment process for future appointments [to the Board] is as follows: All future shortlists will be gender balanced (an equal number of male and female candidates will be presented for interview)” (p. 100: IP Group PLC – Annual Report 2020)
Recruit returners	“An additional initiative agreed in 2015 was a pilot returner program – this scheme targets individuals who have taken a career break and now wish to return to the workforce. (p. 43: Man Group PLC – Annual Report 2015)
Offer mentoring, networking, and sponsorship	“Building on the success of our LGBTQ+, ‘Just-LikeQ’, and Neurodiversity employee led networks we launched a Gender Balance network” (p. 42: Qinetiq Group – Annual Report 2020)
Improve workplace flexibility for men and women	“We are progressing towards a more agile environment with flexible work arrangements encouraged where appropriate” (p. 176: Investec PLC – Annual Report 2018)

Encourage the uptake of shared parental leave	“(…) the Group’s parental leave policy encourages both men and women to share childcare commitments.” (p.85: Big Yellow Group – Annual Report 2018)
EE Actions	Examples
<i>Effective Actions</i>	
Offer childcare policy	“Free Emergency Back-up Child/Elder Care” (p. 35: PageGroup – Annual Report 2020)
Provide employee referrals schemes	“(…) the introduction of Referral Reward Program that provides colleagues with a thank you payment if they successfully introduce someone they know to fill a job vacancy” (p. 33: Dignity PLC – Annual Report 2021)
<i>Mixed Evidence Actions</i>	
Diverse selection panels	“The Group is nonetheless pleased with the overall progress (…) and continues to be committed to addressing our gender pay gap with a number of initiatives which are now well established. It continues to increase talent diversity and foster a culture of inclusivity through: Recruitment: (…) maximising diversity on our interview panels to moderate bias;” (p. 98: ICG Group PLC – Annual Report 2021)
Diversity statements	“Diversity Policy (https:// bankofgeorgiagroup.com/ governance/documents)” (p. 112: Bank of Georgia Group – Annual Report 2020)
Performance self-assessments	“At Vedanta we promote growth and nurturing of our internal talent pool by encouraging internal dialogue between senior leaders and their young mentees and peers. For this reason, we have launched 360 feedback”. (p. 74: Vendata Resources PLC – Annual Report 2019)
Diversity training	“Examples of current business unit initiatives include the creation of employee resource groups, focused diversity and inclusion programs, and mandatory unconscious bias training for leaders.” (p. 69: Melrose Industries PLC – Annual Report 2021)
Leadership training	“We have launched a women in leadership program as part of our global leadership curriculum. The program, which has been designed by one of our own high potential female technology leaders, is targeted towards any female who aspires to be a leader or female leaders who want to build their confidence and capability.” (p.47: William Hill PLC – Annual Report 2018)

Appendix 2.3: Word list to support the search of EE actions.

Gender
Diversity
Inclusion
Target
Shortlist
Bias
Recruit
Interview
Returner
Flexible
Promotion
Mentor
Sponsor
360
Feedback
Leader
Training
Parental
Paternity
Maternity
Childcare
Nursery
Referral

3 Tones at the Top: The Impact of Board Leadership Structure on the Quality of Performance Commentary

3.1 Introduction

This chapter investigates whether the presence of an (independent) board Chair impacts corporate disclosure by examining if commentary authored by the Chair is incrementally informative beyond commentary authored by the CEO and senior management. This is an important question as it speaks to the role of the board Chair in creating a communication benefit for shareholders through the provision of performance commentary that carries incremental insights beyond those provided by management. While researchers and practitioners have discussed the governance benefits of the board Chair at length (Boyd, 1995; Brickley et al., 1997; Dahya et al., 1996; Dedman, 2016; Elsayed, 2007), the extent to which the Chair contributes to the informativeness of the annual report in their role as the cornerstone of corporate reporting to shareholders remains unclear. I rely on a sample of London Stock Exchange (LSE)-traded firms that operate under the UK Corporate Governance Code, compliance with which requires separation of the CEO and Chair roles with the latter also being independent of management at their date of appointment. As the bulk of LSE firms comply with this provision, the decision to appoint a separate and independent board Chair is predominantly exogenous in my setting.³²

The separation of board leadership roles is a provision of the first edition of the Code from 1992, while the Chair independence criterion has been included in the Code since 2003 (Cadurry Committee, 1992; Financial Reporting Council, 2003). Accordingly, the division of responsibilities between Chair and management and the independence of the board Chair lies

³² The FRC's 2020 Corporate Governance Review highlights that, in 2018, 99% of the FTSE350 and the Small Cap Index firms comply with the UK Corporate Governance Code provision to separate the roles of the CEO and Chair. In 2012, a governance report by Grant Thornton, highlights that compliance with the Code is very high as 97% of firms indicate to be in full compliance.

at the center of board effectiveness in the UK (Dedman, 2016). While the CEO is primarily responsible for decision management, including defining and executing corporate strategy and maximizing value to investors, the Chair is primarily responsible for decision control, including managerial oversight on behalf of shareholders (Fama and Jensen, 1983). In a corporate disclosure context, this involves mitigating disclosure bias and providing a balanced and fair assessment of performance. In support of this oversight role, annual reports for LSE-listed firms usually include a separate section authored by the board Chair (often labelled “Chair’s Letter to Shareholders”, “Chair’s Statement”, “Introduction from the Board Chair”, etc.) that precedes management commentary and synthesizes key corporate outcomes and events during the reporting period. The Chair’s commentary section is typically one-to-two pages long and has some of the characteristics of an abstract in an academic research paper. I examine whether this summary statement from the Chair adds value to the governance and reporting process beyond the discussion and analysis that management provide.³³

Two factors motivate my research focus. First, prior literature does not examine how board leadership structure impacts performance reporting. This is partly due to researchers focusing on the US setting where the board Chair is either closely affiliated with the company, or the roles of Chair and CEO are combined in the same individual (Goergen et al., 2020). For example, 50% of S&P500 constituents combined the roles of Chair and CEO in 2018 , while 69% of non-CEO Chairs are affiliated with management (Stuart Spencer, 2023). Further, because separating the roles of Chair and CEO is a management choice in the US,

³³ I acknowledge that there is evidence showing that annual report disclosures are not written exclusively by the executives of the firm; it is common for marketing and legal professionals to be involved in the process. In this respect, it is possible that the Chair’s letter is not written exclusively by the board Chair (Amel-Zadeh et al., 2019). Discussions with industry consultants responsible for supporting the process of writing annual reports reveal information consistent with board Chairs having an active role in writing their letter to shareholders, both in selecting what to write and how to write it. It is therefore unlikely that the Chair letter does not reflect the board Chair’s view of the company or includes a statement or content that the board Chair does not agree with.

attempts to understand the impact of leadership structure on corporate outcomes face serious endogeneity challenges (Iyengar and Zampelli, 2009). This problem is mitigated to a large extent in the UK where compliance with the Code requires firms to appoint an independent Chair.

Second, it remains an open question whether performance commentary authored by the board Chair serves a stewardship role, a decision usefulness role, neither function, or both functions. If Chair commentary primarily serves a decision usefulness role, then I expect it to include material forward-looking content that provides insights relevant for predicting future performance. Conversely, if it serves a stewardship role then it should be backward-looking and correlated with reported performance. This is consistent with the perspective that Chair commentary is particularly relevant for monitoring and confirmation purposes (Cascino et al., 2013; Michelon et al., 2021). Whether Chair-authored disclosures serve a decision usefulness or a stewardship role, and whether this role varies with reported performance and management's reporting incentives, nevertheless remains an open question.

Given the Chair's responsibility to mitigate managerial reporting bias and their accumulated expertise from prior appointments, I hypothesize that Chair commentary should provide incremental insights on firm performance beyond commentary authored by the senior management team in the same report.³⁴ On the one hand, management face powerful incentives to present performance in an optimistic light, with the resulting bias reducing the objectivity and usefulness of their analysis (Arslan-Ayaydin et al., 2016, 2020; X. Huang et al., 2014). The independent board Chair, meanwhile, brings objectivity and neutrality as a consequence of their monitoring responsibilities. On the other hand, as an outsider and independent non-executive board member, the Chair leverages accumulated expertise,

³⁴ I do not provide a formal test to distinguish between the incentives and expertise effects. Still, I attempt to disentangle these by conducting cross-sectional analyses where each effect should be particularly pronounced.

experience and knowledge that may bring broader business insights and hence should be reflected in a commentary with implications for future performance (Higgs, 2003; Krause et al., 2016; Schabus, 2022).

My sample of LSE-traded firms includes 8,898 annual reports with fiscal-year ends between 2005 and 2019.³⁵ I measure the properties of performance commentary authored by the Chair and management at the sentence level and focus on the tone of the relevant annual report sections. Descriptive evidence shows that the median Chair commentary includes thirty-five sentences whereas the median management commentary includes one hundred and twenty-seven sentences. I also document that Chair commentary is more forward-looking, more long-term focused, and more positively toned than management commentary (using Henry (2008) lists of positive and negative words).

I develop and test the hypothesis that Chair commentary is incrementally informative beyond management commentary by 1) testing whether the explanatory power of Chair tone is higher than that of management tone in the regression of realized earnings on tone and 2) testing whether the Chair commentary carries incremental information beyond management when predicting one-year ahead earnings. Both tests confirm my hypothesis that Chair commentary is incrementally informative beyond management commentary.

I conduct additional cross-sectional analyses and propose a set of explanations for the incremental predictive ability of Chair commentary for future earnings. My hypothesis identifies two roles that may explain incremental informativeness of Chair commentary: monitoring (as predicted by agency theory) and information. I further theorize that the information role arises from two non-mutually exclusive functions: confirmation (as predicted by legitimacy theory) and resource provision (as predicted by resource dependency

³⁵ I did not extend the sample period beyond 2019 to avoid the impact of COVID-19 on corporate disclosure. COVID-19 represents an abnormal period where several firms experienced substantial performance changes that are unrelated to business decisions.

theory). I start by exploring the monitoring role of the Chair by partitioning the sample using earnings losses as a proxy for management incentives for obfuscation and impression management. The monitoring role predicts that the incremental informativeness will be more pronounced where the incentives for impression management are more acute. I do not find evidence that earnings predictability is higher for loss firms; indeed, results reveal that incremental predictive ability of Chair tone is due mainly to profitable firms. This unexpected result prompts me to conduct additional tests. I find that the monitoring role of the Chair manifests in Chair tone that is more pessimistic relative to management when there are incentives for impression management. I also find that the predictability of management commentary is weaker when the Chair is more positive than management. Based on these results, I conclude that Chair commentary plays a monitoring role in annual reporting but is limited and focuses mainly on weak realized earnings performance. The Chair's monitoring role over corporate reporting, however, does not appear to explain the incremental predictive ability of their commentary, nor the fact that this effect proves particularly strong for profitable firms. I then examine the information role of the board Chair.

From a legitimacy perspective, the Chair may serve an information role by endorsing and confirming management disclosures. This view is consistent with the argument that the Chair collaborates with the management team as opposed to monitoring (Boivie et al., 2021). As market participants are aware that managers may engage in impression management and overstate earnings, the role of the Chair in confirming management commentary becomes particularly important for firms with strong fundamentals. In this respect, the fact that the incremental predictability of Chair commentary is particularly strong for profitable firms indicates that the Chair may serve an information role by confirming management information. I therefore proceed by testing whether the predictiveness of Chair commentary is consistent with an information role. On the one hand, the information role of the Chair may

arise from serving a confirmation function. On the other hand, this role is also consistent with serving a resource provision function. I next examine this possibility.

Chair commentary may benefit from the knowledge and experience that is expected from an independent board Chair (Higgs, 2003; Krause et al., 2016). Such expectation is consistent with the Chair providing resources to the firm in the form of information skills. I therefore posit that if the Chair serves an information role due to resource provision, then the incremental predictive ability of their commentary for future earnings should be stronger when firms operate in environments with high information demand by analysts. Results support this prediction. I conclude that this is preliminary evidence consistent with the information role. Specifically, I interpret the fact that the incremental predictive of Chair commentary is strong for 1) profitable firms as consistent with a confirmation function and for 2) firms operating in high information demand as consistent with a resource provision function. Both non-mutually exclusive functions are associated with the information role of the board Chair. Still, as my tests do not directly differentiate between information resulting from confirmation or information resulting from resource provision, I seek to distinguish between these explanations using additional predictions and analysis in Chapter 4.

This chapter contributes to the literature examining the role of the independent board Chair (Krause, 2017; Yu, 2023) in two ways. First, my study explores a previously overlooked aspect of corporate governance research: how the presence of an independent board Chair affects the informativeness of annual report performance commentary. By providing evidence that annual report Chair commentary exhibits incremental information content beyond management commentary, I show that the Chair's letter is a valuable element of the annual report. This suggests that despite having less firm-specific knowledge than management, an independent Chair provides useful insights on realized performance and future earnings. Second, my work answers the call by Banerjee et al. (2020) and Boivie et al.

(2021) to develop an understanding of the value of the board Chair beyond their monitoring role. I propose that the Chair has an information role that is consistent with a resource provision function and a confirmation function. While RDT has been used to examine firms that combine the roles of the CEO and Chair under the argument that this promotes organizational effectiveness, I examine the role of the board Chair through the lens of RDT in a setting where the roles are separated by default. Additionally, board interactions are hard to observe and therefore research relies on qualitative methods (e.g., interviews) and small sample evidence to study board dynamics (Brennan, 2021; Boivie et al., 2021). Analyzing annual report Chair commentary allows me to directly observe the head of the board exercising one of their primary governance responsibilities in terms of promoting transparency and accountability.

I also add to the body of large-sample research investigating the properties of annual report commentary, the majority of which focuses on 10-K filings. Extant studies typically concentrate on either the entire report (Lang and Stice-Lawrence, 2015; Li, 2008) or specific report sections such as the MD&A (Li, 2010), risk disclosures, or the shareholders' letter (Abrahamson and Amir, 1996; Patelli and Pedrini, 2014). This approach fails to recognize if and how the properties of annual report commentary vary within the document. I address this issue in a setting where there is variation in the authorship, given that research shows that variation in author characteristics affects writing style and content (Amel-Zadeh et al., 2019; Argamon et al., 2009; Schler et al., 2006). Because most studies do not compare the properties of sections from the same report, the incremental usefulness of these commentaries remains unclear despite preparers and regulators routinely seeking to disaggregate and categorize annual report content. I examine the differential predictive ability of two of the most important annual report sections by exploiting a setting where authors' incentives vary across sections in the same report. By focusing on *within-report* differences between Chair

and management commentary, I extend Dikolli et al., (2020) and Davis and Tama-Sweet (2012) who study the impact of differential reporting settings on the properties of management commentary while holding preparers' incentives constant. Conversely, I hold the reporting setting constant and explore the impact of reporting incentives on annual report commentary.

3.2 Institutional setting, prior literature, research question, and prediction development

3.2.1 The UK Corporate Governance Code

In 1992, the Cadbury Committee published the first version of the UK Corporate Governance Code (the Code) aimed at promoting board effectiveness by defining the norms of best practice for directors and shareholders to follow. The Code builds on the argument that agency conflicts stem from the separation of ownership and control and that managers act opportunistically (Dedman, 2016). The Chair and board of directors therefore play a crucial role as the Code attributes them the responsibility of managing firms' governance arrangements (Financial Reporting Council 2018). To ensure board effectiveness, the Code established provisions on board structure that include the recommendation that CEOs should not hold the role of board Chair, as the latter should be independent with no other business or personal links to the firm (provision 9: 2018 UK Corporate Governance Code). This provision is included in all subsequent versions of the Code including the most recent 2025 update. The recommendation reflects the agency theory perspective that the presence of an independent board Chair is a necessary condition to ensure managerial oversight and, hence, minimize the effects of opportunistic behavior. Protecting and reporting to shareholders also lies at the heart of effective governance, and the Code states it is the board's responsibility to

provide a balanced, fair and understandable assessment of the company's position (Financial Reporting Council, 2012). This recommendation seeks to mitigate reporting bias.

The Code works under the principle “comply or explain”. This means that firms are free to deviate from the recommendations as long as they explain why. While deviations do occur, most firms treat the Code provisions as de facto mandatory and so compliance rates are high. In 2019 and 2018, for example, 99% of FTSE 350 firms separated the CEO and Chair roles (Financial Reporting Council, 2020). These board leadership norms contrast with the approach adopted in the US where firms have traditionally combined the roles of CEO and Chair in a single individual, or appointed a board Chair that is affiliated with the company (Goergen et al., 2020; Stuart, 2023).

3.2.2 UK corporate reporting

UK reporting rules provide firms with substantial discretion regarding annual report structure and content. El-Haj et al. (2020) note that although UK annual report content is typically shaped by legal mandate and securities laws, regulations do not prescribe the order in which information is presented, mandate the precise format in which disclosures must be provided, or require use of standard titles for mandatory sections.³⁶ In addition, regulation does not limit the amount of voluntary information that management can provide in their annual report. While US 10-K filings involve a rigid reporting structure that limits management discretion over content and presentation, UK firms are afforded substantial flexibility when it comes to the structure and the content of the annual report. While there is no legal requirement for firms to include separate discussions of performance by the board

³⁶ For example, firms listed on the London Stock Exchange are required to include in the annual reports narratives, a section regarding the risks and uncertainties faced by the firm, the Strategic Report, a Corporate Governance statement, the Directors' Report and their biographies, and a remuneration report.

Chair and CEO, the majority of firms elect to do so where the two roles are split (see ICSA (2015) for a list of sections that are expected in a UK annual report).

The management commentary section of the annual report provides management's view of financial and operating performance during the reporting period and is a legal requirement. The core elements of annual report management commentary are the Strategic Report and the Directors' Report, key aspects of which are mandated by the Companies Act 2006 (Strategic Report and Directors' Report) Regulations 2013.³⁷ Management commentary is signed by the CEO, often in conjunction with other key executives including the Finance Director. The Chair's letter (or letter to Shareholders) is signed by the Chair of the board and provides a summary of firm performance and key corporate events occurring during the reporting period (Clatworthy and Jones, 2003). This contrasts to the US where the letter to shareholders is often signed by the CEO and referred to as CEO Letters (Boudt and Thewissen, 2019; Patelli and Pedrini, 2014; Pawliczek et al., 2021). The clear delineation in performance commentary provides two distinct perspectives on company performance as viewed through the lens of the board Chair and the senior management team. The UK therefore provides a natural setting to examine how the presence of an independent board Chair impacts corporate disclosure. I leverage availability of performance commentary authored by the two top board members and ask whether Chair commentary is incrementally informative beyond management commentary and how the role of the Chair shapes corporate disclosure.

3.2.3 Narrative disclosure

Firms benefit from multiple disclosure channels through which they communicate with the market. These include earnings conference calls (Huang et al. 2014), social media

³⁷ Available here: <https://www.legislation.gov.uk/ukdsi/2013/9780111540169> [Accessed on August 13, 2025]

(Blankespoor et al., 2014) and annual reports (or 10-K filings). I focus on the annual report as the cornerstone of corporate reporting to shareholders (Holland, 1998; El Haj et al., 2020). Annual reports comprise two main components: the financial statements (FS) and narrative commentary (Lewis and Young, 2019). The FS provide structured information including the statement of financial position, the statement profit and loss and other comprehensive income, the statement of changes in equity, and a summary of the accounting policies and other notes to the FS. The narrative component includes unstructured information (also called “soft” data) regarding the entity’s operating and financial performance, executive remuneration policy, a corporate governance report, and other elements comprising both voluntary and mandatory disclosures. In the UK this includes the Strategic Report and the Directors’ report.³⁸ The Strategic Report is designed to allow shareholders to understand “how directors have performed their duty to promote the success of the company” (p.8: FRC 2012). Similarly in the US, the MD&A is a section of the 10-K filings where firms are expected “provide a narrative explanation of a company’s financial statements that enables investors to see the company through the eyes of management” (SEC, 2003). Recent evidence examining MD&A disclosures finds that firms report longer and more readable MD&As and issue more forward-looking statements when financial statements have low value relevance (Brown et al., 2024; Hribar et al., 2022). This evidence hints at a central role and goal of annual report narratives, namely providing context about a company, complementing the financial statements, and allowing stakeholders to understand the company in an integrated manner, considering not only its financial performance, but also its strategy, its business model, its future performance goals, and how all are aligned. This

³⁸ The classification of mandatory and voluntary sections follows the regulation proposed by UK company law or mandated by the UK Corporate Governance Code issued by the Financial Reporting Council (see El-Haj et al., 2020).

therefore implies that annual report narratives should be informative about a firm's contemporaneous and future performance.

To analyze the informativeness of annual report narratives and test whether these are associated with firm performance, research focuses on studying what firms say, how they say it, and how much they say about it (Bochkay et al., 2023; Brown et al., 2020a; Loughran and McDonald, 2014). This means that research has studied the content of narrative disclosures, the sentiment surrounding the content described, and the length dedicated to each subject discussed. Currently, it is an open question whether annual report narratives are a source of incremental information or a reporting tool that managers use to engage in impression management (Bushee et al., 2018; Z. Huang et al., 2014; Li, 2008).

Smith and Taffler (2001) examine the Chair's statement in UK annual reports and find it has predictive power for financial distress. Specifically, they find that the occurrence of negative words is positively associated with bankruptcy risk. Similarly, Abrahamson and Amir (1996) find that the President's letter in US reports contain information useful for predicting future performance. Bryan (1997) studies the MD&A section of 10-K filings and finds a positive association between future variation in earnings per share and discussion of future capital expenditures. Sun (2010) focuses on firms with disproportionate increases in inventory to assess whether MD&A explanations contain predictive ability for future performance. The paper argues that it is unclear if a disproportionate increase in inventory is associated with increasing or decreasing performance in the absence of additional information and context. Results show that favorable (unfavorable) explanations predict higher (lower) return on assets. Such evidence supports the view that financial narratives carry incremental information. Nevertheless, there is also evidence that managers use financial narratives as a source of manipulation and impression management.

Merkel-Davies and Brennan (2007) provide an extensive review of the impression management literature. The authors conclude that managers engage in impression management through biased reporting, by obfuscating bad news, and via self-attribution bias. Examples of biased reporting include adopting an abnormal level of positive tone that is not aligned with reported performance, due to career and reputational concerns, or focusing on forward-looking performance when realized earnings is poor (Arslan-Ayaydin et al., 2020, 2016; Hassanein and Hussainey, 2015). Intentionally disclosing information in a complex and ambiguous way to increase information processing costs represents an attempt to obfuscate bad news (Schleicher, 2012). Meanwhile, self-attribution bias involves attributing good news about performance to management actions while ascribing poor performance to external factors (Clatworthy and Jones, 2003).

In the first large sample study examining the relation between financial narratives and financial performance, Li (2008) studies the relation between earnings persistence and the readability of the entire 10-K annual report. Results show that firms with low earnings persistence report low readability. This is interpreted as evidence that managers obfuscate poor performance by disclosing information in a complex manner. The paper's primary assumption is that describing a good performance period is associated with the same level of complexity as describing a bad performing period. In this respect, it is unclear whether increased complexity reflects managers' intention to obfuscate bad news or is the consequence of describing poor performance (Bloomfield, 2008). With the aim of disentangling these two effects, Huang et al. (2014) study manager's tone during earnings press releases. The paper argues that positive tone that is unrelated with firm-specific features reflects strategic behavior. Consistent with this argument, results show that positive abnormal tone is negatively associated with one-period ahead earnings. Similarly, Davis and Tama-Sweet (2012) argue that managers' incentives to report strategically are stronger when firms

fail to meet earnings expectations. The paper posits that these incentives manifest more clearly in earnings press releases, where in comparison to the annual report, disclosures are more price-sensitive and the reporting channel is less regulated. The paper finds that managers tend to be more optimistic in the earnings press release and more pessimistic in the MD&A. Such evidence is consistent with literature concluding that financial narratives may be a source of manipulation. Osma and Guillamón-Saórin (2011) study the role of governance mechanisms in limiting such behavior and show that firms with strong governance mechanisms are more likely to present negative information and to adopt a more balanced (i.e., less optimistic) tone. They argue that this result reflects the monitoring role of the board in constraining managers' level of impression management. Accordingly, governance mechanisms seem to impact corporate disclosure.

3.2.4 The role of the Chair and board leadership structure, and prediction development

The role of the Chair as the head of the board of directors has been widely examined across different areas and through the lens of different theories. Research suggests that the board Chair may serve a monitoring role as predicted by agency theory, and an information role as predicted by legitimacy theory and resource dependency theory, respectively (Di Vito and Trottier, 2022; Krause, 2017; Krause et al., 2014; Yu, 2023).

The agency theory perspective is the most established view in literature. Banerjee et al. (2020) review more than 200 academic articles and find that fifty percent rely on the agency theory perspective to explain the role of the board Chair. This research builds on the seminal work that posits that the separation of ownership and control leads to agency conflicts between shareholders and managers (Fama and Jensen, 1983). The agency viewpoint is based on the assumption that managers act in an opportunistic manner and that their incentives are not aligned with those of shareholders. Under this view, the primary role

of the Chair is to monitor CEO's behavior and to protect shareholders' interests (Krause et al., 2014). This theory is largely supported by evidence that increased board oversight has a positive impact on performance (Dahya et al., 1996; Rechner and Dalton, 1991). In a corporate disclosure setting and under the agency theory perspective, a manager's opportunistic behavior may translate into a misalignment between firm performance and the way firm performance is described. Agency theory therefore predicts that managers strategically choose what to say and how to say it, using their commentary as an impression management tool (Arslan-Ayaydin et al., 2020, 2016; Li, 2008; Merkl-Davies and Brennan, 2007). The board Chair, on the other hand, is expected to provide a more balanced and fairer representation of firm performance than management commentary. The monitoring role of the Chair implies that Chair commentary carries incremental information beyond management commentary. Further, this monitoring effect should be more pronounced when incentives for impression management are particularly strong, such as when firms report negative earnings, experience a decrease in earnings growth, or fail to meet analysts' forecasts.

Focusing exclusively on the monitoring role of the board Chair nevertheless ignores the possibility that Chair-authored disclosures serve a confirmation function that is consistent with an information role. The institutional view of legitimacy theory explains a firm's need for legitimacy from the external factors and the dynamics that pressure firms to adopt behaviors that comply with socially acceptable norms and values (Suchman, 1995). Although it is not mandatory for UK firms to appoint an (independent) Chair and provide a Chair-authored statement, this is the expected board leadership structure and behavior. In this respect, the Chair may serve an information role by acting as a confirmation channel for management information. This is consistent with the view that the Chair collaborates with and supports the management team, rather than simply monitoring and controlling it (Boivie

et al., 2021). Given that managers have incentives to obfuscate bad news and overstate performance, capital market participants may discount good news disclosures by management on the basis that optimism may reflect an attempt to deceive investors (Blau et al., 2015; Cohen et al., 2020). In this setting, the Chair may serve an information role by confirming and legitimizing the information provided by management commentary. This implies that Chair commentary should carry information content beyond the management commentary and that this effect should be more pronounced for good-performing firms.

In addition to monitoring the board Chair's information role may also reflect a resource provision function. Resource dependency theory (RDT) argues that organizations are constrained by the forces that dominate the environment where they operate. It is the role of the Chair to support an organization by being a resource provider (or by taking actions that increase a firm's resources) and by reducing resource dependence and uncertainty. It is the responsibility of board members to create channels of communication between the firm and external stakeholders and to provide advice (Drees and Heugens, 2013; Hillman et al., 2009; Hillman and Dalziel, 2003). Such activities are particularly important for firms operating in highly complex and uncertain environments (Withers and Fitza, 2017).

Given this evidence, RDT predicts that the availability of Chair commentary may provide a resource provision function in two ways. First, an independent board Chair may provide resources in the form of information skills and guidance acquired through expertise and experience from prior appointments (Higgs, 2003; Hillman et al., 2000). Second, the Chair's letter can establish a communication channel between the firm and any stakeholder group, which in turn may lead to improved access to resources (Ntim et al., 2013). RDT therefore implies that the Chair commentary may be incrementally informative beyond management commentary.

The preceding discussion identifies two non-mutually exclusive roles to expect that Chair commentary provides incremental information content beyond management commentary: monitoring and information. Collectively, therefore, these arguments lead to the following testable hypothesis regarding the informativeness of annual report commentary authored by the board Chair relative to commentary in the same report provided by the CEO and other members of the senior management team:

All else equal, annual report Chair commentary provides incremental insights on firm performance beyond discussion and analysis authored by the senior management team in the same report.

3.3 Research design, key variables, and sample

3.3.1 Research design

In contrast to the 10-K filing for US registrants that follows a standardized template, there is no standardized structure governing the format and content of annual reports in the UK (El-Haj et al., 2020). I therefore identify annual report sections as Chair commentary and management's commentary using the tool developed by El-Haj et al. (2020). This tool defines a set of twelve generic annual report sections that include the Chair's letter to shareholders and aggregate management commentary including the CEO review, the report by the Finance Director, and other commentary reflecting discussion and analysis of financial performance. The tool then uses a crawler algorithm with a comprehensive set of n-grams for each report element (e.g., Chair's Message, Shareholders' Letter, Chairman's Statement, etc. for the Chair's letter) to search for relevant sections in the report table of contents and classify them into Chair versus management commentary. I construct an aggregate measure of management commentary, equivalent to the US MD&A section, using the following generic annual report

sections, where they exist: CEO Review, Financial Review, Business Review, Operating Review, and Performance Highlights.

I focus on textual tone to examine the informativeness of the Chair and management commentary because research demonstrates that tone (sign and magnitude) correlate strongly with contemporaneous and future performance (Arslan-Ayaydin et al., 2020, 2016; Blau et al., 2015; Boudt et al., 2018; Davis et al., 2015; Feldman et al., 2010; Huang et al., 2023). I follow Henry and Leone (2016) and compute tone using the classification of positive and negative words as identified by Henry (2008). Tone is the number of positive sentences minus negative sentences, scaled by the total number of sentences in the respective annual report section. A sentence is classified as positive (negative) if the number of positive words is higher (lower) than the number of negative words within the same sentence.

To test the prediction that Chair commentary is incrementally informative beyond management commentary I rely on use realized earnings from continuous operations. If Chair commentary carries incremental information content beyond management commentary, then the tone of Chair commentary for realized performance should have explanatory power after controlling for the tone management commentary. I use one period-ahead earnings to examine the incremental predictive ability of Chair commentary. I posit that Chair commentary carries incremental information content beyond management commentary if the tone of the Chair's letter carries incrementally predictive ability for future earnings beyond the aggregate management review.

3.3.2 Sample selection and descriptive statistics

I rely on a sample of annual reports with fiscal year end between 2005 and 2019 by LSE-listed firms. Table 3.1 reports the sample selection process. I extract all available PDF reports for LSE-quoted firms over this period from Perfect Filings. The initial population of

reports with fiscal-year ends between 2005 and 2019 is 42,367 reports, financial firms (10,585 reports), private firms (2,257 reports) and those with download errors (525 reports). I use the text extraction tool described in El Haj et al. (2020) to retrieve text on section-by-section basis according to document structure represented by the report table of contents or the PDF bookmarks. I exclude reports that cannot be processed with the algorithm and those where the output is likely to contain material measurement error (6,374 reports). Remaining reports are mapped to Datastream identifiers using a fuzzy matching procedure based on firm name, supplemented by manual matching where the quality of the match is dubious or no candidate match exists (approx. 30% of reports). I exclude 3,452 non-matched reports. I then proceed with additional standard filtering steps such as removing duplicates and missing observations and dropping variables' outliers. Specifically, I trim the number of sentences of Chair commentary and management commentary, current and one-period-ahead scaled earnings from continuous operations, and market capitalization at the extreme percentiles. Due to the presence of outliers at the right-tail of the distribution I also trim observations above percentile 99 for twelve-month stock returns, leverage, and book to market ratio. The final sample comprises 8,898 reports from 1,610 firms, all of which have a leadership structure where the roles of CEO and board Chair are split.

Table 3.2 reports descriptive statistics. Panel A reports the descriptive statistics of linguistic features for Chair and management commentary. The median Chair's letter comprises 42% of sentences classified as positive compared to 30% for aggregate management commentary. These statistics suggest that Chair commentary is more positive than management commentary. The evidence is not in-line with the expectation that the board Chair provides a more balanced view of firm performance. I reconcile this finding with evidence suggesting that the Chair's letter may serve as a channel to advertise a firm (Rajan et al., 2023).

The median firm reports that aggregate management review comprises one hundred and twenty-seven sentences whereas the median Chair's letter contains thirty-five sentences. This difference is consistent with the view that suggests that the Chair commentary provides a summary of corporate events (Clatworthy and Jones, 2006). In addition, Chair commentary is more forward-looking and long-term oriented than management commentary. I interpret this as preliminary evidence consistent with the view that management commentary focuses on explaining decisions about the reporting entity's assets and environment, whereas Chair commentary provides an outlook statement and discusses broader themes related with future strategy, governance and sustainability plans (ICSA, 2015).

Panel B of Table 3.2 provides descriptive statistics for the accounting and market measures of firm performance, as well as firm characteristics. Contemporaneous and one-year-ahead earnings, scaled by market value at the fiscal year-end, for the median firm are 0.042 and 0.0046, respectively. Almost 31% percent of firms report a loss in year t . The median firm has a book-to-market ratio of 0.62, debt-to-equity of 24.5%, market value of £118 million at the fiscal year-end, 12-month returns ending four months after the fiscal year of 1.2% and operate in two geographic and business segments. Appendix 3.1 summarizes variable definitions.

