Corporate Social Responsibility, Diversity, and Corporate Communication: Natural Language Processing and Machine Learning Approaches

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Dedication

This dissertation is dedicated to my family, especially my parents, my sisters, my brothers, my wonderful wife Areij, and my son Hamza. I deeply felt my family's tremendous encouragement and support throughout the program and while writing this dissertation.

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ABSTRACT

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In the second chapter, we rely on collaborative intelligence, which combines human and artificial intelligence (i.e., supervised machine learning), to construct a textual feature that measures firm-level gender diversity talk (GDT), as reflected in the share of gender diversity discussion in the narrative of quarterly earnings conference calls. We show that the MeToo movement, an unequivocal social movement shock, led to a significant increase in GDT. We however document positive short-term stock market reaction to GDT during the first post-MeToo quarter, indicating that GDT is, on average, perceived by investors as value-relevant. We also show that post-MeToo, high-GDT firms engage in less substantive female-friendly initiatives, indicating that firms do not walk the talk of gender diversity.

In the third chapter, using industry-relevant documents and the most-cited CSR/ESG papers to develop a new CSR dictionary, we show that the COVID-19 incentivized firms to engage in overselling of their CSR. We find that more CSR talk during COVID translates into value depression, indicating that investors, on average, do not perceive CSR overselling as value-relevant. Our evidence suggests that firms do not walk their CSR talk and that CSR Talk is

positively (negatively) associated with the use of positive (negative) words. Our evidence suggests that ‘cheap talk is not cheap’.

In the fourth chapter, we use Natural Language Processing to measure supply chain risk (SCR) faced by US firms, as expressed in narratives of quarterly earnings conference calls. We show that exposure to SCR reached unprecedented levels during COVID-19. The effect of COVID-19 on SCR is more pronounced in firms with a greater dispersion of analyst forecasts, increased complexity, and more financial constraints. We document a negative effect of SCR on conference call short-term returns and future profitability. High-SCR firms are also associated with longer cash conversion cycles and more ESG overselling.

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1. Introduction

"The world cries out for repair" (Margolis Walsh 2003, p. 268) more than ever before, recognition of environmental, social, and governance (ESG) issues have been on the rise for decades. However, these issues have gained more prominence in the wake of the COVID-19 pandemic (COVID), urging the need for a more socially responsible corporate agenda. However, engaging in voluntary corporate actions and initiatives that take into account the social and environmental impact of the firm operations and account for the interests of a range of stakeholders, such as employees, customers, communities, and the environment, in addition to shareholders, remains largely in the realm of voluntary effort, providing corporations with discretion on the extent of their corporate social responsibility (CSR). This dissertation will shed light on the extent to which firms engage in overselling of their CSR, while resorting to mere lip service (or greenwashing) and lacking substantive action.[1]

It is important to note that CSR, which can be defined as a company's voluntary initiatives that aim to "further some social good, beyond the interests of the firm and that which is required by law" (McWilliams and Siegel, 2001, p. 117) and address stakeholders' expectations beyond legal obligations (Clarkson, 1995), is at the core of academic, industry, and policy agenda. For instance, the 2016 PWC Global CEO Survey shows that 64% of CEOs believe that CSR "is core

[1] This thesis will be presented in the form of three separate articles, structured to provide focused analysis and contribute to the existing body of knowledge within their respective topics.

to [their] business rather than being a stand-alone program." KPMG (2020) documents that over 90% of the world's 250 largest companies report on sustainability.[2] The 2017 CFA Institute global survey indicates that 73% of institutional investors consider ESG issues an essential matrix in their investment decisions. According to a survey by Deloitte in 2016, 87% of Millennials believe that a business's success should be evaluated based on factors beyond just financial performance.

Against this backdrop, CSR continues to serve as a thought-provoking research topic in academia and has produced a lively theoretical and empirical debate (Attig and Cleary 2015). All else equal, two competing views have long dominated the theoretical debate on the desirability of CSR. The orthodox view, which builds on Berle's (1931) shareholder primacy and popularized by Friedman (1970), posits that companies fulfill their societal responsibilities by maximizing profits and adhering to relevant laws and regulations. This, in turn, will result in maximizing social well-being.

The alternative view, rooted in Dodd's (1932) idea that corporations have a responsibility to both their shareholders and the wider society in which they operate, asserts that CSR plays a significant role in maintaining and enhancing a company's competitive advantage by satisfying the interests of its stakeholders (e.g. Davis, 1973; Freeman, 1984). The empirical literature on the relationship between corporate social responsibility (CSR) and corporate financial performance is mixed, with some studies showing a positive correlation and others showing no relationship. For instance, Margolis and Walsh (2003) show that 48 of 109 reviewed studies do not find a

[2] In this thesis we use CSR, ESG, and sustainability interchangeably.

distinguishable relationship between CSR and financial performance, and 54 (7) document a positive (negative) relationship. However, the meta-analytic study by Orlitzky et al. (2003) found a modest positive correlation between CSR and financial performance. Recent evidence, however, supports the idea that CSR can contribute to creating shareholder value (e.g. El Ghoul et al., 2011; Attig et al., 2013; Deng et al., 2013; Cheng et al., 2014; Lins et al., 2017, among others). Of note, Attig (2023) argues that CSR investments are associated with short-term costs and uncertain long-term benefits, providing evidence that relaxing financial constraints leads to higher CSR. He concludes that the link between financial constraints and CSR provides at least partial explanations for the mixed evidence on a link between CSR and corporate performance.

While society has some expectations for CSR because business and society are intertwined (Wood, 1991), firms may resort to symbolic CSR reporting and communication without engaging in substantive CSR initiatives. This is plausible given the uncertainty around CSR benefits and the lack of reporting standards (Attig 2023; Parguel et al., 2011). An emerging line of research, still seeking to gather momentum, has investigated the extent to which firms use selective disclosure and communication strategies to manage impressions of stakeholders and gain social legitimacy. The objective of this thesis is to add to this recent literature by addressing three novel questions:

- *Did firms engage in more 'gender diversity washing' during the MeToo movement?*
- *Did firms oversell their CSR performance during the COVID-19 pandemic?*

- *Did supply chain risk increase during COVID-19?*

I choose to work on these research questions because, in the realm of corporate governance and sustainability, gender diversity, ESG practices, and supply chain risk management have recently emerged as focal points. The choice of these questions reflects also growing recognition of the interconnectedness between various dimensions of sustainable development and the achievement of the United Nations Sustainable Development Goals (UN SDGs).[3] For instance, my first article focuses on gender diversity, which has been identified as a catalyst for improved decision-making and social progress and draws on SDG 5 (Gender Equality) and SDG 8 (Decent Work and Economic Growth). In the second article, I investigate the extent to which firms are embracing ESG principles, which can contribute to SDG 13 (Climate Action) and SDG 16 (Peace, Justice, and Strong Institutions). Finally, my third article delves into the critical area of supply chain risk management, which relates to SDG 12 (Responsible Consumption and Production) and SDG 17 (Partnerships for the Goals).

2. Theoretical background and prior literature

To answer the research questions of my dissertation, I draw on two strands of literature: (i) the use of corporate communication and selective disclosure to promote the societal appearance of

[3] UN SDGs represent a comprehensive framework to address the world's most critical social, economic, and environmental challenges.

conformity and (ii) the use of textual analysis and machine learning to extract features from corporate documents.

Corporate communication, including narrative disclosures in corporate documents such as annual reports (e.g. 10-k) and quarterly reports (e.g. earnings calls), has recently garnered increased attention from policymakers, academics, and the public at large. In fact, the importance of disclosure in corporate narratives was clearly emphasized in a Securities and Exchange Commission (SEC, 1987) report: "*The Commission has long recognized the need for a narrative explanation of the financial statements, because a numerical presentation and brief accompanying footnotes alone may be insufficient for an investor to judge the quality of earnings and the likelihood that past performance is indicative of future performance*." [4]

As part of corporate communication, firms can use CSR communication and selective disclosure to promote their societal appearance of conformity and possibly divert stakeholders' attention from activities that are inherently controversial and gain legitimacy. This strand of literature is old, yet scarce. Meyer and Rowan (1977), for instance, introduced the concept of decoupling, which refers to organizations adapting their visible structures, but not their core operations, to align with social norms. Nystrom and Starbuck (1984) suggest that managers construct organizational facades to conceal activities or results they want to hide and mislead stakeholders. A growing line of inquiry studies impression management, which refers to the behavioral strategies used to create desired social images or identities (Tetlock & Manstead, 1985)

[4] Report available at: https://www.sec.gov/rules/petitions/petnappx-12312001.htm and accessed on June 24, 2021, at 12:05 pm.

in order to control or manipulate the reactions of others (e.g., Leary & Kowalski, 1990). Nystrom and Starbuck (1984) suggest that managers construct organizational facades to conceal activities or results they want to hide and mislead stakeholders. A growing line of inquiry studies impression management, which refers to the behavioral strategies used to create desired social images or identities (Tetlock & Manstead, 1985) in order to control or manipulate the reactions of others (e.g., Leary & Kowalski, 1990).[5]