3.4 Main tests

3.4.1 Association with realized earnings

To examine whether Chair commentary carries information content beyond management commentary, I start by examining the explanatory power of performance commentary for realized earnings. I expect that the performance commentary with the highest explanatory power should be more strongly correlated with performance. In this respect, I compare the r -squared of the following regressions:

$$EARN_{it} = \gamma_0 + \gamma_1 Chair\ Tone_{it} + \varepsilon_{it} \quad (3.1a)$$

$$EARN_{it} = \delta_0 + \delta_1 Management\ Tone_{it} + \mu_{it} \quad (3.1b)$$

where *EARN* is reported earnings from continuing operations (scaled by market value). These models do not include any control variables and fixed effects as I seek to compare the total (unconditional) explanatory power associated with the tone of Chair and management commentary. I also test whether *Chair Tone* has incremental explanatory power for realized earnings beyond *Management Tone* using the following regression. Relatively to Equations (3.1a) and (3.1b), the following equation allows to understand if the correlation between Chair tone and realized earnings is robust to the inclusion of management tone.

$$EARN_{it} = \lambda_0 + \lambda_1 Chair\ Tone_{it} + \lambda_2 Management\ Tone_{it} + v_{it} \quad (3.1c)$$

Results are presented in Table 3.3 and include three model specifications that refer to Equations (3.1a), (3.1b) and (3.1c). The dependent variable in Models 1-3 is realized earnings. Coefficient estimates of *Chair Tone* and *Management Tone* are positive and significant (p -value < 0.01). Model 1, which includes *Chair Tone*, has an R-squared of 6.5%. The corresponding value for Model 2, which includes *Management Tone*, has an R-squared of 4.4%. A Vuong test confirms that the difference in R-squared is statistically significant. This means that Chair tone seems to be more strongly correlated with realized earnings than management tone.

Model 3 presents results of estimating Equation (3.1c) and reveals that *Chair Tone* is incrementally relevant beyond *Management Tone*. The coefficient of *Chair Tone* is 0.190 whereas the coefficient of *Management Tone* is 0.122 and both are significant at a 1% level ($p < 0.01$). This means that the tone of Chair commentary for realized performance still carries explanatory power after controlling for the tone management commentary. Such result is therefore consistent with the prediction that Chair commentary is incrementally informative beyond management commentary. Overall, results from Table 3.3 confirm extant evidence

that management commentary aligns with realized earnings but a comparison of coefficients and R-squared suggests Chair commentary is more strongly aligned with realized earnings. Results are therefore consistent with Chair commentary offering additional insights on realized earnings and beyond management commentary. Results from this section are consistent with theory-based arguments presented in the previous chapter and are consistent with the hypothesis that Chair commentary provides incremental insights on firm performance beyond commentary authored by the senior management team in the same report and that the presence of an independent board Chair affects the informativeness of annual report disclosures. I interpret these results as preliminary evidence indicating that the Chair's letter contains insights related to realized performance that are additional to the insights provided in management commentary.

3.4.2 Predictiveness for future earnings

In this section, I examine the ability of annual report performance commentary to predict one-year-ahead earnings. Specifically, I test the incremental ability of Chair commentary to predict future earnings beyond management commentary:

$$\begin{aligned}
 Earn_{it+1} = & \beta_0 + \beta_1 Chair\ Tone_{it} + \beta_2 Management\ Tone_{it} + \beta_2 Earn_{it} \\
 & + \sum_{k=1}^K Controls_{kit} + \psi_{it+1}
 \end{aligned} \tag{3.2}$$

where $Earn_{it+1}$ is one-year-ahead earnings, and *Chair Tone* and *Management Tone* are as defined in the previous section. Controls refers to a set of variables from prior research that are known to predict earnings: realized earnings, book-to-market, leverage, 12-month stock returns, number of business segments, number of geographic segments, and an indicator variable for losses. I also include industry and year fixed effects. Results are presented in Table 3.4. Models 1 to 4 exclude contemporaneous stock returns to avoid collinearity with

Chair and management commentary. Remaining include stock returns and therefore test whether Chair and management commentary also provide predictive ability beyond information available to market participants.

Model 1 in Table 3.4 is the baseline model where I replicate prior literature and focus on the predictive ability of management commentary. I first exclude *Chair Tone* and the indicator variable for losses. *Management Tone* loads positively, which is consistent with prior literature that performance commentary carries predictive ability for future earnings. In model 2 I test the incremental predictive ability of Chair commentary beyond management commentary by adding the variable *Chair Tone*. This variable loads with a positive and significant coefficient estimate. Further, *Management Tone* is no longer statistically significant. Results suggest that the Chair's letter includes additional information that is relevant for predicting future earnings and that the predictive information in management commentary evidenced model 1 is subsumed by Chair commentary. Comparing models 1 and 2 nevertheless reveals that adding *Chair Tone* is associated with a trivial increase in R-squared by 0.002, although a Wald test confirms that the increase is statistically significant. Results suggest that the additional insight in Chair commentary may be limited in practical terms despite being statistically significant. Despite appearing to have higher predictive ability than management comments, these tests suggest that *Chair Tone* is not a first order predictor of future earnings.

In model 3 I add the indicator variable *Loss*, to control for structural differences in earnings predictability conditional on the sign of current earnings. Controlling for poor realized earnings perform firms does not affect the evidence that Chair commentary carries information content beyond management commentary. To understand the effect of Chair commentary in predicting future earnings, I compare the economic significance of *Chair Tone* with that of $EARN_t$, which is known predictor of future earnings (Frankel and Litov,

2009). I therefore compute the change in future earnings associated with an IQR increase in *Chair Tone*. In model 3, future earnings is 0.012 higher at the 75th percentile of *Chair Tone* relative to the 25th percentile.³⁹ Similarly, moving from the 25th to the 75th percentile of current earnings is associated with 0.038 higher future earnings. The effect for *Chair Tone* is therefore equivalent to approximately 31% of the effect for current earnings, indicating that *Chair Tone* is an economically meaningful predictor. Model 4 includes additional linguistic features of narrative reporting to determine if tone is a fundamental predictive measure or if it is capturing other aspects of language. I follow prior literature and include controls for length commentary, forward-looking language, and the degree of long-term orientation (Brochet et al., 2015; Hassanein and Hussainey, 2015; Loughran and McDonald, 2014). In each case, I compute separate measures for Chair commentary and management commentary. *Chair Tone* continues to load positively in model 4, suggesting that tone is an important and distinctive predictive feature of the Chair's letter. Of the additional linguistic features, long-term orientation in both Chair and management commentary loads positively. Forward-looking of management commentary loads with a negative coefficient, albeit with marginal statistical significance ($p=0.09$). This result is consistent with obfuscation behavior whereby management attempt to deviate attention from weak current performance by focusing attention on the future (Merkl-Davies and Brennan, 2007).

Models 5-8 in Table 3.4 repeat the analysis after including 12-month contemporaneous returns ending four months after the fiscal year-end. *Returns* load positively in models 6-8, which is consistent with evidence that share prices lead earnings (Kothari, 1992). *Management Tone* is insignificant in all models. *Chair Tone* continues to load positively in models 6 and 7 but loses significance in model 8 where I control for other

³⁹ Economic significance is calculated by subtracting percentile 75 to percentile 25 and then multiply this by the coefficient estimate. For example, the economic significance of Chair Tone is as follows: $(0.538-0.300) \times 0.051 = 0.012$.

linguistic features. Still, long-term orientation in Chair and management commentary loads positively and continues to predict future earnings. Evidence from models 6 and 7 suggests that the tone of Chair commentary contains “new” information for future earnings beyond that which the market is pricing. However, results in model 7 suggest that the insights contained in Chair commentary that are incremental to market information are associated with analysis of the long-term. The fact that the tone of Chair commentary is not incremental to returns and future-oriented discussion does not overturn my key finding that Chair commentary contains information for future earnings that is additional to the information in management commentary.

Collectively, Table 3.3 and Table 3.4 support the prediction that Chair commentary carries additional information content beyond management commentary.⁴⁰ Results indicate that the presence of an independent board Chair impacts the informativeness of corporate reporting. However, these findings do not provide a basis for determining the role of monitoring, confirmation and resource provision as potential drivers of incremental informativeness. I address this question in the following section.

3.5 What roles(s) explain the incremental informativeness of Chair commentary?

In this section, I propose a set of explanations for why Chair commentary contains insights about earnings performance (realized and one-period-ahead) that is incremental to information provided by management in their annual report commentary. I posit that the role of the board Chair in shaping corporate disclosure may derive from a monitoring role and an information role. I conjecture that the information role arises from two separate functions:

⁴⁰Appendix 3.2 to Appendix 3.5 show that results documented in this section are robust to using 1) two alternative ways of computing tone (one with a different scalar and another one with an alternative word list proposed by García et al. (2023)), 2) an alternative source of management commentary (constructing management commentary using the CEO review only), and 3) using firm fixed effects, respectively.

confirmation and resource provision. I treat these as three non-mutually exclusive explanations where the importance of each explanation may vary with firm conditions.

3.5.1.1 Monitoring role

Agency theory's primary assumption is that managers act in an opportunistic manner, which, in a corporate disclosure setting, may be associated with impression management behavior. Under this view, the role of a board Chair is to monitor the CEO, which involves mitigating impression management behavior by offering an unbiased assessment of realized performance (evaluated against the business model) and expectations of future value creation. In this subsection, I ask whether the board Chair serves a monitoring role, as predicted by agency theory, by testing if the informativeness of Chair commentary is more pronounced when incentives for management to engage in impression management are particularly pronounced. Specifically, I test whether the incremental predictive ability of Chair commentary is conditional on the sign of contemporaneous earnings. I hypothesize that if the board Chair serves a monitoring role, then the incremental predictive ability of Chair commentary should be higher when the incentives for obfuscation are especially high, such as when firms report a loss.

Table 3.5 present results of estimating Equation (3.2) separately for firms reporting losses and profits in period t , respectively. I measure a firm's earnings using earnings from continuous operations and excluding extraordinary items. This means that firms are classified as loss or profitable firms based on the earnings generated by their recurring and continuous operations which should be directly related to their performance commentary. Models 1 and 2 do not include 12-month stock returns whereas models 3 and 4 do. Models 1 and 3 regress one-year-ahead earnings on narrative tone for the subsample of firm-year observations where firms report a loss, whereas models 2 and 4 present comparable results for the subset of firm-

years where earnings are positive. Results show that the ability of Chair commentary to predict future earnings firms for loss firms-years is weak, as the coefficient estimate on *Chair Tone* is only marginally significant ($p = 0.08$) in model 1 and insignificant in model (3). Results for models 2 and 4 show that the ability of Chair commentary to predict future earnings appears to be driven by firms that report a profit, with *Chair Tone* loading positively in both models ($p < 0.01$). Nevertheless, an F-test cannot reject the null hypothesis that the coefficient estimates on *Chair Tone* are different across models 1 and model 2, and models 3 and 4. As such, it remains unclear whether the informativeness of *Chair Tone* for future earnings is conditional on the sign of realized earnings. Critically for the monitoring hypothesis, however, I find no support for the view that Chair commentary is more predictive of future earnings when management's incentives for obfuscation are especially high.

Overall, findings reported in this subsection offer limited evidence that Chair commentary carries incremental predictive ability of future earnings when firms report a loss. Nevertheless, the absence of evidence that Chair commentary has more pronounced predictive ability when realized earnings performance is weak does not rule out the possibility that Chair commentary serves a monitoring role in the face of management's optimistic reporting bias. Accordingly, to probe the lack of prima facie evidence regarding the monitoring role of Chair commentary, I conduct additional analyses.

3.5.1.1.1 The determinants and predictive power of Chair pessimism

In an attempt to understand the findings in Table 3.5 that fail to support the view that Chair commentary displays more pronounced incremental predictive ability when the incentives for obfuscation by management are high, I focus more specifically on cases where the board Chair is more pessimistic than one might expect given management tone as a way to further assess whether commentary authored by board Chair serves a monitoring role.

Specifically, I focus on instances when Chair commentary is less positive than management commentary and test if this relative pessimism is more likely when management has incentives to disclose an overly positive view of performance. All else equal, the monitoring hypothesis predicts that Chair commentary is likely to be less positive than management commentary when managerial incentives to be abnormally positive are more pronounced. I expect that the Chair is more likely to be pessimistic relative to management when management incentives for impression management are strong. I use the following regression to build my measure of Chair pessimism relative to management:

$$Chair\ Tone_{it} = \pi_0 + \pi_1 Management\ Tone_{it} + \omega_{it} \quad (3.3)$$

My measure of Chair pessimism is an indicator variable (*Chair Pessimism*) equal to one where the residuals from Equation (3.3) are negative, and zero otherwise. Negative residuals indicate cases where Chair tone is less positive than predicted by management tone.⁴¹

Table 3.6 reports the results of a logistic regression of the probability of *Chair Pessimism* on incentives for managerial impression management and a vector of control variables. I use four proxies for impression management incentives related to weak current-period performance. *Loss* takes the value of one for firm-years with negative earnings from continuing operations (scaled by market value at fiscal-year end), and zero otherwise; *Decline* is an indicator variable equal to one for firm-years where the change in earnings is negative, and zero otherwise; *Negative Returns* is a market-based measure of weak performance equal to one where 12-month stock returns ending four months after the fiscal year-end are negative, and zero otherwise; and *Change EARN_t* is the ratio of current

⁴¹ Coefficient estimates for π_0 and π_1 of Equation (3.3) are, respectively, 0.0268 and 0.491. Both are positive and statistically significant at a 1% level ($p < 0.01$). The r-square of the model is 0.203. Discussions with annual report consultants reveal that the Chair's letter is written after management commentary is prepared. In this respect, *Chair Tone* is regressed on *Management Tone* to reflect the direction of causality.

earnings scaled by lag current earnings minus one. I expect all four variables to increase the likelihood of *Chair Pessimism* if Chair commentary provides a monitoring function on commentary authored by management. Estimated log odds ratios in Table 3.6 for *Loss*, *Decline* and *Negative Returns* are positive and significant in all models as expected. Results for model 2 that includes a vector of control variables reveal that loss firms' annual reports are 1.46 ($e^{0.377}$) times more likely than profit firms' reports to include Chair commentary that is more pessimistic than management commentary. The comparable odds ratio for firms experiencing decline in earnings negative contemporaneous returns are 1.15 and 1.48, respectively. The effects are therefore economically meaningful as well as statistically significant. The coefficient estimate of $Change\ EARN_t$ is not statistically significant. These findings suggest that the board Chair adjusts the tone of her commentary in response to managerial incentives to engage in obfuscation and impression management. However, it is unclear whether more pessimistic tone translates into incremental informativeness.

I posit that management is engaging in obfuscation when the Chair is more pessimistic than management. In this respect, if the board Chair adopts a more negative tone that is more informative than that of management commentary, then I expect management commentary to have lower predictive ability for next-period earnings when Chair commentary is pessimistic relative to management commentary. I focus on the tone of management commentary as I posit that the board Chair potentially identifies cases of obfuscation and adjusts its commentary to correct this disclosure bias. I test this expectation with versions of the following regression:

$$\begin{aligned}
\text{Earn}_{it+n} = & \theta_0 + \theta_1 \text{Chair Tone}_{it} + \\
& \theta_2 \text{Management Tone}_{it} + \theta_3 \text{Management Tone} \times \text{Chair Pessimism}_{it} \\
& + \sum_{k=1}^K \text{Controls}_{kit} + \psi_{it+1}
\end{aligned} \tag{3.4}$$

The dependent variable is one-period-ahead earnings ($n = 1$) and the remaining variables keep the same interpretation; θ_3 is the main coefficient of interest as it captures the predictability of *Management Tone* stemming from instances when Chair commentary is more pessimistic than management commentary. Table 3.7 reports the results of estimating Equation (3.4). Models 1 and 2 do not include 12-month stock returns whereas models 3 and 4 do. Model 1 omits *Chair Tone* and examines the explanatory power of *Management Tone* for one-year-ahead earnings conditional on Chair pessimism. The coefficient estimate for *Management Tone* is positive and significant while the interaction with *Chair Pessimism* is negative. This confirms the expectation that management commentary has a weaker correlation with one-year-ahead earnings when Chair commentary is relatively more negative due to concerns about obfuscation and impression management in management commentary.

When I extend regression 3.4 to include *Chair Tone* in model (2), *Management Tone* and its interaction with *Chair Pessimism* are no longer statistically significant, whereas *Chair Tone* loads positively. This result suggests that *Chair Tone* subsumes the reduced informativeness of management commentary when the incentives for impression management and obfuscation are high. The evidence is therefore consistent with Chair commentary serving a monitoring function for management commentary in the face of optimistic management reporting due to impression management behavior. Adding contemporaneous stock returns to the regression in models 3 and 4 renders both *Management Tone* and its interaction with *Chair Pessimism* insignificant, while *Chair Tone* continues load positively [in model 4]. Findings suggest that information in management commentary and

the incremental impact of impression management are subsumed in share returns (i.e., investors are not fooled), but that Chair commentary remains incrementally informative. I therefore interpret this evidence as consistent with the view that Chair commentary mitigating the effects of impression management behavior in management commentary through a monitoring role that is consistent with the monitoring role afforded by market participants.

Results in Table 3.6 contrast with conclusions from Table 3.4. Specifically, while findings in Table 3.6 suggest that the Chair commentary mitigates bias in management commentary when impression management incentives are high, results in Table 3.4 fail to demonstrate evidence that Chair commentary provides incremental predictive ability for one-period-ahead earnings in such circumstances. These results appear counterintuitive. However, tests to date do not examine directly whether the association between Chair commentary and both realized and future earnings is conditional on the sign of current period earnings. Research shows that losses are less persistent and carry less information content than profits (Frankel and Litov, 2009; Hayn, 1995). It is possible that the board Chair provides additional discussion relating to realized earnings as part of their monitoring role during poor performance years. Relatively greater focus by the Chair on weak earnings realizations and their causes could account for a lack of commentary that provides incremental insights about future earnings for firms reporting losses. I explore this possibility in the next section.

3.5.1.1.2 Relative importance of realized earnings and future earnings

The correlation of Chair commentary and earnings – realized and future earnings – speaks to the overall role of performance commentary. On the one hand, if performance commentary correlates more strongly with future earnings, then it is future oriented and therefore serves a decision usefulness role. This is consistent with Chair commentary containing information that speaks to earnings persistence and future profitability. On the

other hand, if performance commentary correlates more strongly with realized earnings, then this is evidence of discussions and insights that are more backward-looking and hence more consistent with a stewardship role that seeks to explain how effectively management have used resources at their disposal. The stewardship view implies that the tone of Chair commentary is driven by a focus on realized performance.

I use a dominance analysis to examine if Chair commentary devotes greater importance to realized earnings or future earnings, and whether the focus varies conditional on realized performance. Dominance analysis (DA) is a technique used to determine the relative importance of explanatory variables by computing the individual incremental contribution of each variable to the model's explanatory power. For each set of variables, DA conducts a regression of all the possible combinations and averages the individual contribution to explanatory power (R-squared). There are three levels of dominance computed in DA: complete dominance, conditional dominance and general dominance (Luchman, 2021, 2014). I will focus on general dominance as this decomposes a model's fit statistic into separate components and ranks each explanatory variable according to its general dominance statistic. Additionally, general dominance statistics are normalized to ensure that the sum of the DA statistic of each variable adds up to 100%. This allows me to compare the relative importance of different variables across different models.

To test whether the board Chair changes focus from current performance to future performance and vice-versa conditional on the sign of current earnings I conduct dominance analysis using the following model:

$$Chair\ Tone_{it} = \alpha_0 + \alpha_1 EARN_{it+1} + \alpha_2 EARN_{it} + v_{it} \quad (3.5)$$

Chair Tone, $EARN_{t+1}$ and $EARN_t$ are as defined in previous analyses. The model does not include control variables or fixed effects as I seek to understand the total individual relative importance (rather than incremental importance) of current earnings and future

earnings for the tone of Chair commentary. Results are presented in Table 3.8. I present each variable's standardized dominance statistics and ranking for a model estimated using the full sample in Panel A, the subset of firms that report a loss in Panel B, and the subset of firms that report a profit in Panel C. Results from the full sample and the subset of firms that report a loss show that realized earnings ranks first in the marginal contribution to the model's R-squared. Specifically, standardized dominance statistics in Panel B for a model estimated with observations of loss firms reveals that realized earnings account for 70% of the R-squared. This result suggests that Chair commentary aligns closely with realized earnings when earnings are negative. Conversely, standardized dominance statistics in Panel C for a model estimated using a subsample of profitable firms reveals that future earnings account for 98% of model's R-squared. Chair commentary therefore aligns much more closely with future earnings when earnings are positive. Results are consistent with the board Chair devoting additional attention to current performance during periods of poor performance; and at the same time, they also account for evidence that the predictive power of Chair commentary for future earnings tends to be more pronounced for profitable firms.

I interpret my collective results as evidence that the board Chair serves a monitoring role during periods of weak earnings performance by moderating management positive tone through more pessimistic (balanced) commentary, and by redirecting the focus of the discussion to realized earnings. Performance commentary authored by the Chair therefore has a stewardship function that allows investors and shareholders to understand how the firm delivers its current performance (Cascino et al., 2013). The evidence supports the view that Chair commentary serves a decision usefulness role that at least mirrors market expectations of one-year-ahead earnings and possibly provides additional insights in some cases.

At the same time, my earnings prediction results suggest that in addition to this monitoring function, Chair commentary also plays an information role when realized

earnings are positive. The Chair's monitoring role over corporate reporting does not appear to explain the incremental predictive ability of their commentary, nor the fact this effect proves particularly strong for profitable firms. In the next section I explain how this result may be consistent with the Chair serving an information role that may arise from two non-mutually exclusive functions: confirmation and resource provision.

3.5.1.2 Information role

3.5.1.2.1 Confirmation function

Legitimacy theory predicts that one of the roles of the Chair may be associated with granting legitimacy to the firm by acting as a confirmation mechanism. In this respect, in a corporate disclosure setting, the role of the Chair in acting as a confirmatory channel for management commentary is particularly important for firms with strong fundamentals (e.g., profitable firms) as investors are aware that managers may overstate earnings and adopt an overly positive tone that is not matched by performance. Here, the role of the Chair is to help market participants distinguish between good performing companies from those where management tries to manipulate perceptions by confirming the information disclosed by management. I therefore interpret results for models 2 and 4 in Table 3.5 – showing that the ability of Chair commentary to predict future earnings appears to be driven by profitable firms – as evidence consistent with the board Chair serving an information role that arises from a confirmation function as predicted by legitimacy theory.

Nonetheless, an information role may also arise from serving a resource provision function. I conduct additional tests in the next section aimed at providing preliminary evidence on the resource provision function by conditioning on information demand by analysts. Importantly, the analyses in this chapter are not aimed at distinguishing between the two functions of the information role. Instead, I report preliminary evidence consistent with

the information role and seek to distinguish between these alternative information explanations using additional predictions and analysis in Chapter 4.

3.5.1.2.2 Resource provision function

RDT is one of the most used theories, alongside agency theory, in corporate governance research examining the role of the Chair (Banerjee et al., 2020). This theory argues that the primary goal of the Chair and board of directors is to increase the firm's resources and to reduce the uncertainty it faces (Hillman et al., 2009; Hillman and Dalziel, 2003). Among other actions, this theory states that establishing communication channels between the firm and external stakeholders and is an activity that a board of directors can take in the exercise of their responsibilities (Hillman et al., 2009; Pfeffer and Salancik, 1978). An independent board Chair may provide resources to the entity in the form of an information advantage that is reflected in Chair commentary and that leads to incremental informativeness. Such an expectation follows evidence showing that board members bring information skills from previous appointments and respective networks (Schabus, 2022). I therefore posit that incremental predictive ability of Chair's letter for future earnings should be especially pronounced during periods of high information demand by analysts. I follow Fu et al. (2021) and Hribar et al. (2022) and measure information demand using analyst following. I hypothesize that the incremental predictive ability of Chair commentary for future earnings should be higher for firms with high analyst following, where demand for the skills, experience and network that the Chair brings are more pronounced.

Table 3.9 presents the results of estimating Equation (3.2) separately for firms with high analyst following and low analyst following in period t , respectively. The median firm is followed by four analysts; I split the sample based on the median level of analyst following per year. Each firm-year observation is classified as having high analyst following if the

number of analysts covering a company in a given year is equal to or greater than the sample median number of analysts for that year.

Models 1 and 2 do not include 12-month stock returns whereas models 3 and 4 do. Models 1 and 3 regress one-year ahead earnings on tone using the subsample of firms with high analyst following. Results show that the ability of Chair commentary to predict future earnings as documented in Table 3.4 is more pronounced for firms with high analyst following, whereas the coefficient estimate on *Chair Tone* in models 2 and 4 for the low analysts following sample is not statistically significant. An F-test confirms that coefficient estimates on *Chair Tone* are larger for the subset of observations with high analyst following. This therefore provides evidence consistent with the board Chair serving an information role that arises from a resource provision function. This result must, however, be interpreted with caution as it is not free from caveats. It is possible the analyst following is correlated with omitted variables such as firm size, information asymmetry and any other factors affecting a firms' information environment and likelihood of analyst following. I interpret this as modest evidence consistent with the board Chair having an information role that arises from serving a confirmatory function. In this respect, in the next chapter, I attempt to provide sharper tests to further examine the information role of the Chair that arises from confirmation (as predicted by legitimacy theory) and resource provision (as predicted by resource dependency theory) by focusing on the content of performance commentary.

Overall, results from this section confirm my hypothesis that Chair commentary carries incremental information content beyond that of management commentary. This means that the presence of an independent board Chair affects corporate disclosure. Cross-sectional analyses reveal that the Chair serves a monitoring role that is confined to firms with weak performance. Additional analyses provide preliminary evidence consistent with the board Chair having an information role that arises from serving two non-mutually exclusive

functions: a confirmation function and a resource provision function. Additional analyses confirm that the board Chair also has a monitoring role that is confined to firms with weak performance.

3.6 Conclusion

In this chapter, I ask whether and how board leadership structure affects the informativeness of performance commentary. Prior work focuses on studying the implication of board leadership structure on firm performance (Krause et al., 2014; Yu, 2023). Additionally, this evidence largely relies on the comparison between firms that choose to separate the positions of the Chair and CEO and firms that choose to have a board Chair that is not the CEO. Conversely, I focus on the impact of board leadership structure on informativeness of narrative disclosure and rely on a set of firms that operate under the UK Corporate Governance where the separation of the Chair and CEO positions and the appointment of an independent Chair is predominantly exogenous.

It is unclear whether Chair commentary carries information content beyond management commentary. First, management is responsible for managing the daily operations of the firm and for defining strategy. This therefore implies that management has more firm-specific knowledge than the board Chair and supports the view that Chair commentary should not be incrementally informative. At the same time, however, management faces reporting incentives that may negatively affect the informativeness of their commentary. In this respect, by being responsible for protecting and reporting to shareholders, the board Chair is expected to mitigate managers' disclosure bias through the provision of a neutral and balanced description of performance. This supports the view that Chair commentary should carry information content beyond management commentary. Furthermore, an independent Chair is expected to disclose a commentary that benefits from

the expertise and the experience acquired in previous appointments. I find consistent evidence that Chair commentary carries information content beyond management commentary. Specifically, I show that Chair commentary has higher explanatory power for realized performance and has stronger predictive ability for future earnings than management commentary. This result implies that the presence of an independent Chair affects the informativeness of performance commentary and creates a communication benefit for shareholders through the provision of commentary that has implications for future performance. Importantly, I do not make the argument that separating the roles of the CEO and Chair is the optimal board leadership structure. Instead, I argue that the provision of Chair commentary that provides useful insights about future performance can only be observed in a setting where firms have a board Chair that is not the CEO.

Cross-sectional analysis is consistent with the view that the board Chair serves an information role associated with a confirmation and a resource provision function. Specifically, I find that the incremental predictive ability of Chair commentary for future earnings is driven by profitable firms (confirmation function) and firms that operate in environments with high information demand (resource provision function). I also show that the monitoring role of the Chair is limited to weak performing firms.

Additional analyses of the relative weight of realized earnings and future earnings for Chair tone reveals that the focus of the Chair on current or future performance is conditional on the sign of current earnings. Results show that the predictive power of Chair tone is primarily associated with contemporaneous (future) earnings when firms report losses (profits). I interpret this as evidence that performance commentary authored by the board Chair serves a stewardship role when firms report weak performance and a decision usefulness role when firms are profitable.

This chapter provides important insights for academics and corporate governance professionals. For academics, I provide evidence that the annual report is a communication channel that provides relevant insights for understanding a company's reported performance. For corporate governance professionals, this chapter shows that Chair commentary is associated with high quality reporting.

An important limitation of this study is that I do not examine differences in content across management and Chair commentary and I do not differentiate the resource provision function from the confirmation function. This will be addressed in the following chapter.

Table 3.1: Sample selection

	Observations	Firms
Annual Reports Sample	53,243	7,352
Before 2005	(4,091)	(179)
After 2019	(5,785)	(535)
Financial firms	(10,585)	(1,317)
Limited firms	(2,257)	(933)
Population of annual reports of non-financial firms between 2005 and 2019	30,525	4,388
Not downloaded annual reports	(525)	(57)
Unprocessed annual reports	(6,374)	(694)
Missing identifiers from Datastream	(3,452)	(933)
Missing Chair commentary	(2,973)	(203)
Missing management commentary	(4,103)	(413)
Multiple reports during the fiscal year	(268)	(12)
Merging with Datastream Data	(947)	(206)
Missing observations	(1,945)	(201)
Extraction errors	(334)	(13)
Trimming	(706)	(46)
Final Sample	8,898	1,610

Table 3.2: Descriptive statistics

Panel A								
Variable	N	Mean	SD	Min	p25	p50	p75	Max
<i>Chair Tone</i>	8,898	0.416	0.178	-0.286	0.300	0.424	0.538	1.000
<i>Management Tone</i>	8,898	0.302	0.164	-0.400	0.194	0.305	0.408	1.000
<i>Length Chair</i>	8,898	40.209	21.197	8	25	35.5	50	143
<i>N Words before NER Chair</i>	8,898	997.255	540.001	94	623	876	1,231	4,643
<i>N Words after NER Chair</i>	8,898	911.162	491.062	83	569	803	1,128	4,068
<i>N Words after NER & Stop Chair</i>	8,898	890.543	479.648	78	555	784	1,103	3,971
<i>Length Management</i>	8,898	148.954	104.224	4	72	127	202	561
<i>N Words before NER Management</i>	8,898	3,781.026	2709.522	35	1,762	3,204	5,099	17,876
<i>N Words after NER Management</i>	8,898	3,441.268	2461.704	28	1,604	2,927	4,648	15,827
<i>N Words after NER & Stop Management</i>	8,898	3,368.810	2408.919	27	1,565	2,865	4,548	15,570
<i>Forward-looking Chair</i>	8,898	0.241	0.095	0.000	0.176	0.234	0.300	0.800
<i>Forward-looking Management</i>	8,898	0.177	0.079	0.000	0.127	0.170	0.217	0.857
<i>Long-term Chair</i>	8,898	0.174	0.087	0.000	0.111	0.167	0.225	0.700
<i>Long-term Management</i>	8,898	0.132	0.069	0.000	0.088	0.125	0.167	0.800

Panel B

Variable	N	Mean	SD	Min	p25	p50	p75	Max
<i>EARN_{t+1}</i>	8,898	-0.015	0.212	-2.093	-0.048	0.042	0.080	0.465
<i>EARN_t</i>	8,898	0.005	0.168	-1.376	-0.033	0.046	0.083	0.456
<i>BTM</i>	8,898	0.725	0.510	0.000	0.366	0.621	0.957	4.016
<i>Leverage</i>	8,898	0.522	0.846	0.000	0.010	0.245	0.647	7.374
<i>Size</i>	8,898	933,855.500	2,640,887	1,330	27,010	118,330	601,890	29,500,000
<i>Loss</i>	8,898	0.309	0.462	0.000	0.000	0.000	1.000	1.000
<i>N Business Segments</i>	8,898	2.539	2	1	1	2	4	10
<i>N Geographic Segments</i>	8,898	2.692	2	1	1	2	4	10
<i>Returns</i>	8,898	0.056	0.471	-1.000	-0.247	0.012	0.295	2.308
<i>Change EARN_t</i>	8,120	-0.409	24.909	-2022.423	-0.669	-0.166	0.315	415.346
<i>Decline</i>	8,120	0.608	0.488	0	0	1	1	1
<i>Neg Returns</i>	8,898	0.469	0.499	0	0	0	1	1
<i>Analyst Following</i>	6,931	6.675	6.718	1	1	4	10	37
<i>High Analyst Following</i>	6,931	0.533	0.499	0	0	1	1	1

This table provides the descriptive statistics for all variables. Panel A includes linguistic features whereas Panel B includes firm characteristics. Variable definitions are as follows. *Chair Tone* and *Management Tone* measure the difference between the number of positive and negative sentences scaled by the total number of sentences in the Chair commentary and in aggregate management commentary, respectively. *Length Chair* and *Length Management* represent the total number of sentences in Chair commentary and in management commentary, respectively. *Forward-looking Chair* and *Forward-looking Management* represent the percentage of sentences including at least one forward-looking word in the Chair commentary and in the aggregate management commentary, respectively. *Long-term Chair* and *Long-term Management* represents the percentage of sentences including at least one long-term word in the Chair commentary and in aggregate management commentary, respectively. *EARN_{t+1}* (*EARN_t*) is one year ahead EPS (current EPS), respectively, from continuing operations excluding extraordinary items scaled by current (lagged) stock price in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *N Business Segments*. and *N Geographic Segments* are the logarithm of one plus the number business segments or geographic segments, respectively. *Loss* is a binary variable that takes the value one if current earnings are lower than zero and zero otherwise. *Change EARN_t* is computed as current earnings scaled by lag current earnings minus one. *Decline* is a binary variable that takes the value one if change in earnings is lower than zero. *Neg Returns* is a binary variable that takes the value one if the 12-month stock return ending four months after the fiscal year-end are lower than zero. *Analyst Following* is the number of analysts that follow the company. *High Analyst Following* is an indicator variable that takes the value one if the number of analysts covering the company in a given year is equal or exceeds the sample median number of analysts for that year and zero otherwise.