Indeed, managers may use various tactics to shape the way stakeholders perceive the company's current and future performance (Bansal & Clelland, 2004; Boudt & Thewissen, 2019), though in so doing may also "strategically…manipulate the perceptions and decisions of stakeholders" (Yuthas, Rogers, & Dillard, 2002, p. 143). Impression management involves "managers us[ing] judgment in financial reporting…to alter financial reports to…mislead some stakeholders about the underlying economic performance of the company" (Healy & Wahlen, 1999, p. 368). There appears to be a general consensus among researchers regarding the most pervasive impression management techniques. Merkl-Davies and Brennan's (2007) paper highlighting literature on impression management was published in the *Journal of Accounting Literature* and has acquired 967 citations on Google Scholar as of February 2, 2023. The paper classifies impression management into three main categories: verbal (narrative), numeric data (earning management), and graphs and pictures. Further, the authors propose seven types of

[5] The Financial Accounting Standards Board (FASB) has also expressed its concern about the quality of financial reports. In 2001, the FASB issued a Steering Committee Report entitled "Improving business reporting: Insights into enhancing voluntary disclosure"[5] (accessed on June 26, 2021, at 11:10 am). As noted in the SEC (1987) report mentioned above, the SEC encourages the provision of detailed information in corporate narrative disclosure, and this is evident from the increasing size of descriptive sections in corporate documents (Merkl-Davies & Brennan, 2007).

impression management approaches that focus on content analysis. These are: 1) obfuscating bad news; 2) rhetorical manipulation; 3) thematic manipulation; 4) visual and structural manipulation; 5) choosing performance comparison benchmarks; 6) choosing earnings numbers that portray current financial performance in the best possible light; and (7) attribution of performance.

The empirical studies on impression management involve theory testing. Five theories are used to explain, predict, and understand the impression management phenomenon and tactics: agency theory (Abrahamson & Park, 1994; Davidson et al., 2004); signaling theory (Langer et al., 2019); legitimacy theory (Hooghiemstra, 2000); stakeholder theory (Lee et al., 2020); and institutional theory (Bansal & Clelland, 2004). There are clear differences between and among these theories. For instance, agency theory and signaling theory focus on how managers and organizations employ impression management to influence investors' perceptions, while legitimacy theory, stakeholder theory, and institutional theory highlight how managers and organizations use the technique to manipulate societal perceptions (Merkl-Davies & Brennan, 2007).

Releasing more qualitative information in corporate disclosure may improve financial reporting quality and reduce information asymmetry (Mbobo & Ekpo, 2016; Athanasakou, Boshanna, Kochetova, and Voulgaris, 2023), which may inform investors' decisions (Botosan & Plumlee, 2002). However, and since CSR remains largely in the realm of voluntary effort, firms have discretion to selectively disclose information about their CSR performance to create impression management. Impression management can be viewed through the lens of agency problems since managers may use selective disclosure to influence stakeholders' perceptions about the firm's CSR (and future performance) by overselling CSR performance. Impression management is defined as "behavioral strategies that people use to create desired social images or identities" (Tetlock & Manstead, 1985, p. 59) that are intended to control or manipulate the reactions of others (Leary & Kowalski, 1990; Schlenker, 1980). As there are no direct regulations assigning the duty of monitoring the language and writing style of corporate report contents, managers may be incentivized to inflate or manipulate the narrative disclosure, and thus influence stakeholder perceptions (Arslan-Ayaydin et al., 2016; García Osma & Guillamón-Saorín, 2011). Likewise, managers may use impression management in discretionary narrative disclosures because they prepare corporate reports themselves and so voluntarily select the information they wish to disclose (Baginski, Hassell, & Hillison, 2000; Bagnoli & Watts, 2017; Lambert, 2001). For example, companies are not required to issue a corporate social responsibility report, but they voluntarily do so (Bagnoli & Watts, 2017). This establishes preferences for managers who may selectively disclose information that aligns with their interests at the cost of stakeholders' value.

The legitimacy theory, which explains how firms may gain and maintain the perceived legitimacy or acceptance from various stakeholders, through CSR selective disclosure and communication to reduce the incongruence between the actual CSR performance and the desired CSR image. This is plausible since it will be difficult for stakeholders to verify the CSR performance claimed by the firm, given the lack of reporting standards.[6] Indeed, the lack of

[6] Talbot & Boiral (2015) explore how corporate managers use impression management tactics to justify their company's impacts on climate change(Talbot & Boiral, 2015, p. 329). Boiral (2016) examines how organizations use

standards around, for instance, sustainability reporting makes it difficult for investors and other stakeholders to distinguish between truly ‘virtuous’ firms and those that engage in symbolic environmental or CSR initiatives (Parguel et al., 2011). This is because it is easier to manage the stakeholders' impression of a firm's CSR image through communication and selective disclosure than by changing the firm's operations and policies (e.g., Neu, Warsame, and Pedwell, 1998) and promoting the appearance of conformity can be sufficient to attain legitimacy (Oliver, 1991).[7]

The practice of paying mere lip service to CSR issues to posture a socially desirable image to manage impressions is also coined as greenwashing (GW),[8] has recently moved to a central place in the agenda of policymakers, practitioners, and the public at large. For instance, the CFA Institute, in its reports on the integration of ESG in the Americas (2018) and Europe, the Middle East, and Africa (2019, p. 6), concludes that ESG investing is “often used as a marketing slogan.” The Center for Corporate Citizenship at Boston College (2013) reveals that over 70% of surveyed companies cite ‘enhanced reputation’ among the top three business goals of their sustainability efforts. As such, studying GW or the extent to which firms oversell their CSR performance can be relevant to both academics and practitioners.

impression management tactics to demonstrate their responsibility for biodiversity in order to legitimize their impacts. Impression management can be used to manipulate information about firm strategy (Whittington et al. 2016)

[7] Corporate managers may issue official communications, such as qualitative disclosures, to purposely misinform stakeholders for their own benefit (Arslan-Ayaydin et al., 2016; Huang et al., 2014; Nyberg et al., 2013).

[8] GW refers to the practice of selectively communicating or disclosing positive information about a firm environmental or social performance while withholding related negative information to frame activities as 'green' (Lyon & Maxwell, 2011; Laufer, 2003).

The second strand of literature on which my thesis draws is textual analysis and machine learning to extract textual features. Textual analysis, which -to some extent- “resides across many disciplines under various aliases, including computational linguistics, natural (or statistical) language processing, information retrieval, content analysis, or stylometric” has a long history (Loughran and McDonald 2016, page 1187). Textual analysis is still an emerging area in accounting, finance and management and can be considered as “a subset of a broader literature in finance on qualitative information (Loughran and McDonald 2016, page 1188). It is a computer-aided technique that uses the capabilities of computers to extract (soft) information from firm selective disclosure in corporate narratives.

With the recent exponential increase in computing power and decline in computing cost, the use textual analysis has gained momentum. While early related studies use textual analysis to examine either targeted phrases, sentiment analysis, topic modeling, measures of document similarity or the readability and complexity of corporate documents (e.g. Loughran and McDonald 2011, Loughran and McDonald 2012; Loughran and McDonald 2016 for a literature review), recent related research agenda, which began with the pioneering work of Hassan, Hollander, van Lent, and Tahoun (2019), adapted tools from computational linguistics to construct firm-level risk measures that reflect a firm’s exposure to a specific risk. This approach builds on pattern-based sequence-classification method developed in computational linguistics (Song and Wu 2008; Manning, Raghavan, and Schütze 2008, as cited in Hassan et al. 2019) to distinguish between language associated with risk versus non-risk matters. Hassan et al. (2019) were the first to use this approach to construct a new measure of political risk faced by individual U.S. firms: the share of their quarterly earnings conference calls that they devote to political risks. A handful of studies have since made headway in using similar tools from computational linguistics to cyber risk (Florackis et al., 2023), climate risk (Sautner et al., 2022), and geopolitical risk (Caldara & Iacoviello, 2022). In my thesis, we rely heavily on textual analysis and machine learning tools to extract textual constructs relevant to my research questions.

Annual reports are commonly researched corporate documents for managing external impressions, as reported by Merkl-Davies and Brennan (2007) and others. However, we rely on conference earning calls (ECs) to extract the textual features and focus on bigrams. We use ECs because they are an unaudited medium for voluntary disclosure and interactive verbal communications (e.g., Bushee et al., 2003; Bowen et al., 2003; Frankel et al.,1999), providing managers with more discretion in the narrative of their communications. Matsumoto et al. (2011) suggest that, during conference calls, managers are less constrained in providing information and analysts play an important role in uncovering information during the question-and-answer (Q&A) session, making ECs incrementally informative (Matsumoto et al., 2011). Further, the disclosures made during conference calls are particularly useful because they are held quarterly and contain senior management's direct responses to questions from analysts and market participants (Hassan et al., 2019, 2022), and thus may represent a timely source of information (Donovan et al., 2021; Frankel et al., 2022). Campbell et al. (2021) argue that ECs draw significant investor attention because they are one of the first disclosures released by firms.