Table 3.3: Regressions of realized accounting and market performance on contemporaneous tone.
(Probability values reported in parentheses.)

	(1)	(2)	(3)
	Dependent variable: $EARN_t$		
<i>Chair Tone</i>	0.240 (0.01)		0.190 (0.01)
<i>Management Tone</i>		0.215 (0.01)	0.122 (0.01)
Constant	-0.095 (0.01)	-0.060 (0.01)	-0.111 (0.01)
Observations	8,898	8,898	8,898
Adjusted R-squared	0.065	0.044	0.077

The dependent variable in models 1 to 3 is $Earn_t$, measured as EPS from continuing operations excluding extraordinary items scaled by lagged stock price in fiscal year-end. *Chair Tone* and *Management Tone* measure the difference between the number of positive and negative sentences scaled by the total number of sentences in Chair commentary and in management commentary, respectively. Standard errors are clustered by firm.

Table 3.4: Regressions of one-period-ahead earnings on tone. (Probability values reported in parentheses.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: $EARN_{t+1}$							
<i>Chair Tone</i>		0.065 (0.01)	0.051 (0.01)	0.046 (0.01)		0.038 (0.01)	0.027 (0.04)	0.021 (0.12)
<i>Management Tone</i>	0.031 (0.02)	0.007 (0.62)	-0.006 (0.66)	-0.008 (0.54)	0.014 (0.26)	0.000 (0.97)	-0.010 (0.43)	-0.012 (0.36)
$EARN_t$	0.456 (0.01)	0.445 (0.01)	0.330 (0.01)	0.326 (0.01)	0.419 (0.01)	0.414 (0.01)	0.314 (0.01)	0.311 (0.01)
<i>BTM</i>	-0.054 (0.01)	-0.051 (0.01)	-0.053 (0.01)	-0.054 (0.01)	-0.044 (0.01)	-0.042 (0.01)	-0.044 (0.01)	-0.046 (0.01)
<i>Leverage</i>	-0.006 (0.09)	-0.006 (0.11)	-0.006 (0.11)	-0.006 (0.08)	-0.005 (0.20)	-0.004 (0.23)	-0.004 (0.21)	-0.005 (0.16)
<i>Log Size</i>	0.010 (0.01)	0.010 (0.01)	0.007 (0.01)	0.007 (0.01)	0.009 (0.01)	0.009 (0.01)	0.006 (0.01)	0.006 (0.01)
<i>Log Business Segments</i>	0.009 (0.08)	0.009 (0.10)	0.006 (0.27)	0.004 (0.39)	0.010 (0.05)	0.010 (0.05)	0.007 (0.16)	0.006 (0.24)
<i>Log Geographic Segments</i>	0.001 (0.92)	0.000 (0.95)	0.000 (0.94)	0.000 (0.96)	0.001 (0.78)	0.001 (0.80)	0.001 (0.80)	0.001 (0.82)
$Loss_t$			-0.074 (0.01)	-0.070 (0.01)			-0.066 (0.01)	-0.061 (0.01)
<i>Length Chair</i>				0.006 (0.17)				0.005 (0.25)
<i>Length Management</i>				0.000 (0.89)				0.001 (0.71)
<i>Forward-looking Chair</i>				-0.026 (0.22)				-0.019 (0.34)
<i>Forward-looking Management</i>				-0.051 (0.09)				-0.047 (0.12)
<i>Long-term Chair</i>				0.113 (0.01)				0.112 (0.01)
<i>Long-term Management</i>				0.072 (0.02)				0.068 (0.03)
<i>Returns</i>					0.076 (0.01)	0.074 (0.01)	0.070 (0.01)	0.069 (0.01)
Constant	-0.113 (0.01)	-0.132 (0.01)	-0.061 (0.01)	-0.091 (0.01)	-0.111 (0.01)	-0.122 (0.01)	-0.059 (0.01)	-0.089 (0.01)
Observations	8,898	8,898	8,898	8,898	8,898	8,898	8,898	8,898
Adjusted R-squared	0.242	0.244	0.256	0.258	0.264	0.265	0.274	0.277
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is $Earn_{t+1}$ measured as one year ahead EPS from continuing operations excluding extraordinary items scaled by current stock price in fiscal year-end. The independent variables are as follows. *Chair Tone* and *Management Tone* measure the difference between the number of positive and negative sentences scaled by the total number of sentences in Chair commentary and in management commentary, respectively. $Earn_t$ are EPS from continuing operations excluding extraordinary items scaled by lagged stock price of equity in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *Log Business Segments* and *Log Geographic Segments* are the logarithm of one plus the number business segments or geographic segments, respectively. *Loss* is a binary variable that takes the value one if current earnings are lower than zero and zero otherwise. *Length Chair* and *Length Management* represent the total number of sentences in Chair commentary and in management commentary, respectively. *Forward-looking Chair* and *Forward-looking Management* represent the percentage

of sentences including at least one forward-looking word in Chair commentary and in management commentary, respectively. *Long-term Chair* and *Long-term Management* represents the percentage of sentences including at least one long-term word in Chair commentary and in management commentary, respectively. Standard errors are clustered by firm.

Table 3.5: Regressions of one-period-ahead earnings on tone conditional on the sign of contemporaneous earnings. (Probability values reported in parentheses.)

	(1)	(2)	(3)	(4)
	Dependent variable: $EARN_{t+1}$			
	Partitioning on $EARN_t$:			
	Negative	Positive	Negative	Positive
<i>Chair Tone</i>	0.060 (0.08)	0.046 (0.01)	0.012 (0.73)	0.034 (0.01)
<i>Management Tone</i>	-0.022 (0.50)	0.004 (0.75)	-0.015 (0.63)	-0.001 (0.92)
$EARN_t$	0.283 (0.01)	0.381 (0.01)	0.296 (0.01)	0.304 (0.01)
<i>BTM</i>	-0.078 (0.01)	-0.036 (0.01)	-0.067 (0.01)	-0.028 (0.01)
<i>Leverage</i>	-0.015 (0.12)	-0.001 (0.68)	-0.011 (0.23)	-0.000 (0.88)
<i>Log Size</i>	0.022 (0.01)	0.003 (0.01)	0.017 (0.01)	0.004 (0.01)
<i>Log Business Segments</i>	0.013 (0.36)	0.000 (0.96)	0.021 (0.14)	0.000 (0.94)
<i>Log Geographic Segments</i>	0.018 (0.16)	-0.005 (0.29)	0.019 (0.14)	-0.004 (0.30)
<i>Returns</i>			0.105 (0.01)	0.043 (0.01)
Constant	-0.283 (0.01)	-0.001 (0.97)	-0.238 (0.01)	-0.011 (0.60)
Observations	2,747	6,151	2,747	6,151
Adjusted R-squared	0.135	0.075	0.165	0.089
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Model 1 and 3 [2 and 4] partitions the sample on negative [positive] $EARN_t$. $EARN_{t+1}$ is one-year-ahead EPS from continuing operations excluding extraordinary items scaled by current market price of equity in fiscal year-end. The independent variables are as follows. *Chair Tone* and *Management Tone* measure the difference between the number of positive and negative sentences scaled by the total number of sentences in in Chair commentary and in management commentary, respectively. $EARN_t$ are EPS from continuing operations excluding extraordinary items scaled by current market price of equity in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *Log Business Segments* and *Log Geographic Segments* are the logarithm of one plus the number business segments or geographic segments, respectively. Standard errors are clustered by firm.

Table 3.6: Logistic regressions for the determinants of Chair pessimism (Probability values in parentheses and average marginal effects in italics.)

	(1)	(2)
	Dependent variable: <i>Chair Pessimism</i>	
<i>Loss_t</i>	0.628 (0.01) <i>0.149</i>	0.377 (0.01) <i>0.089</i>
<i>Decline</i>	0.138 (0.01) <i>0.032</i>	0.144 (0.01) <i>0.033</i>
<i>Negative Returns</i>	0.472 (0.01) <i>0.112</i>	0.393 (0.01) <i>0.092</i>
<i>Change EARN</i>	-0.003 (0.21) <i>-0.001</i>	-0.002 (0.29) <i>-0.001</i>
<i>EARN_t</i>		-0.812 (0.01) <i>-0.188</i>
<i>BTM</i>		0.414 (0.01) <i>0.096</i>
<i>Log Size</i>		-0.000 (0.99) <i>0.000</i>
<i>Leverage</i>		0.038 (0.29) <i>0.009</i>
<i>Log Business Segments</i>		-0.029 (0.71) <i>-0.007</i>
<i>Log Geographic Segments</i>		-0.029 (0.69) <i>-0.007</i>
Constant	-0.318 (0.03)	-0.421 (0.13)
Observations	8,120	8,120
Year FE	Yes	Yes
Industry FE	Yes	Yes

The dependent variable is $\log(p / 1 - p)$ where p = the latent probability of unexpected positive tone in in the aggregate performance commentary's review. The variable is coded as a binary variable equal to one where residuals from an OLS regression of *Chair Tone* on *Management Tone* are negative, and zero otherwise. *Chair Tone* and *Management Tone* measure the difference between the number of positive and negative sentences scaled by the total number of sentences in Chair

Table 3.6: Logistic regressions for the determinants of Chair pessimism (Probability values in parentheses and average marginal effects in italics.)

commentary and in management commentary, respectively. *Loss* is a binary variable that takes the value one if current earnings are lower than zero and zero otherwise. *Decline* is a binary variable that takes the value one if change in earnings is lower than zero. *NegRet* is a binary variable that takes the value one if the 12-month stock return ending four months after the fiscal year-end are lower than zero. *Change EARN* is computed as current earnings scaled by lag current earnings minus one. *EARN* are the EPS from continuing operations excluding extraordinary items scaled by current market value of equity in fiscal year-end. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Size* is the logarithm of the market value of equity. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Log Business Segments* and *Log Geographic Segments* are the logarithm of one plus the number business segments or geographic segments, respectively. Standard errors are clustered by firm.

Table 3.7: Regression of one-year ahead earnings on tone conditional on Chair pessimism (Probability values reported in parentheses.)

	(1)	(2)	(3)	(4)
	$EARN_{t+1}$			
<i>Chair Tone</i>		0.059 (0.01)		0.034 (0.07)
<i>Management Tone</i>	0.028 (0.03)	-0.015 (0.39)	0.006 (0.67)	-0.019 (0.27)
<i>Chair Pessimism * Tone Management</i>	-0.025 (0.01)	0.010 (0.44)	-0.011 (0.22)	0.010 (0.45)
$EARN_t$	0.334 (0.01)	0.330 (0.01)	0.316 (0.01)	0.314 (0.01)
<i>BTM</i>	-0.054 (0.01)	-0.053 (0.01)	-0.045 (0.01)	-0.044 (0.01)
<i>Leverage</i>	-0.006 (0.10)	-0.006 (0.11)	-0.005 (0.20)	-0.004 (0.21)
<i>Log Size</i>	0.007 (0.01)	0.007 (0.01)	0.006 (0.01)	0.006 (0.01)
<i>Log Business Segments</i>	0.006 (0.26)	0.006 (0.27)	0.007 (0.15)	0.007 (0.16)
<i>Log Geographic Segments</i>	0.001 (0.92)	0.000 (0.94)	0.001 (0.79)	0.001 (0.80)
$Loss_t$	-0.076 (0.01)	-0.074 (0.01)	-0.066 (0.01)	-0.066 (0.01)
<i>Returns</i>			0.071 (0.01)	0.070 (0.01)
Constant	-0.045 (0.02)	-0.063 (0.01)	-0.051 (0.01)	-0.061 (0.01)
Observations	8,898	8,898	8,898	8,898
Adjusted R-squared	0.255	0.256	0.274	0.274
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

The dependent variable is and $Earn_{t+1}$ measured as one year ahead EPS from continuing operations excluding extraordinary items scaled by current market value of equity in fiscal year-end. The independent variables are as follows. *Chair Tone* and *Management Tone* measures the difference between the number of positive and negative sentences scaled by the total number of sentences in Chair commentary and in management commentary, respectively. *Earn* are EPS from continuing operations excluding extraordinary items scaled by current market value of equity in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *Log Business Segments* and *Log Geographic Segments* are the logarithm of one plus the number business segments or geographic segments, respectively. *Loss* is a binary variable that takes the value one if current earnings are lower than zero and zero otherwise. *Chair Pessimism* is a binary variable equal to one where residuals from an OLS regression of *Chair Tone* on *Management Tone* are negative, and zero otherwise. Standard errors are clustered by firm.

Table 3.8: General dominance statistics of regressing tone on contemporaneous and future earnings**Panel A**

	Full sample	
	Standardized Domin. Stat.	Ranking
EARN _{t+1}	0.339	2
EARN _t	0.662	1
Observations	8,898	
R-squared	0.076	

Panel B

	EARN _t < 0 (Loss)	
	Standardized Domin. Stat.	Ranking
EARN _{t+1}	0.294	2
EARN _t	0.707	1
Observations	2,747	
R-squared	0.034	

Panel C

	EARN _t > 0 (Profit)	
	Standardized Domin. Stat.	Ranking
EARN _{t+1}	0.988	1
EARN _t	0.012	2
Observations	6,151	
R-squared	0.008	

This table presents the results of running a dominance analysis procedure for the full sample, the subset of firms that report a loss and the subset of firms that report a profit. $EARN_t$, $EARN_{t+1}$ is one-year-ahead EPS from continuing operations excluding extraordinary items scaled by current market price of equity in fiscal year-end.

Table 3.9: Regressions of one-period-ahead earnings on tone conditional on the level of analyst following. (Probability values reported in parentheses.)

	(1)	(2)	(3)	(4)
	Dependent variable: $EARN_{t+1}$			
	Partitioning on <i>Analyst following</i>			
	High	Low	High	Low
<i>Chair Tone</i>	0.079 (0.01)	0.028 (0.21)	0.056 (0.01)	0.001 (0.97)
<i>Management Tone</i>	0.013 (0.54)	0.017 (0.47)	0.005 (0.82)	0.011 (0.64)
$EARN_t$	0.230 (0.01)	0.346 (0.01)	0.210 (0.01)	0.334 (0.01)
<i>BTM</i>	-0.056 (0.01)	-0.051 (0.01)	-0.045 (0.01)	-0.045 (0.01)
<i>Leverage</i>	-0.002 (0.53)	-0.005 (0.34)	-0.001 (0.80)	-0.003 (0.52)
<i>Log Size</i>	0.008 (0.01)	0.007 (0.02)	0.006 (0.01)	0.004 (0.16)
<i>Log Business Segments</i>	0.001 (0.93)	0.005 (0.56)	0.002 (0.72)	0.006 (0.48)
<i>Log Geographic Segments</i>	-0.008 (0.21)	0.012 (0.14)	-0.006 (0.32)	0.013 (0.12)
$Loss_t$	-0.061 (0.01)	-0.085 (0.01)	-0.057 (0.01)	-0.075 (0.01)
<i>Returns</i>			0.077 (0.01)	0.067 (0.01)
Constant	-0.052 (0.14)	-0.047 (0.28)	-0.057 (0.11)	-0.028 (0.52)
Observations	3,697	3,234	3,697	3,234
Adjusted R-squared	0.180	0.261	0.202	0.279
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Model 1 and 3 [2 and 4] partitions the sample on high [low] analyst following. $EARN_{t+1}$ is one-year-ahead EPS from continuing operations excluding extraordinary items scaled by current market price equity in fiscal year-end. The independent variables are as follows. *Chair Tone* and *Management Tone* measure the difference between the number of positive and negative sentences scaled by the total number of sentences in Chair commentary and in management commentary, respectively. $EARN_t$ are EPS from continuing operations excluding extraordinary items scaled by current market value of equity in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *Business Seg.* and *Geographic Seg.* are the logarithm of one plus the number business segments or geographic segments, respectively. Standard errors are clustered by firm.

Appendix 3.1: Variable definitions

<i>Variable</i>	<i>Definition</i>
<i>Chair Tone</i>	Difference between the number of positive and negative sentences scaled by the total number of sentences in the Chair's letter. A sentence is classified as positive (negative) if the number of positive (negative) words is larger than the number of negative (positive) words in the same sentence (Henry, 2008).
<i>Management Tone</i>	Difference between the number of positive and negative sentences scaled by the total number of sentences in the aggregate management commentary. A sentence is classified as positive (negative) if the number of positive (negative) words is larger than the number of negative (positive) words in the same sentence (Henry, 2008).
<i>Length Chair</i>	Total number of sentences in Chair commentary (Chair's letter).
<i>Length Management</i>	Total number of sentences in management commentary (aggregate management review).
<i>Forward-looking Chair</i>	Percentage of sentences including at least one forward-looking word. It is computed as the number of sentences including at least one forward-looking word scaled by the total number of sentences in the Chair's letter.
<i>Forward-looking Management</i>	Percentage of sentences including at least one forward-looking word. It is computed as the number of sentences including at least one forward-looking word scaled by the total number of sentences in the aggregate management commentary.
<i>Long-term Chair</i>	Percentage of sentences including at least one long-term word (Brochet et al 2015). It is computed as the number of sentences including at least one long-term word scaled by the total number of sentences in the Chair's letter.
<i>Long-term Management</i>	Percentage of sentences including at least one long-term word (Brochet et al 2015). It is computed as the number of sentences including at least one long-term word scaled by the total number of sentences in the aggregate management commentary.
<i>Earn_{t+1}</i>	One-year ahead EPS from continuing operations excluding extraordinary items (WC18208) scaled by current stock price in fiscal year-end (P).
<i>Earn_t</i>	EPS from continuing operations excluding extraordinary items (WC18208) scaled by lagged stock price in fiscal year-end (P).
<i>BTM</i>	Growth opportunities: book to market ratio (BV Equity (WC03995) + BV Debt (WC03255)) / (MV Equity (MV) + BV Debt).
<i>Leverage</i>	Leverage is the debt-to-equity ratio. Total debt (WC03255) scaled by total shareholders' equity (WC03995).
<i>Size</i>	Size is the logarithm of the market value of equity (in thousands) (MV).
<i>Returns</i>	Returns is the 12-month stock return ending four months after the fiscal year-end.
<i>Business segments</i>	Business Segments is the logarithm of one plus the number business segments.
<i>Geographic segments</i>	Geographic Segment is the logarithm of one plus the number geographic segments.
<i>Loss</i>	Indicator variable that takes the value one if <i>Earn_t</i> are lower than zero and zero otherwise.
<i>Change EARN</i>	Changes in earnings is computed as current earnings scaled by lag current earnings minus one.
<i>Decline</i>	Indicator variable that takes the value one if change in earnings is lower than zero.
<i>Negative Return</i>	Indicator variable that takes the value one if the 12-month stock return ending four months after the fiscal year-end are lower than zero.

Appendix 3.2: Regressions of one-period-ahead earnings on an alternative measure of tone.
(Probability values reported in parentheses.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: $EARN_{t+1}$							
<i>Chair Tone</i>		0.042 (0.01)	0.035 (0.01)	0.035 (0.01)		0.020 (0.07)	0.017 (0.14)	0.016 (0.16)
<i>Management Tone</i>	0.006 (0.49)		-0.011 (0.20)	-0.011 (0.19)	-0.003 (0.74)		-0.012 (0.14)	-0.012 (0.14)
$EARN_t$	0.458 (0.01)	0.450 (0.01)	0.332 (0.01)	0.328 (0.01)	0.420 (0.01)	0.416 (0.01)	0.315 (0.01)	0.311 (0.01)
<i>BTM</i>	-0.056 (0.01)	-0.052 (0.01)	-0.053 (0.01)	-0.054 (0.01)	-0.045 (0.01)	-0.043 (0.01)	-0.045 (0.01)	-0.046 (0.01)
<i>Leverage</i>	-0.007 (0.08)	-0.006 (0.10)	-0.006 (0.10)	-0.006 (0.07)	-0.005 (0.18)	-0.005 (0.21)	-0.005 (0.19)	-0.005 (0.16)
<i>Log Size</i>	0.010 (0.01)	0.010 (0.01)	0.007 (0.01)	0.007 (0.01)	0.009 (0.01)	0.009 (0.01)	0.006 (0.01)	0.006 (0.01)
<i>Log Business Segments</i>	0.009 (0.09)	0.009 (0.09)	0.006 (0.27)	0.004 (0.39)	0.010 (0.05)	0.010 (0.05)	0.007 (0.16)	0.006 (0.25)
<i>Log Geographic Segments</i>	0.001 (0.90)	0.001 (0.88)	0.001 (0.91)	0.000 (0.94)	0.001 (0.80)	0.001 (0.78)	0.001 (0.81)	0.001 (0.84)
$Loss_t$			-0.075 (0.01)	-0.070 (0.01)			-0.066 (0.01)	-0.061 (0.01)
<i>Length Chair</i>				0.005 (0.26)				0.004 (0.31)
<i>Length Management</i>				0.000 (1.00)				0.001 (0.82)
<i>Forward-looking Chair</i>				-0.023 (0.27)				-0.018 (0.38)
<i>Forward-looking Management</i>				-0.053 (0.08)				-0.048 (0.11)
<i>Long-term Chair</i>				0.122 (0.01)				0.116 (0.01)
<i>Long-term Management</i>				0.075 (0.02)				0.070 (0.02)
<i>Returns</i>					0.077 (0.01)	0.075 (0.01)	0.070 (0.01)	0.069 (0.01)
Constant	-0.106 (0.01)	-0.136 (0.01)	-0.061 (0.01)	-0.092 (0.01)	-0.104 (0.01)	-0.121 (0.01)	-0.055 (0.01)	-0.087 (0.01)
Observations	8,881	8,881	8,881	8,881	8,881	8,881	8,881	8,881
Adjusted R-squared	0.241	0.243	0.255	0.258	0.264	0.265	0.274	0.277
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is $Earn_{t+1}$ measured as one year ahead EPS from continuing operations excluding extraordinary items scaled by current stock price in fiscal year-end. The independent variables are as follows. *Chair Tone* and *Management Tone* measure the difference between the number of positive and negative sentences scaled by sum of positive and negative sentences in Chair commentary and in management commentary, respectively. A sentence is classified as positive (negative) if the number of positive (negative) words is larger than the number of negative (positive) words in the same sentence (Henry, 2008). $Earn_t$ are EPS from continuing operations excluding extraordinary items scaled by current stock price of equity in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity

*Appendix 3.2: Regressions of one-period-ahead earnings on an alternative measure of tone.
(Probability values reported in parentheses.)*

ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *Business Seg.* and *Geographic Seg* are the logarithm of one plus the number business segments or geographic segments, respectively. *Loss* is a binary variable that takes the value one if current earnings are lower than zero and zero otherwise. *Length Chair* and *Length Management* represent the total number of sentences in Chair commentary and in management commentary, respectively. *Forward-looking Chair* and *Forward-looking Management* represent the percentage of sentences including at least one forward-looking word in Chair commentary and in management commentary, respectively. *Long-term Chair* and *Long-term Management* represents the percentage of sentences including at least one long-term word in Chair commentary and in management commentary, respectively. Standard errors are clustered by firm.

Appendix 3.3: Regressions of one-period-ahead earnings on tone using the word list by García et al. (2023) (Probability values reported in parentheses.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: $EARN_{t+1}$							
<i>Chair Tone</i>		0.061 (0.01)	0.036 (0.01)	0.032 (0.01)		0.036 (0.01)	0.016 (0.09)	0.011 (0.25)
<i>Management Tone</i>	0.057 (0.01)		0.021 (0.05)	0.018 (0.11)	0.039 (0.01)		0.016 (0.14)	0.013 (0.23)
$EARN_t$	0.446 (0.01)	0.439 (0.01)	0.328 (0.01)	0.325 (0.01)	0.412 (0.01)	0.410 (0.01)	0.313 (0.01)	0.310 (0.01)
<i>BTM</i>	-0.053 (0.01)	-0.052 (0.01)	-0.052 (0.01)	-0.054 (0.01)	-0.043 (0.01)	-0.042 (0.01)	-0.043 (0.01)	-0.045 (0.01)
<i>Leverage</i>	-0.006 (0.11)	-0.006 (0.12)	-0.005 (0.13)	-0.006 (0.09)	-0.004 (0.24)	-0.004 (0.24)	-0.004 (0.24)	-0.005 (0.18)
<i>Log Size</i>	0.010 (0.01)	0.009 (0.01)	0.006 (0.01)	0.006 (0.01)	0.009 (0.01)	0.008 (0.01)	0.006 (0.01)	0.006 (0.01)
<i>Log Business Segments</i>	0.009 (0.10)	0.009 (0.10)	0.006 (0.28)	0.004 (0.41)	0.010 (0.06)	0.010 (0.05)	0.007 (0.16)	0.006 (0.26)
<i>Log Geographic Segments</i>	-0.000 (0.94)	0.000 (0.97)	-0.000 (0.99)	-0.000 (0.97)	0.001 (0.88)	0.001 (0.82)	0.001 (0.85)	0.001 (0.88)
$Loss_t$			-0.071 (0.01)	-0.067 (0.01)			-0.063 (0.01)	-0.059 (0.01)
<i>Length Chair</i>				0.007 (0.11)				0.006 (0.20)
<i>Length Management</i>				0.001 (0.58)				0.002 (0.45)
<i>Forward-looking Chair</i>				-0.014 (0.50)				-0.014 (0.49)
<i>Forward-looking Management</i>				-0.047 (0.12)				-0.046 (0.12)
<i>Long-term Chair</i>				0.112 (0.01)				0.112 (0.01)
<i>Long-term Management</i>				0.068 (0.03)				0.063 (0.04)
<i>Returns</i>					0.075 (0.01)	0.073 (0.01)	0.069 (0.01)	0.069 (0.01)
Constant	-0.103 (0.01)	-0.103 (0.01)	-0.045 (0.02)	-0.086 (0.01)	-0.106 (0.01)	-0.106 (0.01)	-0.054 (0.01)	-0.091 (0.01)
Observations	8,898	8,898	8,898	8,898	8,898	8,898	8,898	8,898
Adjusted R-squared	0.243	0.245	0.256	0.259	0.265	0.266	0.274	0.277
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is $EARN_{t+1}$ measured as one year ahead EPS from continuing operations excluding extraordinary items scaled by current stock price in fiscal year-end. The independent variables are as follows. *Chair Tone* and *Management Tone* measure the difference between the number of positive and negative sentences scaled by the total number of sentences in Chair commentary and in management commentary, respectively. A sentence is classified as positive (negative) if the number of positive (negative) words is larger than the number of negative (positive) words in the same sentence (García et al., 2023). $EARN_t$ are EPS from continuing operations excluding extraordinary items scaled by current stock price of equity in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *Business Seg.* and *Geographic Seg.* are the logarithm of one plus the number business segments or geographic segments, respectively. *Loss* is a binary variable that takes the value one if current earnings are lower than zero and zero otherwise. *Length Chair* and *Length Management*

Appendix 3.3: Regressions of one-period-ahead earnings on tone using the word list by García et al. (2023) (Probability values reported in parentheses.)

represent the total number of sentences in Chair commentary and in management commentary, respectively. *Forward-looking Chair* and *Forward-looking Management* represent the percentage of sentences including at least one forward-looking word in Chair commentary and in management commentary, respectively. *Long-term Chair* and *Long-term Management* represents the percentage of sentences including at least one long-term word in Chair commentary and in management commentary, respectively. Standard errors are clustered by firm.

Appendix 3.4: Regressions of one-period-ahead earnings on tone using an alternative proxy of management commentary. (Probability values reported in parentheses.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: $EARN_{t+1}$							
<i>Chair Tone</i>		0.070 (0.01)	0.051 (0.01)	0.047 (0.01)		0.042 (0.01)	0.030 (0.06)	0.026 (0.12)
<i>CEO Review Tone</i>	0.054 (0.01)		0.020 (0.26)	0.016 (0.37)	0.032 (0.06)		0.009 (0.61)	0.007 (0.72)
$EARN_t$	0.450 (0.01)	0.443 (0.01)	0.332 (0.01)	0.326 (0.01)	0.414 (0.01)	0.410 (0.01)	0.317 (0.01)	0.312 (0.01)
<i>BTM</i>	-0.057 (0.01)	-0.054 (0.01)	-0.055 (0.01)	-0.055 (0.01)	-0.046 (0.01)	-0.044 (0.01)	-0.046 (0.01)	-0.047 (0.01)
<i>Leverage</i>	-0.004 (0.38)	-0.003 (0.46)	-0.003 (0.50)	-0.003 (0.44)	-0.003 (0.48)	-0.003 (0.53)	-0.002 (0.56)	-0.003 (0.50)
<i>Log Size</i>	0.011 (0.01)	0.011 (0.01)	0.009 (0.01)	0.008 (0.01)	0.010 (0.01)	0.011 (0.01)	0.008 (0.01)	0.008 (0.01)
<i>Log Business Segments</i>	0.010 (0.10)	0.010 (0.10)	0.008 (0.18)	0.007 (0.28)	0.011 (0.07)	0.011 (0.07)	0.009 (0.12)	0.008 (0.20)
<i>Log Geographic Segments</i>	-0.006 (0.33)	-0.005 (0.37)	-0.005 (0.38)	-0.005 (0.38)	-0.005 (0.35)	-0.005 (0.38)	-0.005 (0.39)	-0.005 (0.39)
$Loss_t$			-0.067 (0.01)	-0.063 (0.01)			-0.058 (0.01)	-0.054 (0.01)
<i>Length Chair</i>				0.008 (0.19)				0.008 (0.19)
<i>Length CEO Review</i>				0.001 (0.90)				0.001 (0.86)
<i>Forward-looking Chair</i>				-0.016 (0.56)				-0.012 (0.66)
<i>Forward-looking CEO Review</i>				-0.063 (0.05)				-0.056 (0.08)
<i>Long-term Chair</i>				0.108 (0.01)				0.102 (0.01)
<i>Long-term CEO Review</i>				0.068 (0.08)				0.058 (0.12)
Returns					0.074 (0.01)	0.073 (0.01)	0.068 (0.01)	0.067 (0.01)
Constant	-0.133 (0.01)	-0.152 (0.01)	-0.095 (0.01)	-0.129 (0.01)	-0.131 (0.01)	-0.143 (0.01)	-0.093 (0.01)	-0.127 (0.01)
Observations	5,212	5,212	5,212	5,212	5,212	5,212	5,212	5,212
Adjusted R-squared	0.245	0.247	0.257	0.260	0.267	0.268	0.275	0.278
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is $Earn_{t+1}$ measured as one year ahead EPS from continuing operations excluding extraordinary items scaled by current stock price in fiscal year-end. The independent variables are as follows. *Chair Tone* and *CEO Review Tone* measure the difference between the number of positive and negative sentences scaled by sum of positive and negative sentences in Chair commentary and in the CEO Review commentary, respectively. A sentence is classified as positive (negative) if the number of positive (negative) words is larger than the number of negative (positive) words in the same sentence (Henry, 2008). $Earn_t$ are EPS from continuing operations excluding extraordinary items scaled by current stock price of equity in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *Business Seg.* and *Geographic Seg.* are the logarithm of one plus the number business segments or geographic segments, respectively. *Loss* is a binary variable that takes the value one if current earnings are lower than zero and zero otherwise. *Length Chair* and *Length*

Appendix 3.4: Regressions of one-period-ahead earnings on tone using an alternative proxy of management commentary. (Probability values reported in parentheses.)

Management represent the total number of sentences in the Chair's letter and in the CEO Review commentary, respectively. *Forward-looking Chair* and *Forward-looking CEO Review* represent the percentage of sentences including at least one forward-looking word in the Chair's letter and in the CEO Review commentary, respectively. *Long-term Chair* and *Long-term CEO Review* represents the percentage of sentences including at least one long-term word in the Chair's letter and in the CEO Review, respectively. Standard errors are clustered by firm.