3. Summary of the chapters

As stated above, the objective of the first chapter of my thesis it to investigate whether firms engaged in more 'gender diversity washing' during the MeToo movement? The driving idea of my first chapter is gender diversity (GD). GD continues to serve as a challenging topic for society and business alike. As of March 2022, 74 female CEOs were running *Fortune* 500 businesses (*Fortune*, 2022), compared to a total of 41 (7) in June 2021 (2002). This suggests female talent is making some strides in breaking the glass ceiling. Nevertheless, a significant imbalance in *Fortune* 500 leadership persists (15% female vs. 85% male),[9] indicating that gender-based disparity remains prevalent in the corporate landscape. Stereotypical perceptions of women's attributes and sexist attitudes are examples of gender-based frictions that can reduce the likelihood of hiring and promoting female talent (e.g., Harvie et al., 1998), and contribute to gender-based disparity in corporate leadership. Arnold and Loughlin (2019), in their literature synthesis, conclude that gender and leadership stereotypes form systemic barriers to the progression of women to leadership positions. Gender stereotypes tend to associate women with communal qualities, while viewing men as agentic (Heilman 1983).[10] Leadership stereotypes refer to the gender-based perception (rather than the actual performance) of the leadership roles, suggesting that leaders are

[9] Although, according to a survey of MBA students, women are equally likely to be in a management position (Hampole, Truffa, and Wong, 2022).

[10] "Caring about others and being kind and helpful" are examples of communal traits (Arnold and Loughlin 2019, p. 96). Competitiveness against others, assertiveness, and ambition are traits that are characteristics of agentic male leaders.

expected to be male and assertive and that women are not fit for senior leadership positions. These stereotypes can create barriers for female to attaining senior leadership positions.

As suggested by Arnold and Loughlin (2019), the think manager-think male, think crisis-think female[11] and think caregiver-think female stereotypes contribute to the gender-perception of leadership roles and to the perception that women are not fit for leadership positions, which will cast doubt on likelihood of success of women as leaders and result in low representation of women in leadership roles. The gender-perception of leadership roles can result in backlash against women leaders when they exhibit agentic attributes (Arnold and Loughlin 2019, and references therein).

Importantly, Arnold and Loughlin (2019) stress that increasing the representation of women in senior leadership roles is a necessary first step to combat these stereotypes an remove barriers faced by women to access (more) leadership position. Bohnet (2016, p. 2007) suggests also that increasing the number of women in leadership positions will enhance their ability to compete in "male-dominated domains". The recommendations of Arnold and Loughlin (2019) and Bohnet (2016) to de-bias the workplace (and the processes and practices) rather than the individuals appear relevant and will likely lead to more leadership female representation. This is likely the case because having more women in leadership positions can change the perception that females are fit for leadership roles. Social role theory (Koeing and Eagly 2014) and role congruity theory (Eagly and Karu 2002) lend credence to this prediction. This is because, according to social role theory, individuals' behavior, attitudes, and identities are shaped by the social roles they occupy in society.

[11] This refers to the increased likelihood of promoting women to leadership positions in times of crisis, commonly coined as glass cliff (Ryan and Haslam 2005).

For instance, individuals' experience of women's roles in society will shape the shared beliefs about what role women are expected to play, forming gender-role stereotypes (Koenig and Eagly, 2014). Relatedly, role congruity theory suggests that prevailing norms and stereotypes determine how a particular group of individuals (e.g. women, men) are expected to behave (Eagly & Karau, 2002).

The stereotypes that result in negative evaluation of women in senior leadership roles, because of the inconsistency between the roles ascribed to women and the perceived leadership role. It, thus, stands to reason to increase women representation in senior leadership positions (Arnold & Loughlin, 2019) to decrease the incongruity between women and leadership roles perceived as requiring male agentic traits. Further, having more female leaders can lead to a "critical mass" in women representation that will likely favor capacity-building and more gender equity and limit tokenism (Bohnet 2016). Removing women's internal barriers to leadership roles or increasing women's representation in these roles poses a chicken-egg problem (Arnold & Loughlin, 2019), the underrepresentation of women in leadership positions will certainly sustain the gender-based stereotypes that women are incompatible with leadership positions and contribute to why we are still far from gender equality.[12]

Unsurprisingly, gender-based frictions have become increasingly prominent on management agendas, as well as on those of policymakers and the public at large. The United

[12] Nordell (2021) argue that that diversifying workplaces benefit organizations when they are less discriminatory and more fair and just. Stated differently, promoting a culture of inclusiveness and tackling unfairness is necessary to benefit from bringing more diversity to the workplace. Nordell (201) focuses on how to address unconscious bias and associated stereotypes.

Nations Development Programme (2021, p. v) stresses the importance of removing barriers that women (and other marginalized groups) face to "thrive in the workplace, to progress in their careers and to reach decision-making levels in their organizations." These goals are vital for businesses to flourish and contribute to the achievement of the United Nations Sustainable Development Goals. The UN views gender equality as "a necessary foundation for a peaceful, prosperous and sustainable world." Its Sustainable Development Goal #5 is: "To achieve gender equality and empower all women and girls."[13]

Building on these insights and #MeToo movement, we use collaborative intelligence, which combines both human intelligence and artificial intelligence (i.e. supervised machine learning), to construct a textual feature that measures firm-level gender diversity (GDT), as reflected in the share of gender diversity discussion in the narrative of quarterly earnings conference calls. We then examine whether the MeToo movement, an unequivocal social movement shock, led to an increase in GDT, plausibly, in their attempt to posture a desirable image and manage stakeholders' impressions of their performance in reducing gender-based frictions in the workplace. We then investigate how gender diversity overselling varies across firms. We particularly focus on the relevance of female-friendly cultures, as measured by the presence of female CEO and female representation on the board of directors.

[13] More broadly, 96% of the CEOs in the 2020 Fortune/Deloitte CEO Survey assert that diversity, equity, and inclusion is a "personal strategic priority" (Deloitte, 2020). The assumption that men are more inclined to take risks than women is probably one of the greatest barriers to equality in corporate leadership faced by female talent.

In the second chapter, we investigate the economic implications of CSR talk. To this end, we use industry relevant documents and the most cited CSR/ESG papers to develop a new CSR dictionary. Since the COVID pandemic has disrupted economies, societies, and industries on a global scale, it is important to understand how firms have navigated this crisis in relation to their sustainability commitments and ESG practices. That is why we examine whether the COVID-19 pandemic incentivized firms to engage in overselling of their CSR. We also investigate the cross-sectional variation of this relationship (i.e. COVID and CSR talk).

The third article delves into supply chain risk management. We namely use Natural Language Processing to construct firm-level measure of supply chain risk, which may reflect the extent to which a firm is exposed to supply chain disruptions. This question is relevant because the COVID-19 pandemic has placed significant strain on supply chains and has firmly rooted supply chain risk in managers' agendas and government and public thinking. Further, supply chain risk is increasingly attracting the attention of investors and other stakeholders. Surprisingly, while a sizable literature has examined managing supply chain risks, extant literature has not given much consideration to an aggregate measure of the supply chain risk that reflects the extent of a firm's vulnerability to supply chain shocks.

Investigating gender diversity, ESG and supply chain issues contributes to our understanding of how these interconnected topics play relevant roles in advancing the UN SDGs and how firms (and more broadly organizations) can contribute to these global goals. In the last chapter, we provide the conclusion of the thesis.

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Chapter 2: Social Movement and Gender Diversity Washing: Evidence from The MeToo Movement

Abstract:

This study relies on collaborative intelligence, which combines human and artificial intelligence (i.e. supervised machine learning), to construct a textual feature that measures firm-level gender diversity talk (GDT), as reflected in the share of gender diversity discussion in the narrative of quarterly earnings conference calls. We show that the MeToo movement, an unequivocal social movement shock, led to a significant increase in GDT, plausibly in an attempt to present a desirable image and manage stakeholders' impressions of their performance in reducing gender-based frictions in the workplace. Gender diversity overselling appears to be more pronounced in firms with less female-friendly culture and with more secondary activist stakeholders of the MeToo movement (e.g. institutional investors). We also show that firms located in low–social capital and less religious states, and those with a high percentage of women workers and in less sexist states, tend to engage in more GDT. We however document positive short-term stock market reaction to GDT during the first post-MeToo quarter, indicating that GDT is, on average, perceived by investors as value-relevant. We also show that post-MeToo, high-GDT firms engage in less substantive female-friendly initiatives, indicating that firms do not walk the talk of gender diversity.