Appendix 3.5: Regressions of one-period-ahead earnings with an alternative structure of fixed effects. (Probability values reported in parentheses.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: $EARN_{t+1}$							
<i>Chair Tone</i>		0.048 (0.01)	0.039 (0.01)	0.036 (0.01)		0.028 (0.01)	0.022 (0.04)	0.019 (0.08)
<i>Management Tone</i>	0.032 (0.02)		0.011 (0.43)	0.009 (0.55)	0.018 (0.20)		0.005 (0.72)	0.003 (0.84)
$EARN_t$	0.169 (0.01)	0.161 (0.01)	0.126 (0.01)	0.125 (0.01)	0.151 (0.01)	0.147 (0.01)	0.117 (0.01)	0.117 (0.01)
<i>BTM</i>	-0.128 (0.01)	-0.126 (0.01)	-0.125 (0.01)	-0.125 (0.01)	-0.115 (0.01)	-0.114 (0.01)	-0.114 (0.01)	-0.114 (0.01)
<i>Leverage</i>	-0.003 (0.58)	-0.003 (0.63)	-0.002 (0.72)	-0.002 (0.72)	-0.002 (0.71)	-0.002 (0.73)	-0.001 (0.81)	-0.001 (0.81)
<i>Log Size</i>	-0.010 (0.15)	-0.011 (0.11)	-0.012 (0.08)	-0.012 (0.10)	-0.009 (0.18)	-0.010 (0.15)	-0.011 (0.12)	-0.010 (0.14)
<i>Log Business Segments</i>	-0.011 (0.26)	-0.011 (0.25)	-0.011 (0.24)	-0.011 (0.24)	-0.008 (0.36)	-0.008 (0.36)	-0.009 (0.34)	-0.009 (0.34)
<i>Log Geographic Segments</i>	-0.012 (0.19)	-0.012 (0.22)	-0.011 (0.24)	-0.010 (0.30)	-0.010 (0.29)	-0.010 (0.31)	-0.009 (0.33)	-0.008 (0.40)
$Loss_t$			-0.028 (0.01)	-0.027 (0.01)			-0.024 (0.02)	-0.023 (0.02)
<i>Length Chair</i>				-0.006 (0.31)				-0.006 (0.31)
<i>Length Management</i>				-0.001 (0.84)				-0.000 (0.90)
<i>Forward-looking Chair</i>				-0.001 (0.96)				-0.002 (0.95)
<i>Forward-looking Management</i>				0.037 (0.29)				0.035 (0.32)
<i>Long-term Chair</i>				0.029 (0.31)				0.036 (0.20)
<i>Long-term Management</i>				0.096 (0.01)				0.090 (0.02)
<i>Returns</i>					0.053 (0.01)	0.051 (0.01)	0.050 (0.01)	0.050 (0.01)
Constant	0.221 (0.01)	0.224 (0.01)	0.247 (0.01)	0.242 (0.01)	0.195 (0.02)	0.198 (0.02)	0.217 (0.01)	0.211 (0.02)
Observations	8,593	8,593	8,593	8,593	8,593	8,593	8,593	8,593
Adjusted R-squared	0.348	0.349	0.351	0.351	0.359	0.360	0.360	0.361
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is $Earn_{t+1}$ measured as one year ahead EPS from continuing operations excluding extraordinary items scaled by current stock price in fiscal year-end. The independent variables are as follows. *Chair Tone* and *Management Tone* measure the difference between the number of positive and negative sentences scaled by the total number of sentences in Chair commentary and in management commentary, respectively. A sentence is classified as positive (negative) if the number of positive (negative) words is larger than the number of negative (positive) words in the same sentence (Henry, 2008). $Earn_t$ are EPS from continuing operations excluding extraordinary items scaled by current stock price of equity in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *Business Seg.* and *Geographic Seg.* are the logarithm of one plus the number business segments or geographic segments, respectively. *Loss* is a binary variable

*Appendix 3.5: Regressions of one-period-ahead earnings with an alternative structure of fixed effects.
(Probability values reported in parentheses.)*

that takes the value one if current earnings are lower than zero and zero otherwise. *Length Chair* and *Length Management* represent the total number of sentences in Chair commentary and in management commentary, respectively. *Forward-looking Chair* and *Forward-looking Management* represent the percentage of sentences including at least one forward-looking word in Chair commentary and in management commentary, respectively. *Long-term Chair* and *Long-term Management* represents the percentage of sentences including at least one long-term word in the Chair's letter and in the management commentary, respectively. Standard errors are clustered by firm.

4 Thematic Content of Performance Commentary: A Topic Modeling

Approach

4.1 Introduction

In the previous chapter, I conclude that the presence of an independent board Chair affects the informativeness of performance commentary and creates a communication benefit for investors. Specifically, results show that Chair commentary carries incremental predictive ability for future earnings beyond management commentary. Cross-sectional analyses reveal that the board Chair serves a monitoring role. Consistent with predictions from agency theory, I find that the monitoring role of the Chair manifests performance commentary tone in the letter to shareholders that moderates managerial optimism when management have incentives to engage in obfuscation and impression management. I also provide evidence that the monitoring role of the board Chair leads to a difference in tone commentary that is conditional on the sign of realized earnings. Specifically, Chair tone correlates closely with realized earnings in periods when reported performance is weak (negative earnings), consistent with the board Chair performing a monitoring role as part of their stewardship function.

Findings also provide modest and inconclusive evidence consistent with the board Chair having an information role that arises from serving two non-mutually exclusive functions: a confirmation function (as predicted by legitimacy theory) and a resource provision function (as predicted by resource dependency theory). Specifically, I show that the incremental predictive ability of Chair commentary for future earnings is largely due to profitable firms (positive earnings) and those operating in an environment with high information demand by analysts. Tests conducted so far, however, do not provide a reliable means of distinguishing between the confirmation and the resource provision explanations.

My goal in this chapter is therefore to test the veracity of the resource provision and confirmation explanations more directly by examining the content of Chair and management commentary, and variation therein. I do this by examining whether the incremental predictive ability of Chair commentary is explained by content that is exclusive to the board Chair or by content that features in both Chair and management commentary.

Under legitimacy theory, the board Chair reinforce management disclosures by reiterating similar content, thereby confirming (aspects of) management information and establishing its credibility. In this case, the incremental predictive ability of Chair commentary for future earnings should be explained by content overlap between Chair and management commentary. Alternatively, under resource dependency theory, an independent board Chair leverages intangible resources such as expertise and experience, which should be reflected in the disclosure of themes that are distinct from those disclosed by management. In this case, the incremental predictive ability of Chair commentary for future earnings should be explained by content that is exclusively disclosed by the board Chair and not mentioned by the management team. In this respect, I theorize that the presence of content that is exclusive to Chair commentary aligns more closely with the resource provision explanation for incremental predictive ability, whereas the incidence of overlapping content aligns more closely with the confirmation explanation.

I examine variation in content disclosed by Chair and management commentary by modeling topics using Latent Dirichlet Allocation (LDA) (Blei et al, 2003) on a corpus of annual reports. I follow the approach by Gad et al. (2025) and identify the optimal LDA model by implementing a grid search over a restricted set of model parameters. In this respect, I estimate models with 25, 35, and 50 topics trained on two alternative specifications of input data; one with unigrams only (e.g., ‘monitoring’, ‘corporate’ and ‘governance’) and another with a combination of unigrams and bigrams (e.g., ‘monitoring’ and ‘corporate

governance’). Overall, I compare a total of twelve LDA models using five alternative evaluation metrics. The best LDA model includes 50 topics, is trained using the Gensim learning algorithm, and is optimized using a combination of unigrams and bigrams (designated as *50_Gensim_Bigrams* or 50-topic model). Throughout the paper, I compare the results produced by this model with a broader and more naïve representation of the topic space based on a model estimated with 25 topics and unigrams only (designated as *25_Gensim_Unigrams* or 25-topic model).

To examine variations across the content of Chair and management commentary, I start by comparing the number of topics discussed in each narrative. I therefore follow Huang et al. (2018) and assign topics to sentences based on the probability of each word in the sentence belonging to a particular topic. The topic with the highest probability score for a sentence is then assigned to that sentence. In line with Huang et al. (2018), I define topic intensity for Chair and management commentary as the percentage of sentences assigned to a topic scaled by the total number of sentences in the respective report section. Results from the 50-topic LDA model show that the average Chair’s letter discusses eighteen topics whereas the average management commentary mentions thirty-one topics. A similar pattern is apparent when I use the more aggregate 25-topic LDA model. This result is consistent with descriptive evidence from Chapter 3 showing that management commentary is substantially longer than Chair commentary, and with the view that the Chair’s letter provides a summary and overview of key information discussed in the annual report (Clatworthy and Jones, 2006). The fact that management commentary is longer and therefore discusses more topics than Chair commentary is also consistent with more onerous regulation governing the content of management commentary. Specifically, the content management commentary is prescribed in large part by UK Company Law through the (extensive) provisions of the Strategic Report.

Nevertheless, comparing counts of topic coverage provides only suggestive evidence on potential content overlap between Chair and management commentary.

To examine the relative importance of each topic across the two report sections, I rank topics based on their intensity and then compare the ranking position of each topic across the two performance commentary sections. Results produced using topics from both LDA models show consistent evidence that Chair commentary places substantial importance on governance- and leadership-related topics, whereas these themes feature less prominently in management commentary. Conversely, management appears to place more importance on topics related to financial management and performance. These patterns are consistent with an ICSA (2015) report that describes the content of UK annual reports. Collectively, these findings provide a level of validation that my topic modelling and labelling strategies generate plausible insights.⁴²

Next, I examine the degree of topic overlap by analyzing the incidence of topics that feature in both management and Chair commentary. My goal with this analysis is to determine the extent to which Chair topics represent a subset of the topics mentioned by management versus topics that are exclusive to Chair commentary. Results using the 25- and 50-topic models report consistent evidence that at least 70% (75%) of the topics mentioned in the average (median) Chair's letter duplicate themes that are also discussed by management. I interpret this result as preliminary evidence that the information role of the Chair likely arises at least in part from their confirmation function.

My final set of tests examines the degree to which the incremental predictive ability of Chair commentary for future earnings correlates with topics that are shared with management commentary versus the subset of topics exclusive to Chair discourse. To

⁴² The outcome of an LDA model is a combination of topics and the respective top n keywords that are correlated with each topic. This means that topics must be labeled by researchers. I leverage ChatGPT to create topic labels due to its ability to identify more complete and informative labels than human coders, particularly as the number of topics increases and the labeling task becomes increasingly complex (Gad et al., 2025).

investigate this question, I decompose the tone of Chair commentary into two components: the tone of common topics and the tone of distinctive topics. Using the 25-topic model, results suggest that the incremental predictive ability of Chair commentary for future earnings is entirely attributable to the tone of common topics, thereby indicating the confirmatory role of the Chair's letter. To gauge the economic significance of this effect, I compare the impact of an interquartile change in the tone of common topics on future earnings to the effect of contemporaneous earnings which research shows to be a strong predictor of future earnings (Frankel and Litov, 2009; Li, 2008). Results show that the tone of common topics accounts for 23% of the predictive effect of current earnings, which I deem as being economically significant.

Results using the 50-topic model provide subtly different insights. Here, the tone of common topics accounts for 19% of the predictive effect of contemporaneous earnings on future earnings, which confirms the confirmation function.⁴³ Meanwhile, the tone of exclusive topics accounts for 20% of the predictive effect of contemporaneous earnings and therefore the findings also support the resource provision view. Results from the more granular topic representation therefore suggest that the tone of common topics and exclusive topics are equally important in predicting future earnings, consistent with incremental informativeness arising from both a confirmation and a resource provision function.

The difference in the conclusions for alternative LDA models is explained by differences in the granularity of content captured by each model. Defining topics at a more aggregate level combines multiple (related) subthemes into a single topic, which tilts the balance towards observing confirmation because themes that are informative for future earnings are more likely to be aggregated into topics that overlap. All else equal, using a

⁴³ The decrease from 23% in the 25-topic model to 19% in the 50-topic model is expected, as greater topic granularity reduces the proportion of topics identified as common between Chair and management commentary.

higher degree of aggregation therefore provides a powerful test of confirmation (low Type I error likelihood), but at the risk of generating undercooked topics that obscure more subtle content differences that may contribute to informativeness via resource provision (higher Type II error likelihood). Defining topics at a more granular level teases subthemes apart and therefore increases the chances of observing exclusive Chair commentary that represents resource provision and contributes to predictive ability. A more granular topic model therefore provides a relatively strong test of resource provision (low Type I error likelihood), but at risk of creating topics that are overcooked and lack appropriate economic interpretation. I find evidence of confirmation using both topic models and therefore I interpret my findings as providing strong support for this explanation of the predictive ability of Chair commentary. In contrast, evidence supporting resource provision is limited to tests using the more granular topic model. I therefore interpret this evidence as providing suggestive rather than conclusive support for the view that the incremental predictive ability of Chair commentary is a consequence of the additional resources that the board Chair brings to the performance reporting function.

This chapter contributes to the literature examining the role of an independent board Chair by exploring how the information role of the board Chair affects the informativeness of Chair commentary. This issue is important for two reasons. First, the literature to date has concentrated mainly on the monitoring role of the board Chair. I show how the board Chair also serves an information role in corporate reporting. My research approach involves comparing the content of performance commentary authored by the management team and the board Chair in the same report. Second, while the literature argues that the board Chair is expected to support management, it is an empirical challenge to observe how the Chair performs this function. I show that the Chair certifies management commentary by calling attention to a subset of themes appearing in their discussion and analysis. I also provide

evidence suggesting the Chair brings additional insight to the performance reporting function through their expertise, experience, and wider network. My research therefore answers the call from governance and management scholars such as Banerjee et al. (2020), Boivie et al. (2021) and Krause et al. (2016) for a more complete understanding of the governance role of the independent board Chair.

My work also contributes to the literature studying the informativeness of corporate disclosure in two ways. First, I model topics to analyze the content of annual report disclosures. This means that I focus on understanding the *content* of performance commentary (i.e., the themes management discuss) whereas prior research often focuses on *how* firms present performance content (e.g., tone, uncertainty, forward-looking orientation, causality) (Bochkay et al., 2023). Content is the fundamental source of information in corporate disclosures; while linguistic features such as tone and length are conditional on content, the informativeness of content is less dependent on surface-level linguistic features. Second, with the exception of Huang et al. (2018), most accounting studies that analyze topics do not model topic sentiment explicitly, thereby effectively assuming that management discuss different themes in a similar manner. I extend extant research by conditioning the informativeness of annual report content on tone and then testing how content, tone and informativeness vary across report sections conditional on author expertise and reporting incentives. As such, my analysis speaks directly to the call by Loughran and McDonald (2016) to better understand the content of corporate disclosure as opposed to exclusively focusing on linguistic features of narrative disclosures.

4.2 Background and predictions

4.2.1 Informativeness of narrative disclosure

Research examining the informativeness of narrative disclosures has mostly relied on examining the effect of surface-level properties of corporate disclosure such as tone (Arslan-Ayaydin et al., 2016; Arslan-Ayaydin et al., 2021; Davis et al., 2015; Henry, 2008, 2006; Henry and Leone, 2016; X. Huang et al., 2014; Loughran and McDonald, 2011), forward-looking orientation (Bozanic et al., 2018; Hassanein et al., 2019; Hassanein and Hussainey, 2015), readability (Bonsall and Miller, 2017; Chakrabarty et al., 2018; Li, 2008; Loughran and McDonald, 2014) and specificity (Cazier et al., 2021). While it is undoubtedly important to understand *how* firms discuss themes disclosed through their various reporting channels, this focus critically ignores *what* firms choose to discuss.

Two factors help to explain the prominence of linguistic features in research employing automated methods to extract information from corporate disclosure. First, these features are often constructed using bag-of-word (BOW) approaches that rely on pre-existent word lists, which makes them easy to implement and replicate (El-Haj et al., 2019). Second, they require less computing power and fewer advanced coding skills when compared to more sophisticated methods, such as Large Language Models (Lewis and Young, 2019).⁴⁴

Ease of implementation was critical in the period before textual analysis methodologies had gained mainstream adoption in the accounting and finance literature. Importantly, linguistic features such as tone, uncertainty, disclosure length and forward-looking orientation are closely linked to the themes conveyed in corporate disclosures. While tone is contingent on the underlying theme being discussed, content is less dependent on tone. In this respect, an exclusive focus on tone and similar linguistic features overlooks the more

⁴⁴ Given that researchers increasingly make their code publicly available and AI technologies such as ChatGPT often support these tasks, computing power and coding skills are less of a problem today than they were when textual analyses methodologies started being used in accounting and finance research.

primitive role of content in determining disclosure informativeness. For example, although disclosure length is a linguistic feature employed to analyze the ability of narrative disclosure to predict future performance, it remains an open question which fundamental theme(s) interact with length to determine overall disclosure informativeness. Dyer et al. (2017) examine trends in 10-K filings content and find that changes in regulatory requirements from FASB and SEC are responsible for a substantial increase in filing length. Notably, while the paper identifies 150 different themes, the observed increase in disclosure length is attributed to just three themes: fair value, internal controls, and risk. This result has at least two implications for research. First, when analyzing features such as tone or length over extended sample periods, researchers risk overlooking both the thematic focus of corporate disclosures and the relative importance assigned to different themes over time. Second, most studies do not model tone conditional on content thereby implicitly assuming that firms discuss different themes in a similar manner and that sentiment remains constant. However, the same way the level of positivity or negativity may vary within different sections of a text [e.g., introduction versus conclusion (Boudt and Thewissen, 2019)], the way in which firms describe regulated themes such as performance commentary versus discretionary themes is likely to differ. Recent research has started to devote increasing attention to thematic content, using topic modeling analysis to uncover the themes that management discuss (Bochkay et al., 2023; Loughran and McDonald, 2016).

Topic modeling is the process used to uncover topics in a corpus that are unknown in advance. In accounting and finance research, topic modeling has been used to (a) identify trends in accounting and finance research by examining the content of academic studies (Aziz et al., 2022; Federsel et al., 2024) and to (b) extract the thematic content from 10-Ks for the purpose of predicting financial misreporting (Brown et al., 2020b), investigating whether firms respond to investors' information needs (Lui et al., 2025) and explaining trends in

corporate disclosure (Dyer et al., 2017). While different algorithms are available for modelling topics, LDA is the most commonly used method in accounting and finance research (Aziz et al., 2022; Bochkay et al., 2023; Brown et al., 2020b; Dyer et al., 2017; Gad et al., 2025; Huang et al., 2018; Lui et al., 2025).

Similar to Dyer et al. (2017) that analyze the content of 10-Ks, Brown et al. (2020b) also focus on 10-K filings and study the incremental predictive power of content to detect financial misreporting. They find that misreporting firms tend to discuss topics related to risk factors less than non-misreporting firms. Further analysis reveals that incorporating information on disclosure content improves detection rates. In a more recent paper, Lui et al. (2025) rely on topic modeling to study the themes that individual and institutional investors discuss and test whether firms incorporate investors' information needs. The paper finds that firms address several firm-related topics that were previously raised by investors and therefore concludes that firms respond to investors' information needs, particularly those of institutional investors. Huang et al. (2018) test whether analysts, as information intermediaries, have a discovery role or an interpretation role by comparing the content of analyst reports with that of conference calls. The authors posit that if analysts discuss new topics in their reports that are not mentioned in conference calls, then their role is more consistent with discovery. Conversely, if analysts discuss topics that also feature in conference calls, then their role is more likely to reflect interpretation. While the evidence supports both roles, the discovery role appears to be especially valued by investors. My work complements Huang et al. (2018) by modelling variation in the content of distinct performance commentaries authored by the board Chair and senior management *in the same report* and then using a measure of this variation to assess if the incremental predictiveness of Chair commentary for one-period-ahead earnings reflects their confirmation function versus their resource provision function.

4.2.2 Confirmation and resource provision functions, and prediction development

Ex-ante, it is unclear how the information role of the board Chair reflects the content discussed in their commentary. On the one hand, several arguments support the view that the incremental predictive ability of Chair commentary could be explained by the selection and synthesis of content similar to that appearing in management commentary. Evidence that the Chair's letter provides a summary of performance and highlights during the reporting period (Clatworthy and Jones, 2006) suggests that, rather than addressing new content, Chair commentary reflects the same topics that management discuss in their performance commentary. From a theoretical standpoint, legitimacy theory argues that the board Chair to may contribute to legitimacy gains for the firm by confirming management-authored disclosures. I posit that the confirmation function involves the Chair filtering and affirming themes discussed by management. I therefore predict that if the confirmation function contributes to the information role of Chair commentary, then I should observe significant overlap between the content of Chair commentary and management commentary, and that the predictive ability of Chair commentary should reflect these common topics.

Arguments also exist to support the view that the incremental predictive ability of Chair commentary can be explained by content that is exclusive to Chair-authored commentary. All else equal, differences in role responsibilities between the board Chair and management coupled with variation in expertise, experience and corporate networks may result in Chair commentary discussing themes that differ from, or extend, those that management cover. This potential difference in focus is particularly relevant considering that it is the Chair's responsibility to report to shareholders under the UK Corporate Governance Code, while management must comply with disclosure requirements under the Companies Act 2006 (Strategic Report and Directors' Report) Regulations 2013. Resource dependency

theory (RDT) argues that one of the primary roles of the board, and by extension the board Chair, is to provide resources for the firm (Hillman and Dalziel, 2003). There are direct and indirect channels through which the board Chair may provide resources. A direct link between the Chair and resource provision can result from the independent board Chair providing intangible resources such as knowledge, skills, and expertise gained through previous roles and professional experience (Krause et al., 2016). These intangible resources may be reflected in performance insight that involves topics that are not covered by management. A less direct link between the Chair and resource provision may occur where the Chair's letter provides a reporting benefit for investors via its incremental informativeness, and the increased transparency resulting from this commentary has a positive impact on firm reputation and its available resources (Ntim et al., 2013). All else equal, I posit that Chair-specific intangible resources and incremental transparency benefits for shareholders are more likely to correlate with content that is exclusive to the Chair's letter as opposed to content that merely rebroadcasts the same themes that management discuss in their commentary. I therefore conjecture that if the information role of the Chair arises from the resource provision function, then Chair commentary will include distinctive topics that are not part of management commentary, and the incremental predictive power of such commentary will correlate with these distinctive topics.

4.3 Research design and sample

4.3.1 Research design

In Chapter 3 I show that the tone of Chair commentary carries incremental predictive ability for future earnings beyond the tone of management. I also provide evidence that the Chair's monitoring role accounts for part of this effect, but that their information role provides a more plausible explanation for profitable firms. Preliminary evidence regarding

their information role nevertheless fails to distinguish between the confirmation and resource provision explanations. To help understand the extent to which the information role of the board Chair derives from a confirmation function versus a resource provision function, I proceed by decomposing the tone of Chair commentary into tone of common topics and tone of new (exclusive) topics. I then regress one-year-ahead earnings on Chair tone of common topics and Chair tone of new topics, while controlling for the tone of management commentary. If the incremental predictive ability of Chair commentary for future earnings loads for the tone of common topics, then I conclude the information role of the board Chair arises, at least in part, from the confirmation function. Similarly, if the incremental predictive ability of Chair commentary for future earnings loads for the tone of new topics, then I conclude that the information role of the Chair arises at least partly from the resource provision function. The relative strength of each function is an empirical question to which my results will speak. The remainder of this section presents the data and explains the approach to modelling and comparing topics.

4.3.2 Sample, corpus and pre-processing steps

The sample used in the previous chapter serves as a basis for the analysis. (The sample selection process is presented in Table 3.1.) However, the sample for subsequent tests varies with the regression specification. I conduct a topic modeling analysis using a corpus of 8,898 annual reports published by 1,610 LSE-traded firms with fiscal year ends between 2005 and 2019.

A key step in topic modeling involves preprocessing of the corpus (Gad et al., 2025; Hickman et al., 2022). Annual report text is extracted using the tool developed by El-Haj et al. (2020). As a preprocessing step, before modeling topics, I lowercase the text and remove any special characters (e.g., percentage and currencies) and numbers. I also remove stop words identified by Gad et al. (2025). Very frequent words do not carry substantial semantic

content and should therefore be removed. Rare words may be too specific and therefore associated with a small subset of documents. In this respect, I follow prior literature and remove words that appear in less than 5% of documents and in more than 50% of the documents (Brown et al., 2023; Gad et al., 2025). The data is tokenized using the Spacy library in python.

4.3.3 Topic modeling

4.3.3.1 Model selection and LDA hyperparameters

I model topics using Latent Dirichlet Allocation (LDA), which is a Bayesian probabilistic model proposed by Blei et al. (2003). Since topics are not known in advance, LDA is an unsupervised method. The intuition behind LDA is to approach document construction in the same way that an author approaches it. A human writer selects the themes (topics) that will be included in a text (document) and then selects the words that best reflect each chosen topic. The LDA algorithm follows a similar logic. It formalizes this process by assuming that all documents are a combination of topics, and that all topics are a combination of words. In this respect, each document is represented by a probabilistic distribution of topics (document-topic distribution – parameter α) and each topic is represented by a probabilistic distribution of words (topic-word distribution – parameter β). LDA then computes a probability that each word belongs to a certain topic. Both the distribution of topics per document and the distribution of words are drawn from the Dirichlet prior, which means the resulting probabilities are normalized and sum up to one (Jelodar et al., 2019).

A key (unknown) parameter is the optimal number of topics that should be modeled. For topic interpretability, there is a tradeoff between selecting a small number of topics versus selecting a large number. On the one hand, selecting too few topics may cause different themes to be pooled into aggregate (and potentially too broad) topics that are overly general

and lack meaningful discriminatory power. Such topics are often referred to as being ‘undercooked’. On the other hand, selecting too many topics can generate topics that are excessively granular, difficult to interpret, and highly overlapping with each other, therefore reducing their distinctiveness. Such topics are often referred to as being ‘overcooked’. The choice of the number of topics should therefore be motivated and conditioned by the research question (Gad et al., 2025). Nonetheless, in the absence of a clear reason and argument for choosing a specific number of topics the use of different levels of topic granularity is particularly relevant.

A set of different evaluation metrics has been proposed in the literature to determine the optimal number of topics and hence the best performing LDA model. These metrics include coherence score, diversity score, perplexity score, granularity score, and word intrusion test (Brown et al., 2020b; Dyer et al., 2017; Gad et al., 2025; Huang et al., 2018; Lui et al., 2025). The coherence score evaluates the interpretability of a model by measuring the level of similarity of words within a topic. The perplexity score measures a model’s predictive accuracy by evaluating its ability to predict word choice in unseen documents. The diversity score is the proportion of unique words in each topic; the higher the diversity score, the higher the proportion of topics that do not share common words in the top n words of the topic. The granularity score measures the specificity level of a topic by indicating if topic keywords are included in fewer documents. In this respect, a higher granularity score implies that topics are more specific. A word intrusion test (WIT) measures a model’s accuracy by testing the ability of a evaluator to identify an intruder (unconnected) word from a list of words linked to a topic. Higher rates of intruder identification indicate topics that are more coherent and interpretable (recognizable).

Prior work in accounting and finance uses coherence and perplexity scores to identify the optimal number of topics (Brown et al., 2024; Lui et al., 2025). A common approach is to

plot the two scores for different numbers of topics holding all remaining LDA parameters constant. The optimal number of topics is then identified by choosing the value with the highest coherence score and lowest perplexity score. A small subset of papers also employ a word intrusion test as an additional check on interpretability (Brown et al., 2020b; Dyer et al., 2017; Lui et al., 2025). Gad et al., (2025) propose complementing coherence and perplexity with diversity and granularity scores. Considering conclusions from a combination of evaluation metrics as opposed to focusing on one or only a small subset is that certain evaluation metrics favor models with specific characteristics. For example, all else equal, a model that has a lower number of topics typically reports a higher diversity score than a model with a higher number of topics. This is because a larger number of topics should be associated with a lower proportion of unique words as these must be distributed across a wider range of topics. Accordingly, using a narrow set of evaluation metrics to select the number of LDA topics can tilt the result towards selecting an aggregate or granular topic representation of the topic space depending on the specific metric(s) used, even when there is no reason, a priori, to favor one representation over the other. Using a comprehensive set of metrics and allowing for multiple ‘best’ topic structures helps to limit researcher bias while also demonstrating robustness to alternative views of the topic space.

To identify optimal LDA model(s), I conduct a grid search across a variety of hyperparameter combinations. As it is not feasible to compare all possible combinations of hyperparameters, I follow Gad et al. (2025) by specifying a core set of hyperparameters, and then for each of these hyperparameter I specify a discrete number of plausible options. I define the number of topics as 25, 35, or 50, keep the default values of α and β (auto option), and set the inference algorithm to either Mallet and Gensim.⁴⁵ The input data to train the

⁴⁵ Gensim implements a variational Bayes algorithm whereas Mallet uses an optimized Gibbs sampling algorithm.

models includes either unigrams or a combination of unigrams and bigrams.⁴⁶ In this respect, I compare a total of twelve models across five different evaluation metrics.

Table 4.1 shows performance metrics of the different LDA models. Panel A ranks the models according to each performance metric, whereas Panel B reports the value of each metric. Results in Panel A highlight two key conclusions. First, no model ranks as best across all evaluation metrics. Second, comparing models based on their inference algorithm shows that, apart from the perplexity score, models trained using the Gensim algorithm consistently rank higher. Both conclusions are consistent with results reported by Gad et al. (2025). The best performing model overall is the version that includes 50 topics, is computed using a combination of unigrams and bigrams, and is trained using the Gensim learning algorithm (model *50_Gensim_Bigrams*). Nevertheless, this model only ranks first when ordered according to the granularity and coherence scores and second using WIT accuracy.

Throughout the subsequent analyses, I assess the robustness of conclusions to the choice of topic model by comparing results using the 50-topic model with the results using the most parsimonious version of this model, i.e., model *25_Gensim_Unigrams*. This simpler version models 25 topics with input data comprising unigrams only.⁴⁷ Panel A of Table 4.1 shows that the 25-topic model does not rank first in any evaluation.⁴⁸ However, Panel B reveals that the diversity score is higher for the 25-topic model than the 50-topic model. This is consistent with the expectation that the diversity score favor models with a lower topic granularity. Panel B shows that while 87.2% of topics of the 25-topic model have unique

⁴⁶ Bigrams are a combination of two unigrams that jointly represent a meaningful expression (e.g., ‘strategic report’, ‘corporate governance’).

⁴⁷ From herein forth I will refer to the model *50_Gensim_Bigrams* as the best performing model or the 50-topic model and will refer to the *25_Gensim_Unigrams* as the 25-topic model.

⁴⁸ Among the low-granularity models comprising 25 topics, Panel A from Table 4.1 shows that the *25_Gensim_Unigrams* model reports superior performance over all Mallet-based models with the same number of topics, as shown by coherence and diversity scores, as well as WIT accuracy. In addition, the evaluation metrics of *25_Gensim_Unigrams* are closely aligned with those of the *25_Gensim_Bigrams* model as shown in Panel B. For example, the coherence score of the *25_Gensim_Unigrams* and *25_Gensim_Bigrams* is 0.594 and 0.609, respectively. In terms of WIT accuracy, the two models report a difference of 12 percentage points with *25_Gensim_Unigrams* clearly outperforming *25_Gensim_Bigrams*.

words in the top ten words of each topic, this percentage is 79.8% for the 50-topic model. Still, for the remaining metrics, Panel A and B show that the 50-topic model always ranks higher than the 25-topic model.

4.3.3.2 Topic labelling

A key feature of topic modeling is the LDA algorithm does not generate topic labels. Instead, labeling is a separate, subjective process that involves interpreting and understanding the correlation and meaning of the words included in each topic. Labeling is often a manual task conducted by researchers. Nonetheless, Gad et al. (2025) show that using OpenAI for topic labeling can generate labels that are richer and informative, and in some cases more so, than labels assigned researchers manually. Algorithmic labeling becomes particularly important as the number of modeled topics increases and manual labeling becomes more complex and less plausible. I therefore follow Gad et al. (2025) and use a sequential prompt engineering strategy designed to produce a reliable and refined prompt to label outputs my two LDA models.

Specifically, I follow prompt engineering guidelines as described by Xiao and Zhu (2025) and Gad et al. (2025). In this respect, my prompt includes an example of the outcome I want to generate with the labeling task. This involves providing a topic and its respective top ten keywords and assigning a label as an example of the output of the task that the prompt is being asked to replicate. I also adopt a problem decomposition strategy where the main labeling task is split into several smaller tasks that are explained in bullet points. This is expected to enhance performance of the overall task and ensure that each label is generated using a similar train of thought. Last, I adopt a referencing approach by providing information about the context of the task and by describing the corpus of annual reports. Specifically, I describe the content of the Chair's Letter by following the ICSA (2015) report

on the content of UK annual reports, plus evidence from Clatworthy and Jones (2006) concluding that the Chair's Letter is often a summary of the annual report and the performance highlights. I also explain the overall goal and respective content of the Strategic Report to help define the themes that I expect to occur in management commentary. In this respect, I follow FRC guidance on the strategic report (FRC, 2014), risk and viability reporting (FRC, 2017) and business model reporting (FRC, 2016). Appendix 4.1 provides details of the sequential prompts used to generate the labels.

Table 4.2 reports topics produced using the *25_Gensim_Unigrams* (Panel A) and best performing model *50_Gensim_Bigrams* (Panel B), along with the labels and rationale produced by ChatGPT4o and the top ten keywords per topic. Besides the difference in the number of topics generated by each model, a key difference between the results is the incidence of bigrams. Panel B reveals that 50% of topics include at least one bigram in the top ten keywords per topic. Example bigrams include 'corporate governance', 'exceptional items', 'foreign exchange', 'general meeting', 'health safety', 'net debt', 'pretax profit', 'risk management', 'share capital', and 'strategic report'. Results highlight the potential importance of bigrams for word sense disambiguation and topic interpretation in my corpus of UK annual reports.

4.3.3.3 Topic visualization

To visualize the importance of different topics at the corpus level and the relationship between topics, I present inter-topic distance maps using the python library PyLDAvis. Figure 4-1 shows the inter-distance topic maps of the model *25_Gensim_Unigrams* (Panel A) and the model *50-Gensim_Unigrams* (Panel B). Each circle represents a topic. Larger circles, indicate topics that are more prevalent in the corpus. Topic similarity is measured by the distance between the center of any two circles. In this respect, well separated and distributed

circles provide evidence that different topics capture distinct themes. Conversely, circles displaying substantial overlap indicate that the corresponding topics may be capturing a similar underlying construct and as such the topics are not distinct.