Keywords: Gender Diversity; Social Movements; #MeToo; Disclosure; Collective Action; Stakeholder Influence; Machine Learning.

1. Introduction

No other event in the recent past has been more effective in raising consciousness about "the prevalence and destructiveness of sexual harassment" (Leopold et al. 2021, p. 461) and gender diversity (GD) issues than the MeToo movement (MeToo). It started as a social media movement resisting sexual harassment of, and misconduct towards, women,[14] and snowballed into street demonstrations and political and regulatory debates worldwide (e.g. MeTooRising), spurring a re-energized focus on gender-based discrimination. This has not only drawn growing public attention to gender diversity (GD) issues,[15] but has also increased societal expectations for more corporate initiatives to reduce gender-based frictions in the workplace.[16] Surprisingly, the extant literature appears to have had limited success in providing evidence of the corporate response to MeToo. Notably missing from the literature is the extent to which firms, in response to MeToo and the associated growing pressure for more GD, turn to selective disclosure and communication to posture a GD desirable image. Our study fills this void by investigating whether MeToo provided

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[14] The moniker "Me Too", first coined by activist Tarana Burke in 2006 (*Chicago Tribune* 2021), gained extensive visibility across the globe after Alyssa Milano posted the hashtag "#MeToo" on October 15, 2017. The hashtag was an invitation for survivors of sexual assault and harassment to speak out about their experiences to raise awareness and hold perpetrators accountable. #MeToo has received more than 500,000 responses within 24 hours (Abeysekera and Fernando 2020), 1,595,453 tweets in the first week (Modrek and Chakalov 2019) and over 19 million tweets within a year (Kallenbach 2020).

[15] GD refers to the presence of more women and the reduction of gender-based frictions in the workplace. Gender-based frictions refer to the mistreatment and biases women face in the workplace (e.g. sexual harassment, abuse, bullying, discrimination, gender pay gap). They reflect hurdles of both the demand side (e.g. discrimination against women) and supply side (e.g. social norms) of the labor market that restrict the demand for female labor (Bertay et al. 2020) and prevent female talent (or ideas) from being hired or promoted (Luo and Zhang 2022).

[16] This is plausible since business and society are intertwined (Wood 1991).

incentives for firms to oversell their GD performance and gender-wash their image by paying mere lip service to GD issues.

MeToo offers an ideal setting for the purpose of our study because it is an exogenous shock to investors' and stakeholders' perception of gender equity issues in the workplace (e.g. Billings, Klein, and Shi 2022; Cook and Luo 2022; Lins et al. 2023). Equally important, MeToo satisfies the factors that facilitate collective action and social movement's influence: mobilizing structures, corporate opportunities, and framing processes (e.g. King 2008b).[17] MeToo has indeed legitimized and motivated collective action for more GD. The extra-institutional tactics (King 2008a), such as large street demonstrations and protests and broadcasting grievances publicly (e.g. Lipsky 1968), have not only drawn attention to perceived gender-based injustices and broadened the political discussion of gender inequality, but have also shaped public opinion on GD issues. In turn, this has, arguably, appealed to legislators, broader organizational audiences, and firm primary stakeholders (e.g. analysts, customers, employees, suppliers, potential investors). This greater attention to GD issues and the increasing stakeholders pressure for more gender equity in the workplace, may translate into financial and reputational threats against firms with less-than-desirable GD performance. Against this backdrop, and since it is easier to manage stakeholders' impression of a firm's GD image through communication and selective disclosure (e.g. Neu et al. 1998) than by undertaking substantive GD initiatives, firms may engage in GD selective disclosure to promote the appearance of conformity. This is plausible since promoting the appearance of (GD)

[17] A discussion of this point is provided in the next section.

conformity can be sufficient to attain legitimacy,[18] given the limited observability of GD investments and the lack of GD reporting standards.

To test this prediction, we adopt a new approach (collaborative intelligence) that combines human intelligence (HI) and artificial intelligence (AI) (i.e. supervised machine learning, SML) to construct a textual feature that captures the extent to which managers discuss GD-related issues (GDT, i.e., GD Talk) during quarterly earnings conference calls (ECs). GDT is a relevant measure for the purpose of our study because managers can use narrative disclosures to communicate with shareholders and stakeholders, and possibly "manage their perceptions" (Merkl-Davies and Brennan, 2007, p. 117).[19] In addition, using textual analysis to capture firm GD presents a unique opportunity for adding "value in capturing the nuances" (Loughran and McDonald 2022, p. 1) of measuring GD.