Panel A does not highlight dramatic variation in the size of different circles, suggesting an overall similar prevalence of different topics in the corpus. The most prevalent topic based on circle size is Topic 2: *Energy and Natural Resource Extraction*. The level of similarity across topics appears to be low as topics are well distributed and display no overlap. Results suggest that the 25_*Gensim*_Unigrams model generates topics that capture distinct themes. Only two topics show a slight overlap with each other. These are Topic 16: *Sustainable Leadership in Governance and Investment Returns*, and Topic 24: *Restructuring and Innovation in Business Operations*. These two topics share governance as one of their top ten words.

Panel B presents the inter-topic distance map of the topics produced by the 50-topic model. The spread and relative importance of topics displays a similar pattern to Panel A. Topics are well distributed despite some minor overlap between a small subset of topics. The most prevalent topic seems to be Topic 7: *Oil and Gas Exploration* as it presents one of the largest circle. Similarly, Topic 36: *Resource Extraction and Mineral Exploration* also shows a large circle. Interestingly, these two topics generate the top ten words of Topic 1: *Energy and Natural Resource Extraction* for the 25-topic model, suggesting that these topics are subsets of Topic 1 in the lower topic granularity model. Panel B shows that three themes in the 50-topic model display some overlap with each other. These are Topic 4: *Pension Scheme Management and Financial Structuring*, Topic 45: *Restructuring and disposal financial strategies*, and Topic 48: *IFRS compliance and financial adjustments*. The term net debt is one of the top ten keywords for all three topics.

Despite differences in evaluation metrics, topic visualization suggests that both the low granularity 25-topic model and the higher granularity 50-topic model produce topics that are distinctive and capture different themes. This highlights the importance of complementing visualization with other metrics to determine appropriate topic representations of the performance commentary corpus.

4.3.4 Key variables

The section describes how the variables that support my analysis are defined and constructed. Descriptive evidence for each of the variables is discussed in the subsequent section (4.3.5).

4.3.4.1 Topic intensity

In this subsection, I explain how I measure the intensity of each topic, how I identify the topics that are mentioned in the Chair and management commentary and how I identify those that are exclusively discussed in each annual report section.

4.3.4.1.1 Intensity of individual topics

To better understand the content discussed by management and the board Chair in their respective performance commentaries, I compute a measure of intensity for each topic using a sentence-level classification approach. I assign topics to sentences based on the probability that a word in a sentence belongs to a given topic. The topic with the highest probability score for a sentence is then assigned to that sentence. I follow Huang et al. (2018) by counting the number of sentences that are assigned to a given topic for each annual report section, and then I scale by the total number of sentences in the respective annual report

section. I rank topics based on their average level of intensity to assess the relative importance of each topic for management and Chair commentary,.

4.3.4.1.2 Intensity of common topics and new topics

I create three indicator variables to identify topics discussed by both the board Chair and the management teams (common topics) in the same report, topics that are exclusive to Chair commentary, and topics that are exclusive to management team commentary. I treat topics that are exclusive to management or Chair commentary as being ‘new’ to the discussion and analysis of performance.

D Common Topic N takes the value of one if topic N is discussed by both the board Chair and management in a given annual report, and zero otherwise (N = 1 to 25 or 50 depending on the LDA model). The mean value of *D Common Topic N* indicates the percentage of annual reports where topic N appears in both management and Chair performance commentary. I sum the number of common topics for each annual report to create the variable *N Common Topics*. This variable measures the total number of common topics per report. I also create the variables *% Common Topics Chair*, which is the number of common topics scaled by the total number of topics in Chair commentary, and *% Common Topics Management*, which is the number of common topics scaled by the total number of topics in management commentary. *% Common Topics Chair (% Common Topics Management)* indicates the proportion of topics discussed by the board Chair (management team) that are also mentioned by the management team (board Chair).

I define new topics as those discussed exclusively by either the board Chair or the management team in the same report. To understand the intensity of those topics, I create the indicator variables *D New Topic N Chair* and *D New Topic N Management* (where N = 1 to 25 or 50 depending on the LDA model). *D New Topic N Chair (D New Topic N Management)*

takes the value of one if topic N is discussed only in Chair commentary (management commentary) and zero otherwise. The mean level of *D New Topic N Chair* (*D New Topic N Management*) indicates the percentage of annual reports where topic N is discussed exclusively in Chair commentary (management commentary). I also create the variables % *New Topics Chair*, which is the number of new topics scaled by the total number of topics in Chair commentary, and % *Common Topics Management*, which is the number of new topics scaled by the total number of topics in management commentary. % *Common Topics Chair* (% *Common Topics Management*) indicates the proportion of topics exclusively discussed by the board Chair (management team).

4.3.4.2 Tone of common topics and tone of new topics

I show in Chapter 3 that the tone of Chair commentary carries incremental predictive ability for future earnings beyond management commentary. To test whether the information role of the board Chair derives from a confirmation function or a resource provision function, I decompose the tone of Chair commentary into *Chair Tone Common Topics* and *Chair Tone New Topics*.

Chair Tone Common Topics is defined as the difference between the number of positive sentences and the number of negative sentences discussing common topics in the Chair commentary, scaled by the total number of sentences discussing common topics in that same section. Similarly, *Chair Tone New Topics* is defined as the difference between the number of positive sentences and the number of negative sentences discussing new topics in the Chair commentary, scaled by the total number of sentences discussing new topics in that same section.

4.3.5 Descriptive evidence

Table 4.2 presents topic labels, the rationale for the label as produced by ChatGPT4o, and the top ten keywords of each topic in the case of the 25-topic model (Panel A) and the 50-topic model (Panel B). Topics produced using both LDA models reflect a combination of themes that are industry-specific and topics that reflect more general business matters and may be common across different industries. For example, in Panel A, while Topic 2: *Energy and Natural Resource Extraction* and Topic 22: *Clinical Healthcare Innovation and Pipeline Development* are industry-specific, Topic 4: *IFRS Financial Governance and Reporting Metrics*, Topic 6: *Pension Scheme Financial Management* and Topic 15: *Financial Health Measures and Currency Effects* are financially oriented topics that likely apply to most sectors. Panel B reveals that the 50-topic model a subset of topics similar to those produced by the 25-topic model in terms of words per topic and topic rationale. For example, Topic 22: *Clinical Healthcare Innovation and Pipeline Development* for the 25-topic model in Panel A is similar to Topic 6: *Clinical Trials and Regulatory Approval* for the 50-topic model in Panel B.

Table 4.3 summarizes the ranking of intensity per topic as discussed by Chair and management commentary. Panel A shows the ranking of topics produced by model *25_Gensim_Unigrams* and Panel B shows the ranking of the topic produced by model *50_Gensim_Bigrams*. The intensity of each topic refers to the percentage of sentences discussing a given topic within an annual report section, as defined in section 4.3.4.1.1. This ranking is based on the mean levels of intensity for each topic. Comparing the ranking positions of the same topic for management and Chair commentary *in the same annual report* allows me to understand if the topics uncovered by my LDA models are consistent with the expected content of UK annual reports.

For simplicity, I focus on the topics that rank in the first five positions of performance commentary section. Panel A from Table 4.3 shows that Topic 11: *Board Committees and Remuneration Governance* ranks first in Chair commentary. Similarly, Panel B shows that Topic 27: *Compliance in Corporate Governance Practices* is the most discussed topic by the board Chair. Conversely, these topics rank eleventh and twenty-seventh, respectively, in management commentary. A similar pattern is evident for Topic 25: *Strategic Partnerships and Vision Alignment* in Panel A and Topic 20: *Cultural Transformation and Leadership in Innovation* in Panel B. These topics rank second and fourth, respectively, in Chair commentary, whereas they rank 13th and 34th, respectively in management commentary. This evidence is consistent with the view that the board Chair places more emphasis on governance-, strategy-, and leadership-related topics compared with management (ICSA, 2015). Furthermore, evidence that governance-related themes rank high in Chair commentary using both LDA models suggests that the models detect similar topic-word correlations.

Both panels show one topic ranking in the same position in Chair and management commentary. This is Topic 7: *Digital Marketing and Media Strategies* in Panel A (fifth position) and Topic 46: *Client-Centric Software* in Panel B (third position). Further, I also topics that rank in the first five ranking positions in both sections. For example, Topic 2: *Energy and Natural Resource Extraction* from Panel A ranks first for the management commentary and fourth for board Chair commentary, while Topic 7: *Oil and Gas Exploration* in Panel B ranks first in management commentary and second in Chair commentary. Results suggests that the board Chair and management team place similar importance on these themes. This result likely reflects the industry specific nature of these topics.

Next, I focus on topics that rank high for management but not for the Chair. Panel A shows that topics 6: *Pension Scheme Financial Management* and 15: *Financial Health Measures and Currency Effects* are the third and fourth most discussed topics by

management. Such topics reflect a strong focus on financial metrics. Similarly, Panel B shows that Topic 2: *Financial Performance Metrics Adjustments* ranks fifth. This is consistent with management commentary emphasizing financial results and asset usage. Results may also reflect the contribution of the CFO to the performance narrative, as the Strategic Report guidance includes a financial review by the CFO (Amel-Zadeh et al., 2019; ICSA, 2015). Notably, none of these topics are among the top ten topics most discussed by the board Chair. This descriptive evidence in Table 4.4 provides preliminary evidence that Chair and management performance commentary place similar importance on some, but not all, topics.

Table 4.4 reports descriptive statistics for the variables defined in Section 4.3.4 for each LDA model. Both models lead to the same conclusion: the number of topics discussed by the board Chair is lower than topic coverage discussed by management in their commentary. Using results for *25_Gensim_Unigrams* (*50_Gensim_Bigrams*), the average Chair letter discusses fourteen (eighteen) topics whereas the average management review covers nineteen (thirty-one) topics. A t-test confirms that the difference in means for *Chair N Topics* and *Management N Topics* is statistically significant.

Descriptive evidence from the 25-topic model reveals that the Chair's letter and management commentary discuss eleven common topics in the typical annual report. On average, 84% of the total number of topics discussed by the board Chair are also discussed by management. This number is even higher for the median annual report where almost 92% of the topics discussed by the board Chair are also feature in the corresponding management commentary section of the same report (see variable *% Common Topics Chair*). Furthermore, approximately 35% of all Chair letters in my sample only discuss topics that are also feature management commentary. In these cases, Chair commentary does not include any new (exclusive) topics.

Repeating the analysis for the 50-topic model, results reveal that the proportion of Chair letters that only mention topics featuring in management commentary drops to approximately 7%. This reduction highlights differences in the level of topic granularity across models and hence the choice of LDA model. Nevertheless, results for the 50-topic representation still reveal a high degree of overlap between Chair and management commentary, with 73% of topics discussed by the board Chair are also featuring in management commentary (see % *Common Topics Chair*) for the average report. The overall distribution of this variable suggests that substantial content overlap between Chair and management commentary is the norm, with 75% of annual reports containing a Chair's letter where at least 61.5% of the topics overlap with those discussed by management. (See 25th percentile of % *Common Topics Chair*.). Additionally, 50% of all reports include a Chair's letter where nearly 78% of the topics discussed by the Chair also feature in management commentary. (See 50th percentile of % *Common Topics Chair*.) Results suggest that, regardless of topic granularity of the LDA model, there is a substantial degree of content alignment between Chair and management commentary in the typical UK annual report. This conclusion provides preliminary evidence that the information role of the Chair arises from its confirmation function.

Additional descriptive evidence from topics generated by both LDA models shows that board Chair commentary is generally more positive than commentary by management. For example, an analysis of the topics generated by *50_Gensim_Bigrams* shows that, on average, 42% of the Chair's sentences relating to common topics are positive in tone (see variable *Chair Tone Common Topics*) compared with 32% in management commentary (*Management Tone Common Topics*). A t-test confirms that the difference in means is statistically significant. This evidence is consistent with the descriptive statistics from

Chapter 3 showing that Chair commentary overall is more positive than management commentary on average.

I provide examples of common topics and new topics in Table 4.5 and Table 4.6, respectively. Table 4.5 tabulates the mean of *D Common Topic N* for Chair and management commentary, where Panel A refers to the topics produced using *25_Gensim_Unigrams* and Panel B refers to those produced using *50_Gensim_Bigrams*. I focus on results in Panel B to simplify the discussion as the conclusions are similar for both panels. The five most common topics mentioned in both Chair and management commentary are Topic 20: *Cultural Transformation and Leadership in Innovation*, Topic 27: *Compliance in corporate governance practices*, Topic 32: *Real estate development and space planning*, Topic 33: *Corporate governance and strategic reporting* and Topic 40: *Customer Base Management and Growth Strategies*. These five topics appear in both sections in more than 38% of the annual reports. Topics 27 and 33 are governance-related and are discussed in both management and Chair commentary in 55% and 42%, of the annual reports, respectively. While governance-related topics are associated with intensity and occupy a high ranking position in the Chair commentary section, management also reference these themes but with a low intensity. Evidence that often management refer to these themes is unsurprising given the requirements of the Strategic Report. Topics 32 and 40 more likely reflect industry characteristics that form the basis of most aspects of annual commentary for firms operating in these sectors.

Table 4.6 presents means of *D New Topic N* for Chair and management commentary, where Panel A shows the topics produced using *25_Gensim_Unigrams* and Panel B shows the topics produced using *50_Gensim_Bigrams*. For parsimony I again focus on Panel B and on the first five topics with the highest means. Results reveal that Topic 1 *Sports Club Performance and Management*, Topic 27: *Compliance in corporate governance practices*,

Topic 28: *Strategic Decision-Making and Profitability*, Topic 41: *Employee and Team Recognition*, and Topic 44: *Project-focused strategic partnerships* tend to be more and exclusively discussed by the Chair. Each of these topics report a mean higher than 18%, which implies that they are mentioned exclusively by the board Chair in almost a fifth of annual reports. By comparison, topics exclusive to management commentary include Topic 8: *Commodity Pricing and Risk Management*, Topic 16: *Financial adjustments compliance measures*, Topic 23: *Management of financial liabilities and compliance* and Topic 34: *Technology Systems and Operational Testing*, and Topic 49: *Real estate portfolio financial management*. Three out of these five topics are related to financial matters, thereby reinforcing the importance of this theme for management discussion and analysis. These topics appear in more than 44% of management performance commentaries, indicating they are discussed exclusively by management in almost half the reports in my sample.

4.4 Results

My main test involves decomposing tone of Chair commentary into tone of common topics and tone of new topics and then testing whether the incremental ability of Chair commentary to predict future earnings is explained by the discussion of common or new topics. I operationalize this analysis using the following model:

$$\begin{aligned}
 EARN_{t+1} = & \beta_0 + \beta_1 \text{Chair Tone Common Topics}_{it} \\
 & + \beta_2 \text{Chair Tone New Topics}_{it} + \sum_{k=1}^K \text{Controls}_{it} + \varepsilon_{it}
 \end{aligned} \tag{4.1}$$

where $Earn_{it+1}$ is one-year-ahead earnings from continuous operations scaled by market value at fiscal-year end. *Chair Tone Common Topics* is the difference between the number of positive sentences and the number of negative sentences in the Chair commentary discussing common topics, scaled by the total number of sentences discussing common topics. *Chair*

Tone New Topics is the difference between the number of positive sentences and the number of negative sentences discussing new (exclusive) topics in the Chair commentary, scaled by the total number of sentences discussing new topics in that same section. *Controls* refers to a set of variables from prior research that are known to predict earnings, including management tone, contemporaneous earnings, book-to-market, leverage, 12-month stock return, number of business segments, number of geographic segments, and an indicator variable for earnings losses. I also include industry and year fixed effects.

Results are presented in Table 4.7. Panel A shows the results of estimating Equation (4.1) using the topics generated by *25_Gensim_Unigrams*, whereas Panel B presents results of estimating Equation (4.1) using topics generated by *50_Gensim_Bigrams*. Models 1-3 do not include stock return as a control variable, whereas returns are included in models 4-6. I exclude *Chair Tone New Topics* in model 1 and *Chair Tone Common Topics* in model 2. I model 3 includes both test variables. If the incremental predictive ability of Chair commentary for future earnings loads for *Chair Tone Common Topics*, I infer that the information role of the board Chair arises in part from the confirmation function. Conversely, if this predictability loads for *Chair Tone New Topics*, I infer that the Chair's information role arises in part from the resource provision function.

Results from model 1 in Panel A show that *Chair Tone Common Topics* reports a positive and significant coefficient ($p=0.01$), suggesting that the predictability of Chair commentary is explained by the discussion of content that is also covered by management. To gauge the economic significance of the tone of common topics discussed by the Chair, I compare the effect of *Chair Tone Common Topics* with the effect for $EARN_t$, which research shows to be an economically important predictor of next period earnings. I find that the effect

of *Chair Tone Common Topics* is approximately 23% of the effect of current earnings, which I interpret as being economically substantive.⁴⁹

Results for model 2 show that *Chair Tone New Topics* is marginally significant ($p = 0.1$). Importantly, the sample used in this regression is a reduced version of the full sample as the variable *Chair Tone New Topics* is missing for approximately 35% of our sample where the Chair's letter does not discuss any new topics. Nevertheless, a test on the difference in coefficients confirms that the difference between the coefficient *Chair Tone Common Topics* in model 1 and *Chair Tone New Topics* in model 2 is statistically significant, consistent with the information role of the Chair arising from a confirmation function as predicted by legitimacy theory. Results from models 4-5, where I control for stock returns, show that tone measures are not statistically significant. I interpret this as evidence that content discussed by the board Chair and management is already incorporated into stock prices.

Panel B yields slightly different conclusions from Panel A. Results from models 1 and 2 show that both *Chair Tone Common Topics* and *Chair Tone New Topics* load positively, suggesting that both topic categories carry incremental predictive ability for future earnings. In model 3 where the two variables are included together, both load continue to load positively with coefficient estimates of 0.029 ($p=0.02$) and 0.018 ($p<0.01$), respectively. I compare each variable's economic significance with realized earnings using coefficients reported in model 3. The economic significance of *Chair Tone Common Topics* is approximately 19% of the effect of current earnings, whereas *Chair Tone New Topics* is approximately 20% of the same effect. The difference in economic significance is therefore marginal. These results indicate that the incremental predictive ability of Chair commentary is equally explained by common topics and new topics, suggesting that the information role

⁴⁹ This is calculated as the economic significance of *Chair Tone Common Topics* scaled by that of $EARN_t$. Economic significance is calculated by subtracting percentile 25 from percentile 75 and then multiplying this by the coefficient estimate. For example, the economic significance of *Chair Tone Common Topics* is as follows: $(0.5454-0.300) \times 0.036 = 0.0088$.

of the board Chair arises from a combination of confirmation function and resource provision function.

Results from models 4-6 show that inclusion of stock returns absorbs the effect of *Chair Tone Common Topics*, suggesting once again that this content is already known to the market. Nonetheless, results from models 5 and 6 show that *Chair Tone New Topics* continues to load positively even after controlling for returns. The finding provides further support for the view that the subset of topics discussed exclusively by the Chair carry important and relevant insights for future performance beyond both management commentary and information priced by market participants at the annual report release date.

The difference in results and conclusions for the analyses reported in Panels A and B is a direct consequence of the variation of topic granularity. Increasing the number of topics from 25 to 50 allows me to observe content on a more granular level. Importantly, though, I find evidence consistent with the confirmation explanation using both levels of topic granularity. I interpret this as consistent and strong evidence that the information role of the Chair is explained by its confirmation function. Conversely, evidence of the resource provision of the board Chair is limited to one level of topic granularity. In this respect, I interpret this as modest evidence supporting the resource provision function of the information role of the Chair.

4.5 Conclusion

In this chapter, I conduct an empirical exercise where I model topics to examine variation in the content of Chair and management commentary. This allows me to test whether the information role of the board Chair arises from serving a confirmation function or a resource provision function, or if it is consistent with both. I argue that the Chair's letter may serve as a legitimacy tool by confirming management information, which involves

discussing the same themes as management does. I therefore follow predictions from legitimacy theory and posit that the Chair may serve a confirmation function if the incremental predictive ability of their commentary is explained by topics that are common to Chair and management commentary. Conversely, I argue that an independent Chair provides resources to the firm in the form of substantial knowledge and experience, which should be reflected in a Chair commentary that addresses new and complex topics that are not mentioned by management. I therefore follow predictions from resource dependency theory and posit that the Chair may serve a resource provision function if the incremental predictive ability of their commentary is explained by topics that are exclusively mentioned by the Chair.

To test the above predictions, I follow a topic modeling approach. In particular, I estimate twelve different LDA models and compare them based on a set of well-established evaluation criteria. I conclude that the optimal LDA model generates 50 topics, is trained with input data that includes a combination of bigrams and unigrams and utilizes Gensim as its inference algorithm. I compare that model with a simpler version of itself. This simpler version models 25 topics, is trained with input data that includes unigrams only and uses Gensim as the inference algorithm.

To understand the variation across Chair and management content, I start by computing the intensity of each topic across the two sections. This measures the percentage of sentences attributed to each topic and therefore allows me to determine which topics are given greater emphasis in each annual report section. Descriptive evidence from both LDA models shows that the Chair tends to focus on topics that refer to intangible but important issues such as leadership and strategy as well as governance-related themes. Conversely management seems to focus more on themes related to financial management and performance. Results from both models further show that, on average, at least 70% of the

topics addressed by the board Chair in their letter are also mentioned by the management team. The overall distribution of this variable suggests that a Chair letter displaying substantial content alignment with management is the norm.

I then test if the incremental predictive ability of Chair commentary for future earnings is explained by the tone of common topics or the tone of new topics. Results from the 25-topic model show that the incremental predictive ability of Chair commentary is higher for the tone of common topics than for the tone of new topics. This finding supports the prediction that the information role of the Chair arises from serving a confirmation function. Conversely, the 50-topic model shows that the predictive ability of new and common topics seems to be equally shared. This means that there is strong evidence supporting the confirmation function of the Chair and some modest evidence supporting the resource provision function of the board Chair.

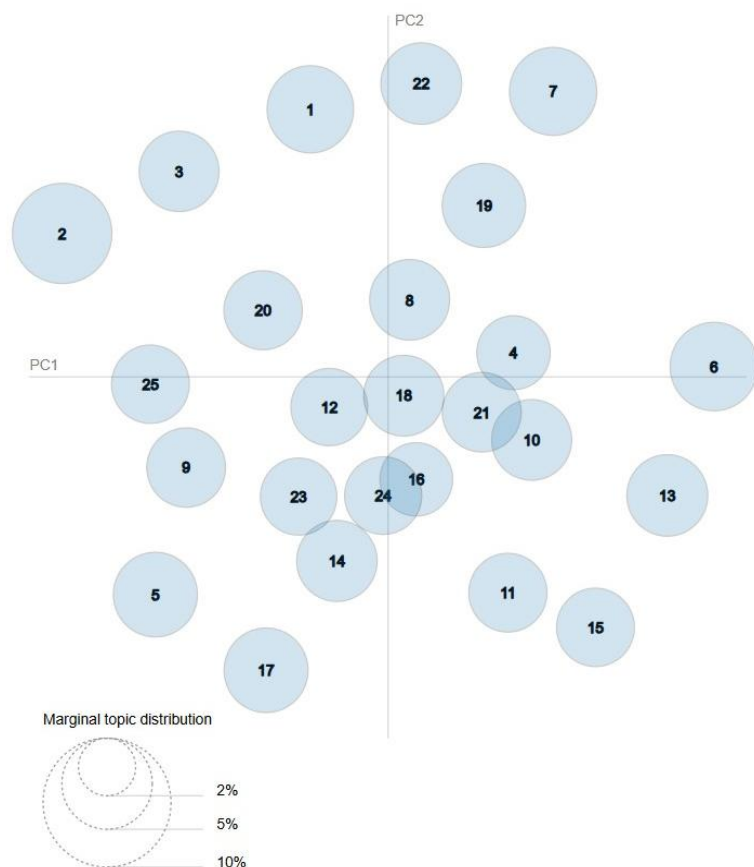
Overall, this chapter contributes to two streams of literature. First it contributes to the role of an independent Chair (Banerjee et al., 2020; Krause, 2017; Krause et al., 2014; Yu, 2023). This chapter models topics from a corpus of annual report disclosures and provides evidence consistent with the board Chair serving an information role that arises from two separate functions. This paper therefore answers the call for a further understanding of the role of the board Chair beyond monitoring (Boivie et al., 2021), especially in a context where the Chair is not affiliated with management (Krause et al., 2016).

Second, this paper contributes to the literature examining the linguistic features of annual report commentary (Bochkay et al., 2023; Bonsall and Miller, 2017; Davis et al., 2015; Henry and Leone, 2016; Li, 2008; Loughran and McDonald, 2016) by adopting a topic modeling approach and examining variation in content between two separate annual report sections (Aziz et al., 2022; Brown et al., 2020b; Federsel et al., 2024; Lui et al., 2025). While the literature focuses on surface-level properties, such as tone and length, this chapter

examines how content affects the informativeness of performance commentary. Additionally, rather than separately considering how firms disclose their information (tone) or what firms choose to disclose (content), I model tone while holding content constant. This means that I jointly account for what information is disclosed and how this information is discussed. To the best of my knowledge, this approach has only been employed by Huang et al. (2018) to distinguish between the discovery and interpretation role of analysts but not in the context of the informativeness of annual report disclosures.

Figure 4-1: Inter-topic distance maps

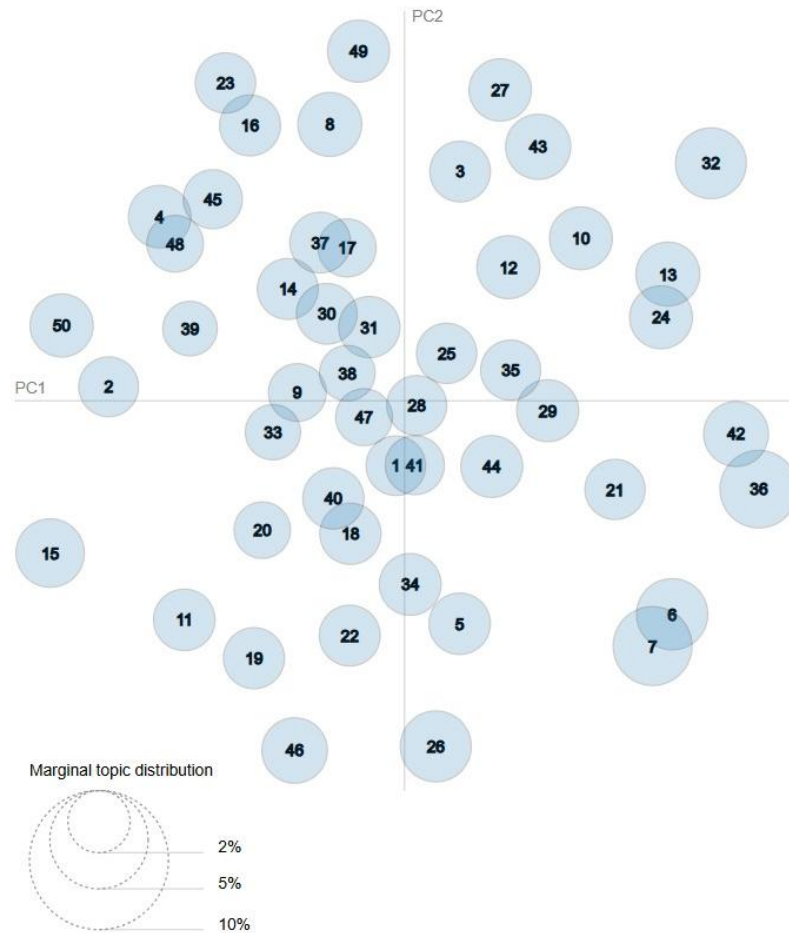
Panel A: 25_Gensim_Unigrams



Topic	Label
Topic 1	Real Estate Development and Management
Topic 2	Energy and Natural Resource Extraction
Topic 3	Retail and Consumer Market Dynamics
Topic 4	IFRS Financial Governance and Reporting Metrics
Topic 5	Client-Focused Business Solutions and Sectoral Expertise
Topic 6	Pension Scheme Financial Management
Topic 7	Digital Marketing and Media Strategies
Topic 8	Investment Strategy and Benchmarking
Topic 9	Community Health and Social Initiatives
Topic 10	Principal Risk Management and Mitigation
Topic 11	Board Committees and Remuneration Governance
Topic 12	Sustainable Distribution and Governance Challenges
Topic 13	Environmental Resource Management in Energy and Construction
Topic 14	Manufacturing Efficiency and Supply Chain Management
Topic 15	Financial Health Measures and Currency Effects
Topic 16	Sustainable Leadership in Governance and Investment Returns
Topic 17	Industrial Manufacturing and Technological Innovation
Topic 18	Financial Reporting in Legal and Regulatory Environment
Topic 19	Strategic Agreements and Development Stages
Topic 20	Hospitality and Leisure Estate Management
Topic 21	Financial Risk Management in Insurance Sector
Topic 22	Clinical Healthcare Innovation and Pipeline Development
Topic 23	Defense and Fleet Management Operations
Topic 24	Restructuring and Innovation in Business Operations
Topic 25	Strategic Partnerships and Vision Alignment

Figure 4-1: Inter-topic distance maps

Panel B: 50_Gensim_Bigrams



Topic	Label
Topic 1	Sports Club Performance and Management
Topic 2	Financial performance metrics adjustments
Topic 3	Investment Funds and Securities Management
Topic 4	Pension Scheme Management and Financial Structuring
Topic 5	Educational Divisions and Specialist Training Services
Topic 6	Clinical Trials and Regulatory Approval
Topic 7	Oil and Gas Exploration
Topic 8	Commodity Pricing and Risk Management
Topic 9	Governance and strategic financial initiatives
Topic 10	Transport Infrastructure and Safety Engineering
Topic 11	Mobile Payments and Consumer Engagement
Topic 12	Viability and Material Agreements
Topic 13	Housing and Community Care Partnerships
Topic 14	Market Conditions Affecting Volumes
Topic 15	Retail Operations and Distribution Channels
Topic 16	Financial adjustments compliance measures
Topic 17	Automotive Insurance and Repair Services
Topic 18	Defense and Specialized Design Capabilities
Topic 19	Collaborative and data-driven marketing strategies
Topic 20	Cultural Transformation and Leadership in Innovation
Topic 21	Energy Supply and Infrastructure
Topic 22	Integrated Security Solutions
Topic 23	Management of financial liabilities and compliance
Topic 24	Environmental Sustainability and Safety
Topic 25	Long-Term Strategic Planning
Topic 26	Industrial Manufacturing and Design
Topic 27	Compliance in corporate governance practices

Topic 28	Strategic Decision-Making and Profitability
Topic 29	Executive management in partnerships and agreements
Topic 30	Analysis of financial performance and exceptional items
Topic 31	Supply Chain and Pricing Dynamics in Food Industry
Topic 32	Real estate development and space planning
Topic 33	Corporate governance and strategic reporting
Topic 34	Technology Systems and Operational Testing
Topic 35	Real estate management in leisure industry
Topic 36	Resource Extraction and Mineral Exploration
Topic 37	Risk assessment and treasury policies
Topic 38	Strategic Initiatives in Mergers and Distribution
Topic 39	Reporting of financial performance metrics
Topic 40	Customer Base Management and Growth Strategies
Topic 41	Employee and Team Recognition
Topic 42	Digital and Media Marketing
Topic 43	Equity and Shareholder Transactions
Topic 44	Project-focused strategic partnerships
Topic 45	Restructuring and disposal financial strategies
Topic 46	Client-Centric Software Solutions
Topic 47	Sustainability and competitive advantage initiatives
Topic 48	IFRS compliance and financial adjustments
Topic 49	Real estate portfolio financial management
Topic 50	Currency Risk Management in Aerospace and Defence

This figure shows the inter-topic distance maps for model 25_ *Gensim_Unigrams* (Panel A) and for model 50_ *Gensim_Bigrams* (Panel B). Each blue bubble represents a topic. The labels are displayed next to each inter-topic distance map.

Table 4.1: Evaluation metrics per LDA model

Panel A: Ranking of LDA models per metric

Ranking	Coherence	Diversity	Granularity	Perplexity	WIT Accuracy
1	50_Gensim_Bigrams	25_Gensim_Bigrams	50_Gensim_Bigrams	25_Mallet_Unigrams	35_Gensim_Unigrams
2	25_Gensim_Bigrams	<u>25_Gensim_Unigrams</u>	25_Gensim_Bigrams	35_Mallet_Unigrams	50_Gensim_Bigrams
3	35_Gensim_Unigrams	35_Gensim_Bigrams	35_Gensim_Bigrams	50_Mallet_Unigrams	<u>25_Gensim_Unigrams</u>
4	<u>25_Gensim_Unigrams</u>	35_Gensim_Unigrams	35_Gensim_Unigrams	25_Mallet_Bigrams	50_Gensim_Unigrams
5	35_Gensim_Bigrams	50_Gensim_Bigrams	50_Mallet_Unigrams	35_Mallet_Bigrams	25_Mallet_Unigrams
6	50_Gensim_Unigrams	50_Gensim_Unigrams	50_Mallet_Bigrams	50_Mallet_Bigrams	35_Gensim_Bigrams
7	25_Mallet_Bigrams	35_Mallet_Unigrams	35_Mallet_Bigrams	50_Gensim_Bigrams	35_Mallet_Bigrams
8	50_Mallet_Unigrams	35_Mallet_Bigrams	25_Mallet_Bigrams	35_Gensim_Bigrams	50_Mallet_Unigrams
9	35_Mallet_Bigrams	25_Mallet_Unigrams	50_Gensim_Unigrams	25_Gensim_Bigrams	25_Gensim_Bigrams
10	50_Mallet_Bigrams	25_Mallet_Bigrams	<u>25_Gensim_Unigrams</u>	50_Gensim_Unigrams	25_Mallet_Bigrams
11	25_Mallet_Unigrams	50_Mallet_Bigrams	35_Mallet_Unigrams	35_Gensim_Unigrams	50_Mallet_Bigrams
12	35_Mallet_Unigrams	50_Mallet_Unigrams	25_Mallet_Unigrams	<u>25_Gensim_Unigrams</u>	35_Mallet_Unigrams

Table 4.1: Evaluation metrics per LDA model

Panel B

Model	Coherence	Diversity	Granularity	Perplexity	WIT Accuracy
<u>25_Gensim_Bigrams</u>	0.609	0.900	0.702	-7.692	0.720
<u>25_Gensim_Unigrams</u>	0.594	0.872	0.679	-7.506	0.840
<u>25_Mallet_Bigrams</u>	0.508	0.356	0.680	-12.781	0.720
<u>25_Mallet_Unigrams</u>	0.453	0.364	0.660	-13.089	0.840
35_Gensim_Bigrams	0.581	0.863	0.697	-7.758	0.829
35_Gensim_Unigrams	0.604	0.834	0.691	-7.549	0.886
35_Mallet_Bigrams	0.489	0.371	0.681	-12.776	0.829
35_Mallet_Unigrams	0.444	0.374	0.664	-13.069	0.629
50_Gensim_Bigrams	0.610	0.798	0.711	-7.843	0.880
50_Gensim_Unigrams	0.580	0.762	0.680	-7.636	0.840
50_Mallet_Bigrams	0.467	0.356	0.683	-12.748	0.660
50_Mallet_Unigrams	0.491	0.344	0.683	-13.047	0.820

This table presents the evaluation metrics for each LDA model. Panel A reports the ranking of each model according to the performance metric whereas Panel B report the values of each performance metric and for each model. The coherence score evaluates the interpretability of a model by measuring the level of similarity of words within a topic. The diversity score is the proportion of unique words in each topic. The higher the diversity score the higher the proportion of topics that do not share common words. The granularity score measures the specificity level of a topic by indicating if topic keywords are included in less documents. The perplexity score measures a model's predictive accuracy by evaluating its ability to predict word choice in unseen documents. A common approach to select an LDA model is to plot the coherence score and the perplexity score for different number of topics. The optimal number of topics is then identified by choosing the one with the highest coherence score and lowest perplexity score. A word intrusion test (WIT) measures a model's accuracy by testing the ability of an evaluator to identify an intruder in a topic. Models are named according to three implementation choices: number of topics ($K = 25, 35$ and 50), inference algorithm (Mallet or Gensim) and the n-grams used to train the model (unigrams only vs combination of unigrams and bigrams). The best performing model is highlighted in bold and the 25-topic model is underlined.

Table 4.2: Topic labels of LDA models

Panel A: 25_Gensim_Unigrams

Topic	Label	Rationale	Top 10 keywords
Topic 1	Real Estate Development and Management	The keywords 'properties', 'rental', 'sq', 'rent', 'ft', 'planning', 'residential', 'space', and 'valuation' suggest a focus on activities associated with real estate development and property management, emphasizing aspects like rental properties and property valuation.	properties, rental, joint, sq, rent, ft, planning, residential, space, valuation
Topic 2	Energy and Natural Resource Extraction	The keywords 'production', 'oil', 'gas', 'exploration', 'mining', 'drilling', 'mine', 'reserves', 'resource', and 'licence' are indicative of activities within the energy and natural resource sectors, specifically focusing on exploration, drilling, and the extraction of oil, gas, and minerals.	production, oil, gas, exploration, mining, drilling, mine, reserves, resource, licence
Topic 3	Retail and Consumer Market Dynamics	The keywords 'retail', 'stores', 'likeforlike', 'brands', 'store', 'food', 'online', 'distribution', 'shopping', and 'consumer' highlight aspects pertinent to retail operations and consumer engagement, such as physical and online stores, brand performance, and distribution strategies.	retail, stores, likeforlike, brands, store, food, online, distribution, shopping, consumer
Topic 4	IFRS Financial Governance and Reporting Metrics	Focuses on financial governance, adherence to IFRS financial reporting standards, and includes corporate financial management-related metrics.	eu, expenses, ebitda, eum, officer, ifrs, equivalents, governance, expense, depreciation
Topic 5	Client-Focused Business Solutions and Sectoral Expertise	The keywords 'division', 'solutions', 'clients', 'client', 'organic', 'security', 'divisions', 'specialist', 'sectors', and 'recruitment' suggest a concentration on delivering tailored business solutions, emphasizing client relationships, sector-specific expertise, and recruitment.	division, solutions, clients, client, organic, security, divisions, specialist, sectors, recruitment
Topic 6	Pension Scheme Financial Management	The keywords highlight financial components related to managing pension schemes, including liabilities, deficits, and borrowings, with compliance to accounting standards such as IAS and IFRS, suggesting a focus on how pension schemes are financially orchestrated and managed within corporate governance.	pension, scheme, liabilities, schemes, deficit, defined, borrowings, ias, ifrs, instruments
Topic 7	Digital Marketing and Media Strategies	The keywords focus on digital media, content creation, and marketing strategies, with emphasis on the use of software and online platforms, indicating a technological approach to reaching and engaging with target audiences across mobile and networked media spaces.	digital, data, marketing, software, online, content, mobile, media, network, recurring
Topic 8	Investment Strategy and Benchmarking	The keywords relate to investment decisions and strategies, mentioning benchmarks, investors, initial public offerings (IPO), and funds, pointing to the processes and criteria used in making and assessing investment choices in financial markets.	usm, course, decision, investors, benchmark, initial, aim, funds, options, ordinary

Topic 9	Community Health and Social Initiatives	The keywords are centered around offering social and health care services, with a focus on training, community outreach, and both national and private practices, reflecting corporate responsibility towards community health and well-being.	health, care, training, social, community, communities, national, private, help, practices
Topic 10	Principal Risk Management and Mitigation	The keywords emphasize the identification and management of risks and uncertainties, with liquidity concern and mitigation efforts, detailing how firms prioritize, address, and mitigate potential risks impacting their operations.	risks, could, uncertainties, principal, liquidity, concern, uncertainty, factors, material, mitigation
Topic 11	Board Committees and Remuneration Governance	Emphasizes corporate governance, especially related to committees, remuneration, and the roles of directors, in the context of annual general meetings and governance codes.	committee, governance, nonexecutive, remuneration, meeting, audit, ordinary, code, agm, independent
Topic 12	Sustainable Distribution and Governance Challenges	This topic focuses on the relationship between distribution processes, their sustainable management, and the governance challenges faced in maintaining profitable volumes over the long term. It highlights the strategic evaluation of operational strengths and the need to overcome declines in distribution efficiency.	distribution, volume, sustainable, decline, challenges, governance, volumes, profitable, strength, longterm
Topic 13	Environmental Resource Management in Energy and Construction	The keywords emphasize the strategic management of environmental resources in industries related to energy and construction. It includes a focus on safety, water, and fuel, with a particular concern for capacity constraints and the impact of carbon and gas prices on sustainability initiatives.	energy, safety, water, environmental, fuel, construction, capacity, carbon, gas, prices
Topic 14	Manufacturing Efficiency and Supply Chain Management	This topic addresses the industrial processes of manufacturing, with a specific focus on supply chain management and packaging. It covers operational efficiency, regional considerations, currency impacts, and the use of raw materials, highlighting the importance of optimizing the manufacturing footprint.	currency, manufacturing, chain, packaging, volumes, footprint, industrial, efficiency, region, raw
Topic 15	Financial Health Measures and Currency Effects	Targets financial metrics assessing firm performance, adjustments in EBITDA, and impacts of currency fluctuations on the financial outcomes.	adjusted, ebitda, statutory, currency, measures, disposal, eps, intangible, impairment, depreciation
Topic 16	Sustainable Leadership in Governance and Investment Returns	Proposes governance structures focusing on sustainability and leadership strategies for long-term value creation and enhanced investment returns.	governance, longterm, overview, priorities, measures, investments, returns, sustainable, leadership, movements
Topic 17	Industrial Manufacturing and Technological Innovation	The keywords revolve around the processes and applications of technology in manufacturing, emphasizing design and production systems. The terms suggest a focus on technology-driven innovations and solutions within industrial manufacturing.	manufacturing, technologies, applications, solutions, technical, system, materials, design, industrial, production

Topic 18	Financial Reporting in Legal and Regulatory Environment	Engages with financial metrics and regulatory considerations, detailing their impact on interim and year-end financial prospects with emphasis on legal aspects.	consideration, fees, experienced, uncertainty, prospects, ifrs, coming, interim, legal, yearend
Topic 19	Strategic Agreements and Development Stages	The keywords suggest a focus on the progression and completion of strategic agreements and placements. The emphasis on discussions, stages, and initial commencement indicates a strategic overview of development projects and contractual rights.	agreement, open, stage, raised, completion, placing, initial, commenced, discussions, rights
Topic 20	Hospitality and Leisure Estate Management	The keywords suggest a focus on the management and development of hospitality and leisure properties, including hotels and travel destinations, highlighting strategic locations and operational management of leisure centers.	centre, centres, estate, great, leisure, travel, locations, managed, hotel, opening
Topic 21	Financial Risk Management in Insurance Sector	Revolves around financial reporting standards, trade and risk management of insurance receivables and losses, addressing asset valuation and associated financial losses.	trade, ifrs, insurance, receivables, proof, charges, impairment, incurred, losses, equipment
Topic 22	Clinical Healthcare Innovation and Pipeline Development	The keywords revolve around the healthcare sector with a focus on clinical research, medical developments, patient treatments, and regulatory approval. The mention of 'pipeline' suggests a focus on the progression of healthcare innovations through various phases of development.	healthcare, clinical, research, medical, phase, patients, regulatory, pipeline, treatment, study
Topic 23	Defense and Fleet Management Operations	This topic seems to relate to logistics and operations within defense, involving fleet and vehicle management, equipment maintenance, and air program sustenance. The mention of 'organic' implies an emphasis on sustainable operations or growth within these areas.	fleet, vehicle, vehicles, network, defence, hire, equipment, air, programmes, organic
Topic 24	Restructuring and Innovation in Business Operations	Covers the strategic actions taken in business restructuring and governance, with particular focus on managing foreign currency and fostering innovation for business growth.	currency, restructuring, headline, grew, actions, innovation, initiatives, foreign, governance, impacted
Topic 25	Strategic Partnerships and Vision Alignment	The keywords emphasize the importance of partnerships and alignment with strategic visions for growth. Terms like 'partners,' 'officer,' and 'vision' suggest the topic is about leadership roles in creating impactful partnerships and scaling business operations.	partners, officer, help, great, create, partnerships, scale, right, vision, partner

Table 4.2: Topic labels of LDA models

Panel B: 50_Gensim_Bigrams

Topic	Label	Rationale	Top 10 keywords
Topic 1	Sports Club Performance and Management	The keywords suggest a focus on a sports club's operations, highlighting elements such as premier league (or equivalent), players, and club management strategies, indicating a narrative around performance and activities of a sports club.	club, great, premier, right, players, wefive, get, direct, even, saw
Topic 2	Financial performance metrics adjustments	The adjusted keyword along with terms as intangible assets depict elements of financial metrics and adjustments.	adjusted, amortisation, intangible_assets, intangibles, eps, diluted, revenue_growth, strategic_report, contingent_consideration, organic_growth
Topic 3	Investment Funds and Securities Management	With keywords like 'equity', 'funds', 'benchmark', and 'securities', this topic revolves around managing investment portfolios and the tools/schemes related to fund management and securities, highlighting processes and strategies within financial portfolio management.	equity, funds, benchmark, usm, fund, securities, convertible, amount, expenses, investments
Topic 4	Pension Scheme Management and Financial Structuring	This topic centers around financial management related to pension schemes, including terms like 'pension', 'deficit', and 'net_debt', indicating discussions around pension liabilities, scheme deficits, and contribution strategies.	scheme, pension, deficit, defined, pension_scheme, hire, net_debt, contributions, employed, schemes
Topic 5	Educational Divisions and Specialist Training Services	The keywords suggest a focus on the organizational structure related to training and specialist education within corporate divisions, with emphasis on skills development across different sectors through specialized agency offerings.	division, divisions, training, specialist, education, divisional, skills, agency, learning, sectors
Topic 6	Clinical Trials and Regulatory Approval	The keywords focus on the healthcare sector, specifically the clinical and research aspects related to patient treatments, various trial phases, and regulatory processes involved in the medical study and approval of treatments.	healthcare, clinical, patients, phase, medical, health, research, study, treatment, regulatory
Topic 7	Oil and Gas Exploration	The keywords are related to the extraction and exploration practices within the oil and gas industry, including production activities, drilling operations, and the management of oil and gas reserves, both onshore and offshore.	production, gas, oil, exploration, oil_gas, drilling, licence, reserves, offshore, licences

Topic 8	Commodity Pricing and Risk Management	This topic is centered around the financial aspects of dealing with commodities, highlighting the associated prices, risks such as credit and liquidity, and strategies for managing volatility through hedging and derivatives.	prices, risks, credit, volatility, hedging, commodity, liquidity, factors, derivative, risk_management
Topic 9	Governance and strategic financial initiatives	The label focuses on governance and devising strategic financial initiatives to tackle variations in financial reports.	grew, strategic_report, governance, decline, yearonyear, saw, soft, initiatives, oneoff, accounts
Topic 10	Transport Infrastructure and Safety Engineering	This topic emphasizes the engineering and maintenance operations within transport sectors, specifically air and rail, focusing on national infrastructure, fleet management, equipment safety, and upkeep operations.	engineering, fleet, air, maintenance, infrastructure, rail, transport, equipment, safety, national
Topic 11	Mobile Payments and Consumer Engagement	The keywords focus on aspects related to mobile payments and consumer engagement, involving the launch of new services, consumer propositions, and the roles of operators in the mobile payments network.	network, mobile, payments, launched, consumers, channel, operators, ebitda, consumer, proposition
Topic 12	Viability and Material Agreements	The keywords indicate discussions related to the viability of projects or agreements, involving various parties and consideration of material situations. This suggests the focus is on assessing ongoing viability and the details around significant agreements.	nt, could, ca, various, parties, viability, agreement, situation, material, detailed
Topic 13	Housing and Community Care Partnerships	The keywords describe activities related to housing in the context of social and private care, community involvement, residential planning, and partnerships, indicating a focus on providing and planning care homes within community settings.	homes, care, housing, social, private, community, home, planning, residential, partnership
Topic 14	Market Conditions Affecting Volumes	The keywords refer to issues such as decreased volumes and market impacts, particularly focusing on declines and losses due to adverse governance and market conditions, highlighting challenges in maintaining volumes under these circumstances.	volumes, decreased, decline, largely, impacted, mainly, decrease, governance, losses, market_conditions
Topic 15	Retail Operations and Distribution Channels	The keywords focus on retail operations, including like-for-like store performance, distribution channels (both online and physical), and interactions with brands and retailers, pointing to strategic concerns in the retail sector.	retail, stores, store, likeforlike, brands, shopping, retailers, distribution, online, food
Topic 16	Financial adjustments compliance measures	Terms suggest an overlap of financial adjustments and compliance measures especially in relation to IFRS rules and standards.	ifrs, exceptional_items, impairment, notes, taxation, adjustment, leases, charges, net_debt, ebitda

Topic 17	Automotive Insurance and Repair Services	The keywords relate to the automotive sector, with terms like insurance, vehicles, car, parts, claims, and repair, indicating a focus on vehicle-related insurance products and repair services for a fleet or motor vehicles.	insurance, vehicle, vehicles, car, parts, claims, fleet, repair, motor, sold
Topic 18	Defense and Specialized Design Capabilities	The keywords highlight capabilities and expertise in sectors like defense, with emphasis on specialist design, technical innovation, and presence in specific markets, pointing to strategic advantages and differentiation.	capabilities, capability, specialist, design, expertise, sectors, defence, presence, technical, innovative
Topic 19	Collaborative and data-driven marketing strategies	A focus on collaboration and data utilization for marketing strategies is depicted.	marketing, partners, data, communications, launch, partner, access, network, launched, direct
Topic 20	Cultural Transformation and Leadership in Innovation	The keywords emphasize a strategic focus on fostering an innovative culture, with leadership driving transformation and engagement among talent and colleagues, as outlined in strategic reports and priorities.	innovation, culture, leadership, transformation, engagement, talent, strategic_report, driving, colleagues, priorities
Topic 21	Energy Supply and Infrastructure	The keywords are related to the generation and supply of energy, including aspects like fuel storage and electricity, emphasizing the infrastructure and domestic capabilities needed for efficient energy supply.	energy, supply, generation, fuel, storage, carbon, capacity, electricity, installation, domestic
Topic 22	Integrated Security Solutions	The keywords indicate a focus on providing secure and integrated security solutions, with capabilities for protection that are critical for government and other sectors requiring high levels of security.	solutions, security, protection, capabilities, provider, integrated, secure, capability, government, critical
Topic 23	Management of financial liabilities and compliance	Keywords indicate a focus on handling financial liabilities and on compliance, especially with regards to impairment and foreign exchange factors.	liabilities, impairment, expense, foreign_exchange, obligations, property_equipment, movements, borrowings, ifrs, decrease
Topic 24	Environmental Sustainability and Safety	The keywords highlight a focus on water management, environmental sustainability, health and safety practices, waste management, and interactions with stakeholders and regulators to ensure sustainable construction practices.	water, environmental, sustainability, safety, health_safety, sustainable, waste, construction, stakeholders, regulatory
Topic 25	Long-Term Strategic Planning	The keywords emphasize planning and decision-making for future operations, targeting substantial long-term efforts and material operations, reflecting an organization's strategic approach to achieving its goals.	target, longterm, could, decision, planned, nature, substantial, efforts, material, operation

Topic 26	Industrial Manufacturing and Design	The keywords focus on various aspects of manufacturing, including materials, production processes, automotive components, and technical applications. These elements synthesize into the broader theme of industrial manufacturing and design.	manufacturing, industrial, production, materials, automotive, packaging, applications, design, components, technical
Topic 27	Compliance in corporate governance practices	A focus on practices of governance and compliance frameworks within a corporate setup is emphasized.	committee, corporate_governance, audit, agm, code, remuneration, director, general_meeting, senior, meetings
Topic 28	Strategic Decision-Making and Profitability	The keywords reflect considerations and challenges in strategic decision-making, emphasizing efforts towards achieving profitability and leading the firm in a forward direction. It highlights the processes of addressing front-facing challenges and delivering profitable outcomes.	proof, front, challenges, accounts, decision, coming, led, right, profitable, efforts
Topic 29	Executive management in partnerships and agreements	The label highlights a role of executive management in the formation and importance of business partnerships.	partners, agreement, signed, agreements, ceo, partner, placing, executive_officer, loss_tax, initial
Topic 30	Analysis of financial performance and exceptional items	The label highlights an analysis perspective of financial performance with an emphasis on exceptional items and their impact.	returns, exceptional_items, pretax_profit, exceptional, trade, net_debt, marginally, bank, strategic_report, increases
Topic 31	Supply Chain and Pricing Dynamics in Food Industry	The keywords focus on aspects of the food industry relating to logistics, supply, and pricing, emphasizing how these impact business volumes and operations.	food, volume, logistics, increases, volumes, site, supply, feed, pricing, rising
Topic 32	Real estate development and space planning	Label focuses on activities in the real estate sector including development and planning of property and office spaces.	property, properties, sq, ft, space, rent, office, planning, site, residential
Topic 33	Corporate governance and strategic reporting	The label sheds light on aspects of corporate governance and strategic reporting, including focus on financial metrics.	strategic_report, officers, corporate_governance, governance, overview, kpis, financial_officer, ipo, financial_highlights, technologies
Topic 34	Technology Systems and Operational Testing	The keywords revolve around system applications, equipment testing, and application assurance, emphasizing technological infrastructure and operational reliability.	system, testing, test, orders, applications, application, equipment, assurance, technologies, monitoring

Topic 35	Real estate management in leisure industry	Label highlights the application of real estate management within the leisure and hospitality industry.	centre, centres, estate, occupancy, leisure, locations, hotel, pipeline, managed, leads
Topic 36	Resource Extraction and Mineral Exploration	The keywords suggest a focus on the extraction and exploration activities in the mining sector, referencing project development, production metrics, and key elements associated with mineral resources.	project, production, mining, mine, resource, tonnes, exploration, grade, ore, mineral
Topic 37	Risk assessment and treasury policies	Derived from risk-related terms, this label focuses on risk management and mitigation for financials, including treasury functions.	risks, net_debt, uncertainties, policies, principal_risks, treasury, uncertainty, credit, risk_management, taxation
Topic 38	Strategic Initiatives in Mergers and Distribution	This topic centers on the strategic and governance issues related to mergers, distribution strategies, and capacity planning, highlighting potential premium product divisions, possibly in the fruit sector.	eum, pro, merger, distribution, strategic_report, capacity, governance, volume, premium, fruit
Topic 39	Reporting of financial performance metrics	The label points to an emphasis on reporting aspects of financial performance metrics, specifically EBITDA and related measures.	ebitda, eu, strategic_report, measures, ebitda_margin, cents, governance, capex, depreciation_amortisation, comparable
Topic 40	Customer Base Management and Growth Strategies	This topic addresses strategic management of customer bases, integrating teams for scale and organic growth, with a focus on enhancing offerings across various sectors.	managed, integration, customer_base, scale, teams, organic_growth, enhancing, chief_executives, sectors, offering
Topic 41	Employee and Team Recognition	The keywords focus on pride, help, and acknowledgment towards teams and individuals in the organization, highlighting themes around employee recognition and appreciating team contributions.	great, proud, help, teams, every, job, always, everyone, looking, delighted
Topic 42	Digital and Media Marketing	The keywords encompass digital, marketing, online, and media, along with references to brands and events, indicating a focus on digital marketing strategies and media presence.	digital, marketing, online, content, media, brands, events, sports, advertising, games
Topic 43	Equity and Shareholder Transactions	The keywords reference terms like shares, issued, options, and share_capital, which are generally associated with corporate activities involving equity and transactions impacting shareholders.	shares, issued, ordinary_shares, options, rights, issue, share_capital, agreement, option, exercise

Topic 44	Project-focused strategic partnerships	The label points toward strategic partnerships focusing on project development.	aim, partner, project, several, director, recently, infrastructure, worked, exciting, stage
Topic 45	Restructuring and disposal financial strategies	The keywords focus on restructuring and disposal activities, suggesting large-scale strategic changes in financial management.	discontinued, disposal, defined, ifrs, exceptional_items, liabilities, items, restructuring, intangible_assets, ias
Topic 46	Client-Centric Software Solutions	The keywords emphasize aspects related to client-focused software solutions and services. There is mention of data, analytics, and recurring client interactions, which are integral to software-driven businesses. Additional keywords like recruitment and fees suggest the human resource and financial aspects of such client-centric services.	clients, software, data, recurring, client, recruitment, solutions, fees, analytics, solution
Topic 47	Sustainability and competitive advantage initiatives	The topic relates to sustainable governance and competitive advantage strategic initiatives.	initiatives, right, every, sustainable, challenges, clear, governance, actions, longterm, competitive
Topic 48	IFRS compliance and financial adjustments	Topics around regulatory compliance and refining financial reports indicate a focus on compliance with IFRS standards and adjustments in financial documents.	items, restated, net_debt, statutory, restructuring, adjusting, amortisation, nonrecurring, ifrs, measures
Topic 49	Real estate portfolio financial management	The topic emphasizes on financial evaluation and management of real estate properties and portfolios.	rental, rental_income, interest_rate, disposals, valuation, lease, fixed, leases, weighted, net_assets
Topic 50	Currency Risk Management in Aerospace and Defence	This topic is about managing currency fluctuations' impacts on aerospace and industrial sectors, with keywords like exchange_rates, currency_basis, and foreign_exchange. The context of defence and restructuring suggests a focus on maintaining financial stability in these industries despite currency volatility.	currency, exchange_rates, headline, translation, defence, currency_basis, aerospace, industrial, restructuring, foreign_exchange

This table provides the topic labels, topic rationale and top ten keywords per topic for topics produced by the LDA model *25_Gensim_Unigrams* in Panel A and *50_Gensim_Bigrams* in Panel B.

Table 4.3: Topic intensity ranking

Panel A: 25_Gensim_Unigrams

Topics	Label	Chair	Management
Topic 1	Real Estate Development and Management	12	6
Topic 2	Energy and Natural Resource Extraction	4	1
Topic 3	Retail and Consumer Market Dynamics	8	8
Topic 4	IFRS Financial Governance and Reporting Metrics	24	15
Topic 5	Client-Focused Business Solutions and Sectoral Expertise	3	2
Topic 6	Pension Scheme Financial Management	19	4
Topic 7	Digital Marketing and Media Strategies	5	5
Topic 8	Investment Strategy and Benchmarking	18	24
Topic 9	Community Health and Social Initiatives	16	19
Topic 10	Principal Risk Management and Mitigation	22	16
Topic 11	Board Committees and Remuneration Governance	1	11
Topic 12	Sustainable Distribution and Governance Challenges	15	22
Topic 13	Environmental Resource Management in Energy and Construction	7	9
Topic 14	Manufacturing Efficiency and Supply Chain Management	20	17
Topic 15	Financial Health Measures and Currency Effects	10	3
Topic 16	Sustainable Leadership in Governance and Investment Returns	6	21
Topic 17	Industrial Manufacturing and Technological Innovation	13	7
Topic 18	Financial Reporting in Legal and Regulatory Environment	17	23
Topic 19	Strategic Agreements and Development Stages	14	14
Topic 20	Hospitality and Leisure Estate Management	11	18
Topic 21	Financial Risk Management in Insurance Sector	23	12
Topic 22	Clinical Healthcare Innovation and Pipeline Development	9	10
Topic 23	Defense and Fleet Management Operations	25	25
Topic 24	Restructuring and Innovation in Business Operations	21	20
Topic 25	Strategic Partnerships and Vision Alignment	2	13

Table 4.3: Topic intensity ranking

Panel B: 50_Gensim_Bigrams

Topics	Label	Chair	Management
Topic 1	Sports Club Performance and Management	19	41
Topic 2	Financial performance metrics adjustments	15	5
Topic 3	Investment Funds and Securities Management	30	26
Topic 4	Pension Scheme Management and Financial Structuring	27	14
Topic 5	Educational Divisions and Specialist Training Services	8	10
Topic 6	Clinical Trials and Regulatory Approval	9	11
Topic 7	Oil and Gas Exploration	2	1
Topic 8	Commodity Pricing and Risk Management	40	23
Topic 9	Governance and strategic financial initiatives	43	44
Topic 10	Transport Infrastructure and Safety Engineering	25	22
Topic 11	Mobile Payments and Consumer Engagement	24	15
Topic 12	Viability and Material Agreements	38	39
Topic 13	Housing and Community Care Partnerships	20	24
Topic 14	Market Conditions Affecting Volumes	26	25
Topic 15	Retail Operations and Distribution Channels	11	7
Topic 16	Financial adjustments compliance measures	39	8
Topic 17	Automotive Insurance and Repair Services	44	38
Topic 18	Defense and Specialized Design Capabilities	31	42
Topic 19	Collaborative and data-driven marketing strategies	28	29
Topic 20	Cultural Transformation and Leadership in Innovation	4	34
Topic 21	Energy Supply and Infrastructure	10	12
Topic 22	Integrated Security Solutions	23	21
Topic 23	Management of financial liabilities and compliance	49	16
Topic 24	Environmental Sustainability and Safety	12	18
Topic 25	Long-Term Strategic Planning	48	50
Topic 26	Industrial Manufacturing and Design	18	9
Topic 27	Compliance in corporate governance practices	1	27
Topic 28	Strategic Decision-Making and Profitability	29	47
Topic 29	Executive management in partnerships and agreements	22	37
Topic 30	Analysis of financial performance and exceptional items	21	40
Topic 31	Supply Chain and Pricing Dynamics in Food Industry	36	36
Topic 32	Real estate development and space planning	5	2
Topic 33	Corporate governance and strategic reporting	13	28
Topic 34	Technology Systems and Operational Testing	41	30
Topic 35	Real estate management in leisure industry	34	31
Topic 36	Resource Extraction and Mineral Exploration	7	4
Topic 37	Risk assessment and treasury policies	47	45
Topic 38	Strategic Initiatives in Mergers and Distribution	50	49
Topic 39	Reporting of financial performance metrics	42	32
Topic 40	Customer Base Management and Growth Strategies	16	33
Topic 41	Employee and Team Recognition	14	43
Topic 42	Digital and Media Marketing	6	6

Topic 43	Equity and Shareholder Transactions	17	20
Topic 44	Project-focused strategic partnerships	32	46
Topic 45	Restructuring and disposal financial strategies	46	35
Topic 46	Client-Centric Software Solutions	3	3
Topic 47	Sustainability and competitive advantage initiatives	45	48
Topic 48	IFRS compliance and financial adjustments	33	19
Topic 49	Real estate portfolio financial management	37	13
Topic 50	Currency Risk Management in Aerospace and Defence	35	17

This table presents the ranking position of each topic based on its intensity in Chair commentary and management commentary. This ranking is based on the mean levels of discussion of each topic. Topic intensity is calculated as the number of sentences that are assigned a given topic scaled by the total number of sentences in the respective annual report section. Panel A shows the ranking of the topics produced by the model *25_Gensim_Unigrams* and Panel B shows the ranking of the topics produced by the model *50_Gensim_Bigrams*.

Table 4.4: Descriptive statistics

LDA Model	Variable	N	Mean	St dev	Min	P25	P50	P75	Max
25_Gensim_Unigrams	<i>Chair N Topics</i>	8,893	14.012	3.896	1	11	14	17	25
25_Gensim_Unigrams	<i>Management N Topics</i>	8,893	19.739	5.280	1	17	22	24	25
25_Gensim_Unigrams	<i>N Common Topics</i>	8,893	11.785	4.310	0	9	12	15	24
25_Gensim_Unigrams	<i>% Common Topics Chair</i>	8,893	0.842	0.196	0.000	0.769	0.917	1.000	1.000
25_Gensim_Unigrams	<i>% Common Topics Management</i>	8,893	0.605	0.166	0.000	0.500	0.600	0.720	1.000
25_Gensim_Unigrams	<i>N New Topics Chair</i>	8,893	2.227	3.051	0.000	0.000	1.000	3.000	23.000
25_Gensim_Unigrams	<i>% New Topics Chair</i>	8,893	0.158	0.196	0.000	0.000	0.083	0.231	1.000
25_Gensim_Unigrams	<i>N New Topics Management</i>	8,893	7.954	3.867	0.000	5.000	8.000	11.000	23.000
25_Gensim_Unigrams	<i>% New Topics Management</i>	8,893	0.395	0.166	0.000	0.280	0.400	0.500	1.000
25_Gensim_Unigrams	<i>Chair Tone Common Topics</i>	8,891	0.418	0.189	-1.000	0.300	0.426	0.545	1.000
25_Gensim_Unigrams	<i>Management Tone Common Topics</i>	5,785	0.399	0.413	-1.000	0.000	0.400	0.667	1.000
25_Gensim_Unigrams	<i>Chair Tone New Topics</i>	8,891	0.319	0.176	-0.500	0.207	0.324	0.434	1.000
25_Gensim_Unigrams	<i>Management Tone New Topics</i>	8,683	0.259	0.236	-1.000	0.120	0.256	0.400	1.000
50_Gensim_Bigrams	<i>Chair N Topics</i>	8,894	18.544	6.213	1	14	18	23	43
50_Gensim_Bigrams	<i>Management N Topics</i>	8,894	31.343	11.051	1	24	33	40	50
50_Gensim_Bigrams	<i>N Common Topics</i>	8,894	13.506	6.047	0	9	13	18	39
50_Gensim_Bigrams	<i>% Common Topics Chair</i>	8,894	0.730	0.211	0.000	0.615	0.778	0.889	1.000
50_Gensim_Bigrams	<i>% Common Topics Management</i>	8,894	0.447	0.156	0.000	0.340	0.429	0.536	1.000
50_Gensim_Bigrams	<i>N New Topics Chair</i>	8,894	5.038	4.717	0.000	2.000	4.000	7.000	39.000
50_Gensim_Bigrams	<i>% New Topics Chair</i>	8,894	0.270	0.211	0.000	0.111	0.222	0.385	1.000
50_Gensim_Bigrams	<i>N New Topics Management</i>	8,894	17.837	8.020	0.000	12.000	18.000	24.000	43.000
50_Gensim_Bigrams	<i>% New Topics Management</i>	8,894	0.553	0.156	0.000	0.464	0.571	0.660	1.000
50_Gensim_Bigrams	<i>Chair Tone Common Topics</i>	8,890	0.422	0.196	-0.556	0.297	0.429	0.556	1.000
50_Gensim_Bigrams	<i>Management Tone Common Topics</i>	8,244	0.402	0.347	-1.000	0.182	0.400	0.615	1.000
50_Gensim_Bigrams	<i>Chair Tone New Topics</i>	8,890	0.327	0.182	-0.667	0.210	0.333	0.446	1.000
50_Gensim_Bigrams	<i>Management Tone New Topics</i>	8,790	0.266	0.199	-1.000	0.143	0.263	0.386	1.000

This table shows the descriptive statistics for each LDA model. *Chair (Management) N Topics* is the count of the number of topics discussed in Chair (management) commentary in a given annual report. *N Common Topics* the count of the number of topics that appear in Chair commentary and management commentary. A topic is common to Chair and management commentary if in a given report it appears in the Chair's letter and in the Management Review. *% Common Topics Chair (Management)* is the number of common topics in a given annual report

Table 4.4: Descriptive statistics

scaled by the total number of a topics in Chair (management) commentary. *Chair (Management) Tone Common Topics* is the difference between the number of positive sentences and the number of negative sentences that are assigned topics that, within the same annual report, appear in Chair commentary and management commentary scaled by the total number of sentences discussing common topics in Chair (management) commentary. *Chair (Management) Tone New Topics* is the difference between the number of positive sentences and the number of negative sentences that are assigned topics that, within the same annual report, appear only on Chair (management) commentary scaled by the total number of sentences discussing new topics in Chair (management) commentary.

Table 4.5: Mean levels of common topicsPanel A: 25_ *Gensim*_ *Unigrams*

Variable	N	Mean
<i>D Common Topic 1</i>	8,893	0.470
<i>D Common Topic 2</i>	8,893	0.376
<i>D Common Topic 3</i>	8,893	0.402
<i>D Common Topic 4</i>	8,893	0.335
<i>D Common Topic 5</i>	8,893	0.605
<i>D Common Topic 6</i>	8,893	0.447
<i>D Common Topic 7</i>	8,893	0.475
<i>D Common Topic 8</i>	8,893	0.455
<i>D Common Topic 9</i>	8,893	0.451
<i>D Common Topic 10</i>	8,893	0.366
<i>D Common Topic 11</i>	8,893	0.745
<i>D Common Topic 12</i>	8,893	0.501
<i>D Common Topic 13</i>	8,893	0.484
<i>D Common Topic 14</i>	8,893	0.448
<i>D Common Topic 15</i>	8,893	0.525
<i>D Common Topic 16</i>	8,893	0.555
<i>D Common Topic 17</i>	8,893	0.466
<i>D Common Topic 18</i>	8,893	0.482
<i>D Common Topic 19</i>	8,893	0.561
<i>D Common Topic 20</i>	8,893	0.525
<i>D Common Topic 21</i>	8,893	0.360
<i>D Common Topic 22</i>	8,893	0.415
<i>D Common Topic 23</i>	8,893	0.248
<i>D Common Topic 24</i>	8,893	0.395
<i>D Common Topic 25</i>	8,893	0.691

Table 4.5: Mean levels of common topics

Panel B: 50_Gensim_Bigrams

Variable	N	Mean
<i>D Common Topic 1</i>	8,894	0.274
<i>D Common Topic 2</i>	8,894	0.361
<i>D Common Topic 3</i>	8,894	0.279
<i>D Common Topic 4</i>	8,894	0.299
<i>D Common Topic 5</i>	8,894	0.357
<i>D Common Topic 6</i>	8,894	0.291
<i>D Common Topic 7</i>	8,894	0.335
<i>D Common Topic 8</i>	8,894	0.223
<i>D Common Topic 9</i>	8,894	0.166
<i>D Common Topic 10</i>	8,894	0.305
<i>D Common Topic 11</i>	8,894	0.307
<i>D Common Topic 12</i>	8,894	0.218
<i>D Common Topic 13</i>	8,894	0.286
<i>D Common Topic 14</i>	8,894	0.323
<i>D Common Topic 15</i>	8,894	0.285
<i>D Common Topic 16</i>	8,894	0.236
<i>D Common Topic 17</i>	8,894	0.139
<i>D Common Topic 18</i>	8,894	0.253
<i>D Common Topic 19</i>	8,894	0.268
<i>D Common Topic 20</i>	8,894	0.384
<i>D Common Topic 21</i>	8,894	0.369
<i>D Common Topic 22</i>	8,894	0.279
<i>D Common Topic 23</i>	8,894	0.148
<i>D Common Topic 24</i>	8,894	0.351
<i>D Common Topic 25</i>	8,894	0.093
<i>D Common Topic 26</i>	8,894	0.313
<i>D Common Topic 27</i>	8,894	0.551
<i>D Common Topic 28</i>	8,894	0.196
<i>D Common Topic 29</i>	8,894	0.305
<i>D Common Topic 30</i>	8,894	0.326
<i>D Common Topic 31</i>	8,894	0.229
<i>D Common Topic 32</i>	8,894	0.387
<i>D Common Topic 33</i>	8,894	0.418
<i>D Common Topic 34</i>	8,894	0.191
<i>D Common Topic 35</i>	8,894	0.204
<i>D Common Topic 36</i>	8,894	0.281
<i>D Common Topic 37</i>	8,894	0.129
<i>D Common Topic 38</i>	8,894	0.065
<i>D Common Topic 39</i>	8,894	0.175
<i>D Common Topic 40</i>	8,894	0.381
<i>D Common Topic 41</i>	8,894	0.307
<i>D Common Topic 42</i>	8,894	0.342

<i>D Common Topic 43</i>	8,894	0.357
<i>D Common Topic 44</i>	8,894	0.197
<i>D Common Topic 45</i>	8,894	0.137
<i>D Common Topic 46</i>	8,894	0.336
<i>D Common Topic 47</i>	8,894	0.124
<i>D Common Topic 48</i>	8,894	0.255
<i>D Common Topic 49</i>	8,894	0.231
<i>D Common Topic 50</i>	8,894	0.242

This table presents a t-test on difference in means of *D Common Topic N* in Chair commentary and management commentary. *D Common Topic N* takes the value one if topic N is discussed by both Chair and management commentary in a given annual report published by firm *i* in year *t* or zero otherwise. , where *N* = 0 to 25 in Panel A and 50 in Panel B. Panel A shows the difference in means for topics generated by the model *25_Gensim_Unigrams* and Panel B shows the difference in means for topics generated by the model *50_Gensim_Bigrams*.

Table 4.6: Mean levels of new topicsPanel A: 25 *Gensim Unigrams*

Variable	Chair (1)		Management (0)	
	N (1)	Mean (1)	N (0)	Mean (0)
<i>D New Topic 1 Chair</i>	8,893	0.068	8,893	0.379
<i>D New Topic 2 Chair</i>	8,893	0.065	8,893	0.368
<i>D New Topic 3 Chair</i>	8,893	0.081	8,893	0.302
<i>D New Topic 4 Chair</i>	8,893	0.068	8,893	0.482
<i>D New Topic 5 Chair</i>	8,893	0.063	8,893	0.241
<i>D New Topic 6 Chair</i>	8,893	0.067	8,893	0.406
<i>D New Topic 7 Chair</i>	8,893	0.064	8,893	0.352
<i>D New Topic 8 Chair</i>	8,893	0.151	8,893	0.294
<i>D New Topic 9 Chair</i>	8,893	0.114	8,893	0.288
<i>D New Topic 10 Chair</i>	8,893	0.092	8,893	0.411
<i>D New Topic 11 Chair</i>	8,893	0.101	8,893	0.123
<i>D New Topic 12 Chair</i>	8,893	0.143	8,893	0.236
<i>D New Topic 13 Chair</i>	8,893	0.077	8,893	0.309
<i>D New Topic 14 Chair</i>	8,893	0.085	8,893	0.338
<i>D New Topic 15 Chair</i>	8,893	0.052	8,893	0.327
<i>D New Topic 16 Chair</i>	8,893	0.098	8,893	0.209
<i>D New Topic 17 Chair</i>	8,893	0.066	8,893	0.355
<i>D New Topic 18 Chair</i>	8,893	0.135	8,893	0.271
<i>D New Topic 19 Chair</i>	8,893	0.081	8,893	0.307
<i>D New Topic 20 Chair</i>	8,893	0.114	8,893	0.259
<i>D New Topic 21 Chair</i>	8,893	0.061	8,893	0.484
<i>D New Topic 22 Chair</i>	8,893	0.077	8,893	0.361
<i>D New Topic 23 Chair</i>	8,893	0.097	8,893	0.364
<i>D New Topic 24 Chair</i>	8,893	0.079	8,893	0.360
<i>D New Topic 25 Chair</i>	8,893	0.129	8,893	0.129

Panel B: 50_Gensim_Bigrams

Variable	Chair (1)		Management (0)	
	N (1)	Mean (1)	N (0)	Mean (0)
<i>D New Topic 1</i>	8,894	0.189	8,894	0.267
<i>D New Topic 2</i>	8,894	0.053	8,894	0.348
<i>D New Topic 3</i>	8,894	0.092	8,894	0.442
<i>D New Topic 4</i>	8,894	0.091	8,894	0.372
<i>D New Topic 5</i>	8,894	0.090	8,894	0.301
<i>D New Topic 6</i>	8,894	0.092	8,894	0.358
<i>D New Topic 7</i>	8,894	0.075	8,894	0.347
<i>D New Topic 8</i>	8,894	0.078	8,894	0.466
<i>D New Topic 9</i>	8,894	0.100	8,894	0.351
<i>D New Topic 10</i>	8,894	0.087	8,894	0.396
<i>D New Topic 11</i>	8,894	0.076	8,894	0.426
<i>D New Topic 12</i>	8,894	0.121	8,894	0.389
<i>D New Topic 13</i>	8,894	0.095	8,894	0.365
<i>D New Topic 14</i>	8,894	0.086	8,894	0.408
<i>D New Topic 15</i>	8,894	0.074	8,894	0.288
<i>D New Topic 16</i>	8,894	0.060	8,894	0.555
<i>D New Topic 17</i>	8,894	0.093	8,894	0.399
<i>D New Topic 18</i>	8,894	0.141	8,894	0.315
<i>D New Topic 19</i>	8,894	0.090	8,894	0.399
<i>D New Topic 20</i>	8,894	0.136	8,894	0.235
<i>D New Topic 21</i>	8,894	0.086	8,894	0.354
<i>D New Topic 22</i>	8,894	0.083	8,894	0.357
<i>D New Topic 23</i>	8,894	0.046	8,894	0.584
<i>D New Topic 24</i>	8,894	0.095	8,894	0.329
<i>D New Topic 25</i>	8,894	0.126	8,894	0.286
<i>D New Topic 26</i>	8,894	0.074	8,894	0.365
<i>D New Topic 27</i>	8,894	0.192	8,894	0.161
<i>D New Topic 28</i>	8,894	0.210	8,894	0.207
<i>D New Topic 29</i>	8,894	0.145	8,894	0.328
<i>D New Topic 30</i>	8,894	0.139	8,894	0.275
<i>D New Topic 31</i>	8,894	0.112	8,894	0.351
<i>D New Topic 32</i>	8,894	0.070	8,894	0.409
<i>D New Topic 33</i>	8,894	0.081	8,894	0.253
<i>D New Topic 34</i>	8,894	0.072	8,894	0.444
<i>D New Topic 35</i>	8,894	0.085	8,894	0.376
<i>D New Topic 36</i>	8,894	0.084	8,894	0.410
<i>D New Topic 37</i>	8,894	0.090	8,894	0.365
<i>D New Topic 38</i>	8,894	0.092	8,894	0.238
<i>D New Topic 39</i>	8,894	0.059	8,894	0.387
<i>D New Topic 40</i>	8,894	0.137	8,894	0.295
<i>D New Topic 41</i>	8,894	0.223	8,894	0.208
<i>D New Topic 42</i>	8,894	0.081	8,894	0.345

<i>D New Topic 43</i>	8,894	0.117	8,894	0.384
<i>D New Topic 44</i>	8,894	0.201	8,894	0.281
<i>D New Topic 45</i>	8,894	0.053	8,894	0.421
<i>D New Topic 46</i>	8,894	0.069	8,894	0.381
<i>D New Topic 47</i>	8,894	0.114	8,894	0.279
<i>D New Topic 48</i>	8,894	0.062	8,894	0.439
<i>D New Topic 49</i>	8,894	0.062	8,894	0.491
<i>D New Topic 50</i>	8,894	0.058	8,894	0.410

This table presents the means of *D New Topic N* in Chair commentary and management commentary. *D New Topic N* takes the value one if topic N is discussed in a given section of an annual report published by firm *i* in year *t* or zero otherwise, where *N* = 0 to 25 in Panel A and 50 in Panel B. Panel A shows the difference in means for topics generated by the model 25_*Gensim_Unigrams* and Panel B shows the difference in means for topics generated by the model 50_*Gensim_Bigrams*.

Table 4.7: Regression of one-year ahead earnings on tone of performance commentary (probability values in parentheses.)

Panel A: 25_Gensim_Unigrams

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$EARN_{t+1}$					
<i>Chair Tone Common Topics</i>	0.036 (0.01)		0.016 (0.32)	0.016 (0.20)		-0.002 (0.89)
<i>Chair Tone New Topics</i>		0.010 (0.10)	0.009 (0.15)		0.005 (0.37)	0.005 (0.37)
<i>Management Tone</i>	-0.001 (0.92)	0.005 (0.72)	-0.000 (0.99)	-0.007 (0.61)	-0.005 (0.70)	-0.004 (0.76)
$EARN_t$	0.332 (0.00)	0.351 (0.00)	0.349 (0.00)	0.315 (0.00)	0.336 (0.00)	0.336 (0.00)
<i>BTM</i>	-0.054 (0.00)	-0.054 (0.00)	-0.053 (0.00)	-0.045 (0.00)	-0.045 (0.00)	-0.045 (0.00)
<i>Leverage</i>	-0.006 (0.10)	-0.008 (0.14)	-0.008 (0.14)	-0.004 (0.21)	-0.005 (0.33)	-0.005 (0.33)
<i>Size</i>	0.007 (0.00)	0.007 (0.00)	0.007 (0.00)	0.006 (0.00)	0.006 (0.00)	0.006 (0.00)
<i>Log Business Segments</i>	0.006 (0.28)	0.008 (0.23)	0.008 (0.24)	0.007 (0.16)	0.010 (0.12)	0.010 (0.12)
<i>Log Geographic Segments</i>	0.000 (0.94)	-0.001 (0.91)	-0.001 (0.89)	0.001 (0.80)	0.000 (0.98)	0.000 (0.98)
$Loss_t$	-0.075 (0.00)	-0.080 (0.00)	-0.080 (0.00)	-0.066 (0.00)	-0.069 (0.00)	-0.069 (0.00)
<i>Returns</i>				0.070 (0.00)	0.070 (0.00)	0.070 (0.00)
Constant	-0.055 (0.01)	-0.048 (0.05)	-0.052 (0.04)	-0.055 (0.00)	-0.051 (0.04)	-0.050 (0.04)
Observations	8,891	5,785	5,783	8,891	5,785	5,783
Adjusted R-squared	0.255	0.267	0.267	0.274	0.285	0.285
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.7: Regression of one-year ahead earnings on tone of performance commentary (probability values in parentheses.)

Panel B: 50_Gensim_Bigrams

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$EARN_{t+1}$					
<i>Chair Tone Common Topics</i>	0.031 (0.01)		0.029 (0.02)	0.012 (0.33)		0.012 (0.35)
<i>Chair Tone New Topics</i>		0.020 (0.00)	0.018 (0.00)		0.016 (0.01)	0.015 (0.01)
<i>Management Tone</i>	0.000 (1.00)	0.009 (0.46)	-0.002 (0.89)	-0.005 (0.68)	-0.003 (0.84)	-0.007 (0.60)
$EARN_t$	0.332 (0.00)	0.329 (0.00)	0.327 (0.00)	0.315 (0.00)	0.311 (0.00)	0.310 (0.00)
<i>BTM</i>	-0.054 (0.00)	-0.054 (0.00)	-0.053 (0.00)	-0.045 (0.00)	-0.044 (0.00)	-0.044 (0.00)
<i>Leverage</i>	-0.006 (0.10)	-0.007 (0.07)	-0.007 (0.08)	-0.005 (0.21)	-0.005 (0.17)	-0.005 (0.18)
<i>Size</i>	0.007 (0.00)	0.008 (0.00)	0.008 (0.00)	0.006 (0.00)	0.007 (0.00)	0.007 (0.00)
<i>N Business Segments</i>	0.005 (0.28)	0.007 (0.22)	0.006 (0.25)	0.007 (0.16)	0.008 (0.12)	0.008 (0.13)
<i>N Geographic Segments</i>	0.000 (0.93)	-0.002 (0.75)	-0.002 (0.74)	0.001 (0.79)	-0.000 (0.92)	-0.001 (0.92)
$Loss_t$	-0.075 (0.00)	-0.075 (0.00)	-0.074 (0.00)	-0.066 (0.00)	-0.065 (0.00)	-0.065 (0.00)
<i>Returns</i>				0.070 (0.00)	0.070 (0.00)	0.070 (0.00)
Constant	-0.054 (0.01)	-0.057 (0.01)	-0.065 (0.00)	-0.054 (0.01)	-0.061 (0.00)	-0.064 (0.00)
Observations	8,890	8,244	8,240	8,890	8,244	8,240
Adjusted R-squared	0.255	0.254	0.254	0.274	0.273	0.273
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the regression of one-year ahead earnings on Chair and management tone. Panel A presents this regression for *Chair Tone Common Topics* is the difference between the number of positive sentences and the number of negative sentences that are assigned topics that, within the same annual report, appear in Chair commentary and management commentary scaled by the total number of sentences discussing common topics in Chair commentary. *Chair Tone New Topics* is the difference between the number of positive sentences and the number of negative sentences that are assigned topics that, within the same annual report, appear only on Chair commentary scaled by the total number of sentences discussing new topics in the Chair commentary. $EARN_{t+1}$ ($EARN_t$) is one year ahead EPS (current EPS), respectively, from continuing operations excluding extraordinary items scaled by current (lagged) stock price in fiscal year-end. *BTM* represents growth opportunities as measured by the book to market ratio. *Leverage* is measured as the debt-to-equity ratio, computed as total debt scaled by total shareholders' equity. *Size* is the logarithm of the market value of equity. *Returns* is the 12-month stock return ending four months after the fiscal year-end. *N Business Segments*, and *N Geographic Segments* are the logarithm of one plus the number business segments or geographic segments, respectively. $Loss_t$ is a binary variable that takes the value one if current earnings are lower than zero and zero otherwise.

Appendix 4.1: Topic labeling prompt

Prompt 1

For context, in a research project, a corpus of 'Strategic Report' sections from UK annual reports has been created. Specifically, for each firm, the corpus includes a Chair Statement signed by the Board Chair as well as a review signed by the CEO and/or CFO. It may also include a business and operations review and a discussion of the annual highlights. All of these chapters are included in the Strategic Report.

The 'Strategic Report' should provide shareholders of the firm with information that will enable them to assess how the directors have performed their duty to promote the success of the firm.

The 'Strategic Report' has three main content-related objectives:

- (a) to provide insight into the entity's business model and its main strategy and objectives;
- (b) to describe the principal risks the entity faces and how they might affect its future prospects; and
- (c) to provide an analysis of the entity's past performance.

An LDA topic model has then been constructed based on the text. The analysis generated {ntopics} topics.

You are a research associate who is tasked with interpreting the output of topic models generated from corporate disclosures.

Your objective is to provide a label which best represents the semantic meaning of the topic.

You are provided with the top {nwords} words for each of the {ntopics} topics.

Return only the labels and rationales for each topic.

Provide Your labels and rationales in JSON format like in the following example:

```
{“json_output”}
```

Appendix 4.1: Topic labeling prompt 1

Prompt 2

For context, in a research project, a corpus of 'Strategic Report' sections from UK annual reports has been created. Specifically, for each firm, the corpus includes a Chair statement signed by the Board Chair. The Chair statement is the last section written and represents a summary of the annual report and the performance highlights of the year. This is a voluntary section of the report and firms therefore have flexibility in what content to focus on. It may include the following information: 1) results and dividend; 2) overview of trading and business including management, succession planning, diversity and values; 3) governance overview including the impact of governance and risk management processes; 4) comments on corporate responsibility, sustainability and communities; 5) comments on markets and the environment; 6) outlook statement. The corpus also includes at least one of the following: a performance review signed by the CEO and/or CFO, a business review, an operations review and a discussion of the highlights of the year. These sections represent a combination of mandatory and voluntary disclosure. All of these chapters are included in the Strategic Report. The 'Strategic Report' should provide shareholders of the firm with information that will enable them to assess how the directors have performed their duty to promote the success of the firm. The content of the 'Strategic Report' can be grouped into three broad categories: strategic management, business environment and business performance.

The first category is strategic management and refers to how the entity intends to generate and preserve value. This category includes strategy and objectives and a description of the business model. This should include the following information: 1) how the entity generates or preserves value over the longer term; 2) how the entity captures that value; 3) what the entity does and why it does it; 4) what makes the entity different from, or the basis on which it competes with, its peers; 5) high level understanding of how the entity is structured; 6) high level understanding of the markets in which it operates and how it engages with those markets; and 7) broad understanding of the nature of the relationships, resources and other inputs that are necessary for the success of the business. The second category is business environment and refers to the internal and external environment in which the entity operates. This category includes a description of trends and factors, of matters related with the environment, employees, social, community and human rights and of principal risks and uncertainties. Principal risk reporting should include a description of 1) principal risks and how they are specific to the firm; 2) how the firm categorises and prioritises principal risks; 3) any movements and explanations into and out of the principal classification; 3) links to the other parts of annual report and accounts, such as the viability statement, business model, strategy, KPIs and the risk reporting of the financial statements; 4) any mitigating activities along with specific information regarding the firm's response. The third category is business performance category and refers to how the entity has developed and performed and its position at the year end. This category includes analysis of performance and position, key Performance indicators (KPIs) and employee gender diversity. Performance metrics should be 1) aligned to strategy by disclosing metrics that management uses internally, including where and how they link to remuneration; providing a combination of metrics linked to their strategic objectives, competitive advantage and business model, which may involve incorporating operational metrics alongside higher-level KPIs; and explaining what the metrics are and why they are important; 2) presented in a transparent way by providing an explanation for the use of metrics and a full break down of non-GAAP to GAAP metrics; being consistent and using the same, transparent format over a number of years; and demonstrating that metrics which investors would expect to be attributable to specific numbers in the financial statements or reconciliations are directly drawn from them; 3) provided in the context of the firm's aims by disclosing targets for metrics, showing whether performance has achieved its target or not; referencing an industry benchmark when disclosing performance where this is relevant; and providing a market context that is linked to how that context affects the firm; 4) presented in a reliable manner by making the governance and oversight over metrics clear; explaining the levels of scrutiny to which metrics have been subjected; and highlighting third party information in conjunction with internal information where relevant to strategic objectives; 5) consistent by information across reporting formats, even if it is presented differently for different audiences; performance with reference to industry benchmarks or standards; and a five-year track record. An LDA topic model has then been constructed based on the text. The analysis generated {ntopics} topics. You are a research associate who is tasked with interpreting the output of topic models generated from corporate disclosures.

Your objective is to provide a label which best represents the semantic meaning of the topic.

Your goal is to review these keywords, generate specific labels for each topic, and ensure that the labels are mutually exclusive.

You are provided with the top {nwords} words for each of the {ntopics} topics.

Instructions:

1. Read and Analyze Keywords:

- 1.a Carefully read the list of keywords for each of the {ntopics} topics.

- 1.b Identify semantic links between the keywords within each topic.
2. Generate Initial Labels:
 - 2.a Based on your analysis, generate a specific and descriptive label for each topic.
 - 2.b Labels should reflect the specific nature of the risks and uncertainties rather than generic terms like 'risk management' or 'risks.'
3. Ensure Mutually Exclusive Labels:
 - 3.a Compare topics with similar labels.
 - 3.b Identify subtle differences between the topics.
 - 3.c Modify the labels to ensure each one is unique and mutually exclusive.

Example:

Input word lists

Topic 1: ['property', 'planning', 'rental', 'residential', 'care', 'homes', 'joint', 'valuation', 'retail', 'office']

Topic 2: ['gas', 'oil', 'production', 'exploration', 'drilling', 'reserves', 'licence', 'prices', 'drilled', 'petroleum']

Topic 1:

- Label: Property investment
- Rationale: The keywords are centered around core business activities in the property investment and development sector.

Topic 2:

- Label: Commodities Exploration and Production
- Rationale: The keywords are related with the business processes associated with a firm working with production and exploration of commodities.

Return only the labels and rationales for each topic.
 Provide Your labels and rationales in JSON format like in the following example:
 {json_output}

5 Conclusion

In this thesis, I study how governance through disclosure shapes firm behavior. Specifically, I rely on different firm regulations that impact firms' annual report disclosures and test the effect of such regulations on different reporting outcomes, namely adoption of firm policies and informativeness of annual report narratives.

In Chapter 2, I test the impact of the mandatory disclosure of gender pay gap metrics on the adoption of firm policies that target the fundamental causes of the gender pay gap. I argue that the adoption of such policies is a key outcome to examine the effectiveness of the disclosure mandate as it allows me to take the point of view of the legislator when they initially implemented this policy. This is because these actions are evidence-based and their effectiveness in contributing to workplace gender equity and equality has been tested, as well as because they are recommended by UK Government guidelines. My results suggest that the policy was not particularly effective in triggering a change in firm behavior.

My work contributes to the literature examining the impact and effectiveness of pay transparency policies by asking whether the mandatory disclosure of the gender pay gap is associated with companies changing their behavior and taking actions that target the causes of the gender pay gap. This is important because addressing the fundamental causes of the gender pay gap is one of the goals of the policy. In this respect, I am measuring the effectiveness of the policy through the lens of the UK regulator. This chapter also adds to the literature examining the causes of the gender pay gap by highlighting how organizational practices are a step to reducing the pay gap in the medium to long run. This chapter is, however, not free from caveats.

First, the adoption of EE actions is collected from annual report disclosures. In this respect, it is possible that companies disclose further gender-related information through ESG reports and diversity statements. Second, the sample period that follows the implementation

of the disclosure of the gender pay gap metrics includes only a short period that does not fall on the COVID-19 period. The ideal scenario would be to observe firms' response using a longer period that does not fall on the COVID-19 time frame. Additionally, the COVID-19 period is an exceptional one that may have led companies to temporarily redirect their focus away from non-financial matters. It is therefore important to consider how the adoption of EE actions is after this period. Third, the work in this chapter must be interpreted in light of the key assumption of the paper that I measure actions through disclosure. Fourth, it is possible that while companies offer EE actions, employees do not take on those actions. While there is no evidence confirming or denying this possibility, if true, this would limit the ability of organizational practices to reduce the gender pay gap in the long run. Future work may examine whether the disclosure of gender pay gap metrics may be associated with increase in gender washing.

In Chapter 3, I ask whether the presence of an independent board Chair affects corporate disclosure by testing whether Chair-authored commentary is incrementally informative beyond management commentary. I rely on a set of firms that operate under the UK Corporate Governance Code, where separating the roles of the Chair and CEO and appointing an independent Chair is the norm. Such regulation then translates into the provision of performance commentary authored by the Chair and management. I argue that if Chair commentary is incrementally informative then shareholders have a reporting benefit in the form of performance commentary with implications for future performance. I find that Chair commentary carries incremental predictive ability for future earnings beyond management commentary. Further evidence suggests that this is consistent with the Chair serving a monitoring role and an information role that arises from a resource provision function and a confirmation function.

In Chapter 4, I examine variation in the content disclosed by management and Chair commentary and test whether the information role of the board Chair arises from a confirmation function or a resource provision function. I posit that if the Chair serves a confirmation (resource provision) function then the incremental predictability of Chair commentary for future earnings should be explained, at least in part, by themes that are also discussed by management (themes that are exclusively discussed by the Chair) than for those that are exclusively mentioned by the board Chair (themes that are also discussed by management). I compare results across two different LDA models used to conduct a topic modeling analysis. Results from a lower granularity 25-topic model are consistent with the Chair's information role being attributed only to its confirmation function. Nonetheless, results from a higher granularity 50-topic model are consistent with the information role of the Chair equally arising from serving both a confirmation and a resource provision function.

Chapter 3 and Chapter 4 contribute to two streams of literature. Both chapters contribute to the corporate governance and management literature examining the benefits of nominating an independent board Chair in three ways. First, this literature examines the benefits of appointing an independent Chair by focusing on settings (e.g., US) where firms choose to appoint a board Chair that is not affiliated with management therefore raising self-selection concerns (Iyengar and Zampelli, 2009). My work largely mitigates these concerns by relying on a sample of firms where appointing an independent board Chair is the norm. Second, while prior research largely focuses on examining the monitoring role of the Chair, recent evidence has shown that board Chairs believe that their role extends beyond monitoring and therefore calls for future work to examine other roles of the Chair (Boivie et al., 2021). I answer this call by providing evidence that the Chair serves an information role that is consistent with two non-mutually exclusive functions: confirmation and resource provision. Third, prior work examines the CEO-Chair dynamics through the lens of resource

dependency theory supporting CEO-Chair duality (Hillman and Dalziel, 2003; Krause et al., 2014). I provide evidence consistent with the board Chair serving a resource provision function despite not being the CEO.

Chapters 3 and 4 also contribute to the literature examining the informativeness of linguistic features of annual report disclosures in three ways. First, while prior literature has examined variations in informativeness of the same individual across different reporting channels (Davis and Tama-Sweet, 2012), I test differences in the informativeness of two annual report sections that are authored by different individuals with different responsibilities. This means that my empirical strategy allows me to test how differences in reporting incentives affect the informativeness of performance commentary while holding the institutional setting constant. Second, while prior research has examined whether financial reporting serves a decision usefulness or stewardship role, it is unclear whether and how financial narratives contribute to this debate. I show that the role of narrative disclosure may vary with firms' underlying conditions. Last, I test how content affects the informativeness of annual report disclosures. I adopt a topic modelling approach and therefore extend the literature that mainly focuses on tone and other surface linguistic features. Such focus ignores content, despite being a core element of a text, and overlooks its variation across time. I add to this research by modeling topics and by testing how the same topics are discussed within the same report but across different sections.

These chapters, however, present some caveats. First, annual report disclosures are more standardized and benefit from greater preparation than other channels such as earnings conference calls or press releases. Despite this, my results can only be tested in the context of annual report disclosures but not conference calls as it is not possible to observe the Chair's speech in a conference call. Second, I model topics using a Latent Dirichlet Approach. Despite being the most used method to conduct a topic modeling analysis in accounting and

finance, LDA is grounded on assumptions that are not always verified. For example, LDA follows a bag words approach that does not consider the order in which words appear and treats different topics as independent. In this respect, results must be interpreted knowing such limitations.

Overall, my thesis informs on the impact of firm regulation in the form of disclosure on reporting outcomes. This speaks to the use of disclosure as a governance tool that shapes firm behavior and decision making. Importantly, this thesis highlights the role of the annual report as an important communication channel not only to shareholders (Chapter 3 and Chapter 4) but also to stakeholders with interests beyond financial matters (Chapter 2).

References

- Abrahamson, E., Amir, E., 1996. The information content of the President's Letter to Shareholders. *Journal of Business Finance and Accounting* 23, 1157–1182. <https://doi.org/10.1111/j.1468-5957.1996.tb01163.x>
- Adams, R.B., Funk, P., 2012. Beyond the Glass Ceiling: Does Gender Matter? *Management Science* 58, 219–235. <https://doi.org/10.1287/mnsc.1110.1452>
- Alkhawaja, A., Hu, F., Johl, S., Nadarajah, S., 2023. Board gender diversity, quotas, and ESG disclosure: Global evidence. *International Review of Financial Analysis* 90, 102823. <https://doi.org/10.1016/j.irfa.2023.102823>
- Amel-Zadeh, A., Scherf, A., Soltes, E.F., 2019. Creating Firm Disclosures. *Journal of Financial Reporting* 4, 1–31. <https://doi.org/10.2308/jfir-52578>
- Argamon, S.E., Koppel, M., Pennebaker, J.W., Schler, J., 2009. Automatically profiling the author of an anonymous text. *Commun. ACM* 52, 119–123. <https://doi.org/10.1145/1461928.1461959>
- Arslan-Ayaydin, Ö., Bishara, N., Thewissen, J., Torsin, W., 2020. Managerial career concerns and the content of corporate disclosures: An analysis of the tone of earnings press releases. *International Review of Financial Analysis* 72, 101598. <https://doi.org/10.1016/j.irfa.2020.101598>
- Arslan-Ayaydin, Ö., Boudt, K., Thewissen, J., 2016. Managers set the tone: Equity incentives and the tone of earnings press releases. *Journal of Banking & Finance* 72, S132–S147. <https://doi.org/10.1016/j.jbankfin.2015.10.007>
- Arslan-Ayaydin, Ö., Thewissen, J., Torsin, W., 2021. Disclosure tone management and labor unions. *J Bus Fin Acc* 48, 102–147. <https://doi.org/10.1111/jbfa.12483>
- Atkinson, J., 2017. Shared Parental Leave in the UK: can it advance gender equality by changing fathers into co-parents? *International Journal of Law in Context* 13, 356–368. <https://doi.org/10.1017/S1744552317000209>
- Aziz, S., Dowling, M., Hammami, H., Piepenbrink, A., 2022. Machine learning in finance: A topic modeling approach. *Euro Fin Management* 28, 744–770. <https://doi.org/10.1111/eufm.12326>
- Baker, A., Callaway, B., Cunningham, S., Goodman-Bacon, A., Sant'Anna, P.H.C., 2025. Difference-in-Differences Designs: A Practitioner's Guide. <https://doi.org/10.48550/arXiv.2503.13323>
- Baker, M., Halberstam, Y., Kroft, K., Mas, A., Messacar, D., 2023. Pay Transparency and the Gender Gap. *American Economic Journal: Applied Economics* 15, 157–183. <https://doi.org/10.1257/app.20210141>
- Ball, R., Robin, A., Wu, J.S., 2003. Incentives versus standards: properties of accounting income in four East Asian countries. *Journal of Accounting and Economics* 36, 235–270. <https://doi.org/10.1016/j.jacceco.2003.10.003>
- Banerjee, A., Nordqvist, M., Hellerstedt, K., 2020. The role of the board chair—A literature review and suggestions for future research. *Corp Govern Int Rev* 28, 372–405. <https://doi.org/10.1111/corg.12350>
- Behavioral and Insights Team, 2023. How to improve workplace equity: evidence-based actions for employers. Employment and Social Development Canada, Gatineau, Quebec.
- Behavioral and Insights Team, 2021a. How to improve gender equality in the workplace Evidence-based actions for employers. Government Equalities Office, United Kingdom.
- Behavioral and Insights Team, 2021b. How to run structured interviews. United Kingdom.

- Behavioral and Insights Team, 2019. Eight ways to understand your organization's gender pay gap. Government Equalities Office, United Kingdom.
- Behavioral and Insights Team, 2018. How to improve gender equality in the workplace. Evidence-based actions for employers. Government Equalities Office, United Kingdom.
- Bennedsen, M., Larsen, B., Wei, J., 2023. Gender wage transparency and the gender pay gap: A survey. *Journal of Economic Surveys* 37, 1743–1777. <https://doi.org/10.1111/joes.12545>
- Bennedsen, M., Simintzi, E., Tsoutsoura, M., Wolfenzon, D., 2022. Do Firms Respond to Gender Pay Gap Transparency? *The Journal of Finance* 77, 2051–2091. <https://doi.org/10.1111/jofi.13136>
- Beyer, S., 1990. Gender Differences in the Accuracy of Self-Evaluations of Performance. *Journal of Personality and Social Psychology* 59, 960–970. <https://psycnet.apa.org/doi/10.1037/0022-3514.59.5.960>
- Bishu, S.G., Alkadry, M.G., 2017. A Systematic Review of the Gender Pay Gap and Factors That Predict It. *Administration & Society* 49, 65–104. <https://doi.org/10.1177/0095399716636928>
- Blau, B.M., DeLisle, J.R., Price, S.M., 2015. Do sophisticated investors interpret earnings conference call tone differently than investors at large? Evidence from short sales. *Journal of Corporate Finance* 31, 203–219. <https://doi.org/10.1016/j.jcorpfin.2015.02.003>
- Blau, F.D., Kahn, L.M., 2017. The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature* 55, 789–865. <https://doi.org/10.1257/jel.20160995>
- Blau, F.D., Kahn, L.M., 2000. Gender Differences in Pay. *Journal of Economic Perspectives* 14, 75–99. <https://doi.org/DOI:%252010.1257/jep.14.4.75>
- Blau, F.D., Kahn, L.M., 1999. Analyzing the gender pay gap. *The Quarterly Review of Economics and Finance* 39, 625–646. [https://doi.org/10.1016/S1062-9769\(99\)00021-6](https://doi.org/10.1016/S1062-9769(99)00021-6)
- Blei, D.M., Ng, A.Y., Jordan, M.I., 2003. Latent Dirichlet Allocation. *Journal of Machine Learning Research* 3, 993–1022.
- Bloomfield, R., 2008. Discussion of “Annual report readability, current earnings, and earnings persistence.” *Journal of Accounting and Economics* 45, 248–252. <https://doi.org/10.1016/j.jacceco.2008.04.002>
- Bochkay, K., Brown, S.V., Leone, A.J., Tucker, J.W., 2023. Textual Analysis in Accounting: What's Next?* 40.
- Boivie, S., Withers, M.C., Graffin, S.D., Corley, K.G., 2021. Corporate directors' implicit theories of the roles and duties of boards. *Strategic Management Journal* 42, 1662–1695. <https://doi.org/10.1002/smj.3320>
- Bonsall, S.B., Miller, B.P., 2017. The impact of narrative disclosure readability on bond ratings and the cost of debt. *Review of Accounting Studies* 22, 608–643.
- Boone, A., Starkweather, A., White, J.T., 2024. The saliency of the CEO pay ratio. *Review of Finance* 28, 1059–1104. <https://doi.org/10.1093/rof/rfad039>
- Boudt, K., Thewissen, J., 2019. Jockeying for Position in CEO Letters: Impression Management and Sentiment Analytics: Impression Management and Sentiment Analytics. *Financial Management* 48, 77–115. <https://doi.org/10.1111/fima.12219>
- Boudt, K., Thewissen, J., Torsin, W., 2018. When does the tone of earnings press releases matter? *International Review of Financial Analysis* 57, 231–245. <https://doi.org/10.1016/j.irfa.2018.02.002>

- Bowles, H.R., Babcock, L., 2013. How Can Women Escape the Compensation Negotiation Dilemma? Relational Accounts Are One Answer. *Psychology of Women Quarterly* 37, 80–96. <https://doi.org/10.1177/0361684312455524>
- Boyd, B.K., 1995. CEO duality and firm performance: A contingency model. *Strat. Mgmt. J.* 16, 301–312. <https://doi.org/10.1002/smj.4250160404>
- Bozanic, Z., Roulstone, D.T., Van Buskirk, A., 2018. Management earnings forecasts and other forward-looking statements. *Journal of Accounting and Economics* 65, 1–20. <https://doi.org/10.1016/j.jacceco.2017.11.008>
- Brennan, N.M., 2021. Connecting earnings management to the real World: What happens in the black box of the boardroom? *The British Accounting Review* 53, 101036. <https://doi.org/10.1016/j.bar.2021.101036>
- Brickley, J.A., Coles, J.L., Jarrell, G., 1997. Leadership structure: Separating the CEO and Chairman of the Board. *Journal of Corporate Finance* 3, 189–220. [https://doi.org/10.1016/S0929-1199\(96\)00013-2](https://doi.org/10.1016/S0929-1199(96)00013-2)
- Brochet, F., Loumiot, M., Serafeim, G., 2015. Speaking of the short-term: disclosure horizon and managerial myopia. *Review of Accounting Studies* 20, 1122–1163. <https://doi.org/10.1007/s11142-015-9329-8>
- Brown, G.W., Gredil, O.R., Kantak, P., 2023. Finding Fortune: How Do Institutional Investors Pick Asset Managers? *The Review of Financial Studies* 36, 3071–3121. <https://doi.org/10.1093/rfs/hhac090>
- Brown, N.C., Crowley, R.M., Elliott, W.B., 2020a. What Are You Saying? Using *topic* to Detect Financial Misreporting. *J of Accounting Research* 58, 237–291. <https://doi.org/10.1111/1475-679X.12294>
- Brown, N.C., Crowley, R.M., Elliott, W.B., 2020b. What Are You Saying? Using *topic* to Detect Financial Misreporting. *J of Accounting Research* 58, 237–291. <https://doi.org/10.1111/1475-679X.12294>
- Brown, S.V., Hinson, L.A., Tucker, J.W., 2024. Financial statement adequacy and firms' MD&A disclosures. *Contemporary Accounting Research* 41, 126–162.
- Bushee, B.J., Gow, I.D., Taylor, D., 2018. Linguistic Complexity in Firm Disclosures: Obfuscation or Information? *Journal of Accounting Research* 56, 85–121.
- Cadurri Committee, 1992. *The Financial Aspects of Corporate Governance*, Reprinted. ed. Gee, London.
- Card, D., Mas, A., Moretti, E., Saez, E., 2012. Inequality at Work: The Effect of Peer Salaries on Job Satisfaction. *American Economic Review* 102, 2981–3003. <https://doi.org/10.1257/aer.102.6.2981>
- Cascino, S., Clatworthy, M., Garcia Osma, B., Gassen, J., Imam, S., Jeanjean, T., 2013. The use of information by capital providers (Academic Literature Review). EFRAG, ICAS.
- Cazier, R.A., McMullin, J.L., Treu, J.S., 2021. Are Lengthy and Boilerplate Risk Factor Disclosures Inadequate? An Examination of Judicial and Regulatory Assessments of Risk Factor Language. *The Accounting Review* 96, 131–155. <https://doi.org/10.2308/TAR-2018-0657>
- Chakrabarty, B., Seetharaman, A., Swanson, Z., Wang, X.F., 2018. Management Risk Incentives and the Readability of Corporate Disclosures: Risk Incentives and Disclosure Readability. *Financial Management* 47, 583–616. <https://doi.org/10.1111/fima.12202>
- Chang, E.H., Milkman, K.L., 2020. Improving decisions that affect gender equality in the workplace. *Organizational Dynamics* 49, 100709. <https://doi.org/10.1016/j.orgdyn.2019.03.002>

- Clatworthy, M., Jones, M.J., 2003. Financial reporting of good and bad news: evidence from accounting narratives. *Accounting and Business Research* 33, 171–185. <https://doi.org/10.1080/00014788.2003.9729645>
- Clatworthy, M.A., Jones, M.J., 2006. Differential patterns of textual characteristics and company performance in the chairman's statement. *Accounting, Auditing & Accountability Journal* 19, 493–511. <https://doi.org/10.1108/09513570610679100>
- Coffman, K.B., Exley, C.L., Niederle, M., 2021. The Role of Beliefs in Driving Gender Discrimination. *Management Science* 67, 3551–3569. <https://doi.org/10.1287/mnsc.2020.3660>
- Cohen, L., Malloy, C., Nguyen, Q., 2020. Lazy Prices. *The Journal of Finance* 75, 1371–1415. <https://doi.org/10.1111/jofi.12885>
- Cook, R., O'Brien, M., Connolly, S., Aldrich, M., Speight, S., 2021. Fathers' Perceptions of the Availability of Flexible Working Arrangements: Evidence from the UK. *Work, Employment and Society* 35, 1014–1033. <https://doi.org/10.1177/0950017020946687>
- Cullen, Z., 2024. Is Pay Transparency Good? *Journal of Economic Perspectives* 38, 153–180. <https://doi.org/DOI:%252010.1257/jep.38.1.153>
- Dahya, J., Lonie, A.A., Power, D.M., 1996. The Case for Separating the Roles of Chairman and CEO: An Analysis of Stock Market and Accounting Data. *Corporate Governance: An International Review* 4, 71–77. <https://doi.org/10.1111/j.1467-8683.1996.tb00136.x>
- Davis, A.K., Ge, W., Matsumoto, D., Zhang, J.L., 2015. The effect of manager-specific optimism on the tone of earnings conference calls. *Rev Account Stud* 20, 639–673. <https://doi.org/10.1007/s11142-014-9309-4>
- Davis, A.K., Tama-Sweet, I., 2012. Manager's Use of Language Across Alternative Disclosure Outlets: Earnings Press Releases versus MD&A. *Contemporary Accounting Research* 29, 804–837. <https://doi.org/10.1111/j.1911-3846.2011.01125.x>
- Dedman, E., 2016. CEO succession in the UK: An analysis of the effect of censuring the CEO-to-chair move in the Combined Code on Corporate Governance 2003. *The British Accounting Review* 48, 359–378. <https://doi.org/10.1016/j.bar.2015.01.003>
- Di Vito, J., Trottier, K., 2022. A Literature Review on Corporate Governance Mechanisms: Past, Present, and Future*. *Accounting Perspectives* 21, 207–235. <https://doi.org/10.1111/1911-3838.12279>
- Dikolli, S.S., Keusch, T., Mayew, W.J., Steffen, T.D., 2020. CEO Behavioral Integrity, Auditor Responses, and Firm Outcomes. *The Accounting Review* 95, 64–88. <https://doi.org/10.2308/accr-52554>
- Dobbin, F., Kalev, A., 2014. Why Firms Need Diversity Managers and Task Forces, in: *How Global Migration Changes the Workforce Diversity Equation*. Cambridge Scholars Publishing.
- Drees, J.M., Heugens, P.P.M.A.R., 2013. Synthesizing and Extending Resource Dependence Theory: A Meta-Analysis. *Journal of Management* 39, 1666–1698. <https://doi.org/10.1177/0149206312471391>
- Duchini, E., Blundell, J., Simion, S., Turrell, A., 2023a. Pay Transparency and Gender Equality. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3584259
- Duchini, E., Simion, S., Turrell, A., 2023b. A review of the effects of pay transparency. *Oxford Research Encyclopedia of Economics and Finance*, forthcoming.
- Dyer, T., Lang, M., Stice-Lawrence, L., 2017. The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation. *Journal of Accounting and Economics* 64, 221–245. <https://doi.org/10.1016/j.jacceco.2017.07.002>

- El-Haj, M., Alves, P., Rayson, P., Walker, M., Young, S., 2020. Retrieving, classifying and analysing narrative commentary in unstructured (glossy) annual reports published as PDF files. *Accounting and Business Research* 50, 6–34. <https://doi.org/10.1080/00014788.2019.1609346>
- El-Haj, M., Rayson, P., Walker, M., Young, S., Simaki, V., 2019. In search of meaning: Lessons, resources and next steps for computational analysis of financial discourse. *J Bus Fin Acc* 46, 265–306. <https://doi.org/10.1111/jbfa.12378>
- Elsayed, K., 2007. Does CEO Duality Really Affect Corporate Performance?: DOES CEO DUALITY REALLY AFFECT CORPORATE PERFORMANCE? *Corporate Governance: An International Review* 15, 1203–1214. <https://doi.org/10.1111/j.1467-8683.2007.00641.x>
- Fama, E.F., Jensen, M.C., 1983. Separation of Ownership and Control. *Journal of Law and Economics* 26, 301–325. <http://dx.doi.org/10.1086/467037>
- Federsel, F.P., Fülbier, R.U., Seitz, J., 2024. Research-practice gap in accounting journals? A topic modeling approach. *JAL* 46, 368–400. <https://doi.org/10.1108/JAL-03-2023-0047>
- Feldman, R., Govindaraj, S., Livnat, J., Segal, B., 2010. Management’s tone change, post earnings announcement drift and accruals. *Review of Accounting Studies* 15, 915–953. <https://doi.org/10.1007/s11142-009-9111-x>
- Financial Reporting Council, 2020. Annual Review of the Corporate Governance Code.
- Financial Reporting Council, 2018. The UK Corporate Governance Code. London.
- Financial Reporting Council, 2014. The UK Corporate Governance Code. London.
- Financial Reporting Council, 2012. The UK Corporate Governance Code. London.
- Financial Reporting Council, 2008. The Combined Code on Corporate Governance. London.
- Financial Reporting Council, 2003. The Combined Code. London.
- Finley, A.R., Hall, C.M., Marino, A.R., 2022. Negotiation and executive gender pay gaps in nonprofit organizations. *Rev Account Stud* 27, 1357–1388. <https://doi.org/10.1007/s11142-021-09628-2>
- Fletcher, C., 1999. The implications of research on gender differences in self-assessment and 360 degree appraisal. *Human Res Manag J* 9, 39–46. <https://doi.org/10.1111/j.1748-8583.1999.tb00187.x>
- Frankel, R., Litov, L., 2009. Earnings persistence. *Journal of Accounting and Economics* 47, 182–190. <https://doi.org/10.1016/j.jacceco.2008.11.008>
- FRC, 2017. Lab project report: Risk and viability reporting. Financial Reporting Council.
- FRC, 2016. Lab project report: Business Model Disclosure. Financial Reporting Council.
- FRC, 2014. Guidance to Strategic Report. London.
- Fu, X., Wu, X., Zhang, Z., 2021. The Information Role of Earnings Conference Call Tone: Evidence from Stock Price Crash Risk. *J Bus Ethics* 173, 643–660. <https://doi.org/10.1007/s10551-019-04326-1>
- Fuller, S., Hirsh, C.E., 2019. “Family-Friendly” Jobs and Motherhood Pay Penalties: The Impact of Flexible Work Arrangements Across the Educational Spectrum. *Work and Occupations* 46, 3–44. <https://doi.org/10.1177/0730888418771116>
- Gad, M., Park, G., Rawsthorne, S., Young, S., 2025. When Methods Matter: How Implementation Choices Shape Topic Discovery in Financial Text. <https://doi.org/10.2139/ssrn.5134615>
- Gamage, D.K., Kavetsos, G., Mallick, S., Sevilla, A., 2024. Pay transparency intervention and the gender pay gap: Evidence from research-intensive universities in the UK. *Brit J Industrial Rel* 62, 293–318. <https://doi.org/10.1111/bjir.12778>
- García, D., Hu, X., Rohrer, M., 2023. The colour of finance words. *Journal of Financial Economics* 147, 525–549. <https://doi.org/10.1016/j.jfineco.2022.11.006>

- Georgiev, G.S., 2025. Disclosure as a Corporate Governance Tool: Channels and Challenges. <https://doi.org/10.2139/ssrn.5179523>
- Goergen, M., Limbach, P., Scholz-Daneshgari, M., 2020. Firms' rationales for CEO duality: Evidence from a mandatory disclosure regulation. *Journal of Corporate Finance* 65, 101770. <https://doi.org/10.1016/j.jcorpfin.2020.101770>
- Gulyas, A., Seitz, S., Sinha, S., 2023. Does Pay Transparency Affect the Gender Wage Gap? Evidence from Austria. *American Economic Journal: Economic Policy* 15, 236–255. <https://doi.org/10.1257/pol.20210128>
- Hainmueller, J., 2012. Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. *Polit. anal.* 20, 25–46. <https://doi.org/10.1093/pan/mpr025>
- Hassanein, A., Hussainey, K., 2015. Is forward-looking financial disclosure really informative? Evidence from UK narrative statements. *International Review of Financial Analysis* 41, 52–61. <https://doi.org/10.1016/j.irfa.2015.05.025>
- Hassanein, A., Zalata, A., Hussainey, K., 2019. Do forward-looking narratives affect investors' valuation of UK FTSE all-shares firms? *Rev Quant Finan Acc* 52, 493–519. <https://doi.org/10.1007/s11156-018-0717-6>
- Hayn, E., 1995. The information content of Losses. *Journal of Accounting and Economics* 20, 125–153.
- Henry, E., 2008. Are Investors Influenced By How Earnings Press Releases Are Written? *Journal of Business Communication* 45, 363–407. <https://doi.org/10.1177/0021943608319388>
- Henry, E., 2006. Market Reaction to Verbal Components of Earnings Press Releases: Event Study Using a Predictive Algorithm. *Journal of Emerging Technologies in Accounting* 3, 1–19. <https://doi.org/10.2308/jeta.2006.3.1.1>
- Henry, E., Leone, A.J., 2016. Measuring qualitative information in capital markets research: comparison of alternative methodologies to measure tone. *The Accounting Review* 91, 153–178. <https://doi.org/10.2308/accr-51161>
- Hickman, L., Thapa, S., Tay, L., Cao, M., Srinivasan, P., 2022. Text Preprocessing for Text Mining in Organizational Research: Review and Recommendations. *Organizational Research Methods* 25, 114–146. <https://doi.org/10.1177/1094428120971683>
- Higgs, D., 2003. Review of the role and effectiveness of non-executive directors. London.
- Hillman, A.J., Cannella, A.A., Paetzold, R.L., 2000. The Resource Dependence Role of Corporate Directors: Strategic Adaptation of Board Composition in Response to Environmental Change. *J Management Studies* 37, 235–256. <https://doi.org/10.1111/1467-6486.00179>
- Hillman, A.J., Dalziel, T., 2003. Boards of Directors and Firm Performance: Integrating Agency and Resource Dependence Perspectives. 28 3.
- Hillman, A.J., Withers, M.C., Collins, B.J., 2009. Resource Dependence Theory: A Review. *Journal of Management* 35, 1404–1427. <https://doi.org/10.1177/0149206309343469>
- Hribar, P., Mergenthaler, R., Roeschley, A., Young, S., Zhao, C.X., 2022. Do Managers Issue More Voluntary Disclosure When GAAP Limits Their Reporting Discretion in Financial Statements? *J of Accounting Research* 60, 299–351. <https://doi.org/10.1111/1475-679X.12401>
- Huang, A.H., Lehavey, R., Zang, A.Y., Zheng, R., 2018. Analyst Information Discovery and Interpretation Roles: A Topic Modeling Approach. *Management Science* 64, 2833–2855. <https://doi.org/10.1287/mnsc.2017.2751>
- Huang, A.H., Wang, H., Yang, Y., 2023. FinBERT: A Large Language Model for Extracting Information from Financial Text*. *Contemporary Accounting Research* 40.

- Huang, X., Teoh, S.H., Zhang, Y., 2014. Tone Management. *The Accounting Review* 89, 1083–1113. <https://doi.org/10.2308/accr-50684>
- Huang, Z., Teoh, S.H., Zhang, Y., 2014. Tone Management. *The Accounting Review* 89, 1083–1113.
- ICSA, 2015. Contents list for the annual report of a UK company. London.
- Iyengar, R.J., Zampelli, M., 2009. Self-selection, endogeneity, and the relationship between CEO duality and firm performance. *Strategic Management Journal* 30, 1092–1112. <https://doi.org/10.1002/smj>
- Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., Zhao, L., 2019. Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. *Multimed Tools Appl* 78, 15169–15211. <https://doi.org/10.1007/s11042-018-6894-4>
- Jergins, W., 2023. Gender equity and the gender gap in STEM: is there really a paradox? *J Popul Econ* 36, 3029–3056. <https://doi.org/10.1007/s00148-023-00959-9>
- Jewell, S.L., Razzu, G., Singleton, C., 2020. Who Works for Whom and the UK Gender Pay Gap. *Brit J Industrial Rel* 58, 50–81. <https://doi.org/10.1111/bjir.12497>
- Jones, M., Kaya, E., 2022. Organisational Gender Pay Gaps in the UK: What Happened Post-transparency? IZA Institute of Labor Economics. <https://www.iza.org/publications/dp/15342/organisational-gender-pay-gaps-in-the-uk-what-happened-post-transparency>
- Kausel, E.E., Culbertson, S.S., Madrid, H.P., 2016. Overconfidence in personnel selection: When and why unstructured interview information can hurt hiring decisions. *Organizational Behavior and Human Decision Processes* 137, 27–44. <https://doi.org/10.1016/j.obhdp.2016.07.005>
- Kleven, H., Landais, C., Leite-Mariante, G., 2024. The Child Penalty Atlas. NBER, National Bureau of Economic Research. <https://www.nber.org/papers/w31649>
- Kothari, S.P., 1992. Price-earnings regressions in the presence of prices leading earnings. *Journal of Accounting and Economics* 15, 173–202. [https://doi.org/10.1016/0165-4101\(92\)90017-V](https://doi.org/10.1016/0165-4101(92)90017-V)
- Krause, R., 2017. Being the CEO's boss: An examination of board chair orientations. *Strategic Management Journal* 38, 697–713. <https://doi.org/10.1002/smj.2500>
- Krause, R., Semadeni, M., Cannella, A.A., 2014. CEO Duality: A Review and Research Agenda. *Journal of Management* 40, 256–286. <https://doi.org/10.1177/0149206313503013>
- Krause, R., Semadeni, M., Michael C. Withers, 2016. That special someone: When the board views its chair as a resource. *Strat. Mgmt. J.* 37, 1990–2002. <https://doi.org/10.1002/smj.2444>
- Lafferty, J., Blei, D., 2005. Correlated Topic Models, in: Weiss, Y., Schölkopf, B., Platt, J. (Eds.), *Advances in Neural Information Processing Systems*. MIT Press.
- Lagaras, S., Marchica, M., Simintzi, E., Tsoutsoura, M., 2022. Women in the Financial Sector. SSRN Journal. <https://doi.org/10.2139/ssrn.4098229>
- Lang, M., Stice-Lawrence, L., 2015. Textual analysis and international financial reporting_ Large sample evidence. *Journal of Accounting and Economics* 60, 110–135. <http://dx.doi.org/10.1016/j.jacceco.2015.09.002>
- Leibbrandt, A., List, J.A., 2015. Do Women Avoid Salary Negotiations? Evidence from a Large-Scale Natural Field Experiment. *Management Science* 61, 2016–2024. <https://www.jstor.org/stable/24551582>
- Levashina, J., Hartwell, C.J., Morgeson, F.P., Campion, M.A., 2014. The Structured Employment Interview: Narrative and Quantitative Review of the Research Literature. *Personnel Psychology* 67, 241–293. <https://doi.org/10.1111/peps.12052>

- Lewis, C., Young, S., 2019. Fad or future? Automated analysis of financial text and its implications for corporate reporting. *Accounting and Business Research* 49, 587–615. <https://doi.org/10.1080/00014788.2019.1611730>
- Li, F., 2010. The Information Content of Forward-Looking Statements in Corporate Filings-A Naïve Bayesian Machine Learning Approach: the information content of corporate filings. *Journal of Accounting Research* 48, 1049–1102. <https://doi.org/10.1111/j.1475-679X.2010.00382.x>
- Li, F., 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* 45, 221–247. <https://doi.org/10.1016/j.jacceco.2008.02.003>
- Loughran, M., McDonald, B., 2011. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance* 66, 35–65.
- Loughran, T., McDonald, B., 2016. Textual Analysis in Accounting and Finance: A Survey: Textual Analysis in Accounting and Finance. *Journal of Accounting Research* 54, 1187–1230. <https://doi.org/10.1111/1475-679X.12123>
- Loughran, T., McDonald, B., 2014. Measuring Readability in Financial Disclosures. *Journal of Finance* 69, 1643–1671. <https://doi.org/10.1111/jofi.1>
- Luchman, J.N., 2021. Determining relative importance in Stata using dominance analysis: domin and domme. *The Stata Journal: Promoting communications on statistics and Stata* 21, 510–538. <https://doi.org/10.1177/1536867X211025837>
- Luchman, J.N., 2014. Relative Importance Analysis With Multicategory Dependent Variables:: An Extension and Review of Best Practices. *Organizational Research Methods* 17, 452–471. <https://doi.org/10.1177/1094428114544509>
- Lui, D., Moraru-Arfire, A., Tao, C., 2025. The Nexus of Corporate Disclosure and Investors' Information Needs: An Analysis Using Topic Modeling. *Business Fin & Account jbf.12857*. <https://doi.org/10.1111/jbfa.12857>
- Lyons, E., Zhang, L., 2023. Salary transparency and gender pay inequality: Evidence from Canadian universities. *Strategic Management Journal* 44, 2005–2034. <https://doi.org/10.1002/smj.3483>
- Merkel-Davies, D., Brennan, N.M., 2007. Discretionary Disclosure Strategies in Corporate Narratives: Incremental Information or Impression Management? *Journal of Accounting Literature* 26, 116–194.
- Michelon, G., Trojanowski, G., Sealy, R., 2021. Narrative Reporting: State of the Art and Future Challenges. *Accounting in Europe*.
- Miller, P.W., 2009. The Gender Pay Gap in the US: Does Sector Make a Difference? *J Labor Res* 30, 52–74. <https://doi.org/10.1007/s12122-008-9050-5>
- Milliken, F.J., Kneeland, M.K., Flynn, E., 2020. Implications of the COVID-19 Pandemic for Gender Equity Issues at Work. *J Management Studies* 57, 1767–1772. <https://doi.org/10.1111/joms.12628>
- Nicks, L., Roy-Chowdhury, V., Hardy, T., Gesiarz, F., Burd, H., 2021. Increasing applications from women through targeted referrals Research report. Behavioural Insights Team.
- Ntim, C.G., Lindop, S., Thomas, D.A., 2013. Corporate governance and risk reporting in South Africa: A study of corporate risk disclosures in the pre- and post-2007/2008 global financial crisis periods. *International Review of Financial Analysis* 30, 363–383. <https://doi.org/10.1016/j.irfa.2013.07.001>
- Olsen, W., Walby, S., 2004. Modelling gender pay gaps. Equal Opportunities Commission, Manchester.
- Pan, Y., Pikulina, E.S., Siegel, S., Wang, T.Y., 2022. Do Equity Markets Care about Income Inequality? Evidence from Pay Ratio Disclosure. *The Journal of Finance* 77, 1371–1411. <https://doi.org/10.1111/jofi.13113>

- Patelli, L., Pedrini, M., 2014. Is the Optimism in CEO's Letters to Shareholders Sincere? Impression Management Versus Communicative Action During the Economic Crisis. *J Bus Ethics* 124, 19–34. <https://doi.org/10.1007/s10551-013-1855-3>
- Pawliczek, A., Skinner, A.N., Wellman, L.A., 2021. A new take on voice: the influence of BlackRock's 'Dear CEO' letters. *Rev Account Stud* 26, 1088–1136. <https://doi.org/10.1007/s11142-021-09603-x>
- Perrault, E., McHugh, P., 2015. Toward a life cycle theory of board evolution: Considering firm legitimacy. *Journal of Management & Organization* 21, 627–649. <https://doi.org/10.1017/jmo.2014.92>
- Pfeffer, J., Salancik, G.R., 1978. *The External Control of Organizations: A Resource Dependence Perspective*. Harper & Row, New York.
- PwC, 2023. *Women in Work Index*.
- Raghunandan, A., Rajgopal, S., 2021. Mandatory Gender Pay Gap Disclosure in the UK: Did Inequity Fall and Do these Disclosures Affect Firm Value? SSRN Journal. <https://doi.org/10.2139/ssrn.3865689>
- Rajan, R., Ramella, P., Zingales, L., 2023. What Purpose Do Corporations Puport? Evidence from Letters to Shareholders. Working Paper.
- Rechner, P.L., Dalton, D.R., 1991. CEO Duality and Organizational Performance: A Longitudinal Analysis. *Strategic Management Journal* 12, 155–160.
- Rinne, U., 2018. Anonymous job applications and hiring discrimination. *IZA World of Labor*. <https://doi.org/10.15185/izawol.48.v2>
- Roethlisberger, C., Gassmann, F., Groot, W., Martorano, B., 2023. The contribution of personality traits and social norms to the gender pay gap: A systematic literature review. *Journal of Economic Surveys* 37, 377–408. <https://doi.org/10.1111/joes.12501>
- Roth, J., Sant'Anna, P.H.C., Bilinski, A., Poe, J., 2023. What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics* 235, 2218–2244. <https://doi.org/10.1016/j.jeconom.2023.03.008>
- Schabus, M., 2022. Do Director Networks Help Managers Forecast Better? *The Accounting Review* 97.
- Schleicher, T., 2012. When is good news really good news? *Accounting and Business Research* 42, 547–573. <https://doi.org/10.1080/00014788.2012.685275>
- Schler, J., Koppel, M., Argamon, S.E., Pennnebaker, J.W., 2006. Effects of Age and Gender on Blogging, in: *AAAI Spring Symposium: Computational Approaches to Analyzing Weblogs*.
- Securities and Exchange Commission, 2003. *Commission Guidance Regarding Management's Discussion and Analysis of Financial Condition and Results of Operations* (No. 68), Rules and Regulation. Federal Register.
- Seitz, S., Sinha, S., 2022. Pay Transparency, Workplace Norms, and Gender Pay Gap Early Evidence from Germany. SSRN Electronic Journal. <https://dx.doi.org/10.2139/ssrn.4337703>
- Shleifer, A., Vishny, R.W., 1997. A Survey of Corporate Governance. *The Journal of Finance* 52, 737–783. <https://doi.org/10.1111/j.1540-6261.1997.tb04820.x>
- Simintzi, E., Xu, S.-J., Xu, T., 2022. The Effect of Childcare Access on Women's Careers and Firm Performance. SSRN Journal. <https://doi.org/10.2139/ssrn.4162092>
- Son Hing, L.S., Sakr, N., Sorenson, J.B., Stamarski, C.S., Caniera, K., Colaco, C., 2023. Gender inequities in the workplace: A holistic review of organizational processes and practices. *Human Resource Management Review* 33, 100968. <https://doi.org/10.1016/j.hrmr.2023.100968>

- Stamarski, C.S., Son Hing, L.S., 2015. Gender inequalities in the workplace: the effects of organizational structures, processes, practices, and decision makers' sexism. *Front. Psychol.* 6. <https://doi.org/10.3389/fpsyg.2015.01400>
- Stuart, S., 2023. 2023 U.S. Spencer Stuart Board Index.
- Suchman, M.C., 1995. Managing Legitimacy: Strategic and Institutional Approaches. *Academy of Management Review* 20, 571–610.
- Trauth, E., Connolly, R., Dublin City University, 2021. Investigating the Nature of Change in Factors Affecting Gender Equity in the IT Sector: A Longitudinal Study of Women in Ireland. *MISQ* 45, 2055–2100. <https://doi.org/10.25300/MISQ/2022/15964>
- Wang, C.S., Whitson, J.A., King, B.G., Ramirez, R.L., 2023. Social Movements, Collective Identity, and Workplace Allies: The Labeling of Gender Equity Policy Changes. *Organization Science* 34, 2508–2525. <https://doi.org/10.1287/orsc.2021.1492>
- Windscheid, L., Bowes-Sperry, L., Kidder, D.L., Cheung, H.K., Morner, M., Lievens, F., 2016. Actions speak louder than words: Outsiders' perceptions of diversity mixed messages. *Journal of Applied Psychology* 101, 1329–1341. <https://doi.org/10.1037/apl0000107>
- Wiswall, M., Zafar, B., 2018. Preference for the Workplace, Investment in Human Capital, and Gender*. *The Quarterly Journal of Economics* 133, 457–507. <https://doi.org/10.1093/qje/qjx035>
- Withers, M.C., Fitza, M.A., 2017. Do board chairs matter? The influence of board chairs on firm performance. *Strategic Management Journal* 38, 1343–1355. <https://doi.org/10.1002/smj.2587>
- Women Returners, Timewise, 2018. Returner Programmes: Best Practice Guidance for Employers. Government Equalities Office, United Kingdom.
- Xiao, T., Zhu, J., 2025. Foundations of Large Language Models. <https://doi.org/10.48550/arXiv.2501.09223>
- Yu, M., 2023. CEO duality and firm performance: A systematic review and research agenda. *European Management Review* 20, 346–358. <https://doi.org/10.1111/emre.12522>