We use ECs when extracting GDT because they are an unaudited medium for voluntary disclosure and interactive verbal communications (e.g., Bushee, Matsumoto, and Miller 2003; Bowen, Davis, and Matsumoto 2002; Frankel, Johnson, and Skinner 1999), providing managers with more discretion in the narrative of their communications. Matsumoto, Pronk, and Roelofsen (2011) suggest that during conference calls managers are less constrained in providing information and analysts play an important role in uncovering information during the question-and-answer

[18] This argument is builds on Oliver's (1991, p. 155) argument that "the appearance rather than the fact of conformity is often presumed to be sufficient for the attainment of legitimacy".
[19] The unobservability of GD investments and the lack of GD reporting standards will likely make investors and stakeholders susceptible to impression management about firm GD performance. As discussed in Merkl-Davies and Brennan (2007), managerial discretionary disclosure choices can be opportunistic when viewed through the lens of impression management. Alternatively, they can have value-relevant incremental information for equity investors. We test these predictions in the empirical section.

session, making ECs incrementally informative. Further, conference call disclosures can be particularly useful as they are held quarterly and contain senior management's direct responses to questions from analysts and market participants (Hassan et al. 2019; Hassan et al. 2021), and thus, may represent a timely source of information (Donovan et al. 2021; Frankel et al. 2022). Campbell, Zheng, and Zhou (2021) argue that ECs draw significant investor attention because they are one of the first disclosures released by firms.

In our collaborative intelligence approach, we combine bigrams (i.e., a sequence of two adjacent words) lists developed based on HI and SML to develop a GD dictionary. We focus on bigrams because they are less ambiguous (Bloom, Hassan, Kalyani, and Lerner 2020) than unigrams and tend to convey more information than single-word keywords. We extract GD bigrams from (i) two relevant textbooks, (ii) press articles of four major newspapers (i.e., *New York Times* and *USA Today* in the U.S.; *Hamilton Spectator* and *Toronto Star* in Canada) between January 2014 and December 2019, and (iii) the most-cited GD academic studies.[20] We supplement this list with two concurrent working papers on #MeToo: Calder-Wang and Gompers (2021) and Lins et al. (2023) and various GD practitioners' frameworks and documents: the 2020 and 2022 Bloomberg Gender-Equality Index, the 2020 European Women on Boards Gender Diversity Index, the USA Women on Board: Gender Diversity Index over the period 2015–2020, and the 2019 MeToo Impact Report. Since "no algorithm understands the context of human conversations better

[20] We use the Web of Science to identify the most-cited GD-relevant academic studies and end up selecting studies published in the *Academy of Management Journal, American Sociological Review, Strategic Management Journal, Journal of Business Ethics, Corporate Governance: An International Review, and Human Resource Management*.

than human beings" (Li et al. 2022, p. 11), we rely on HI to identify keywords (i.e. bigrams) that are relevant to GD issues. In the empirical section, we provide details of our multi-step disambiguation process through which manual inspection of 1,361,795 bigrams narrowed the list of bigrams to 1,200.

We then apply SML tools to identify GD-relevant bigrams. After training the algorithm on annotated training data, we use Random Forest (RF) to classify the extracted features and apply the area under the curve (AUC) for model evaluation. Using bigram-frequency, we ask the winner model (RF) to report the 500 most important bigrams (using bigram-frequency) that are used to achieve 99.9% performance in classifying documents into GD vs. non-GD documents. Using bigram-frequency-inverse documents frequency (BF-IDF), we also ask the winner model (RF) to report the 500 most important bigrams (using BF-IDF) that are used to achieve 99.9% performance in classifying documents into GD vs. non-GD documents. We retain bigrams that appear to agree with both approaches: bigram frequencies and bigram-frequency-inverse document frequencies. We then keep bigrams that are in both word lists: the HI list and the SML list and end up with 202 bigrams.

We argue that the MeToo effects extended beyond sexual harassment litigation and accelerated a larger effort for changes around women in the workplace (Heminway 2019). Increased public attention to the issues of gender-based violence and harassment in the workplace may create incentives for managers to communicate to stakeholders a desirable GD image of their firms. We explore this prediction in four ways. We first show that MeToo incentivized managers to engage in more GDT. This suggests that MeToo provided incentives for managers to oversell the GD performance of their firms. This result remains valid even after measuring GD Talk by the residual from regressing GDT on various textual features, including a textual measure of ESG/CSR.[21] This result is important as it shows that GDT is distinct from other textual measures.

Second, we show that firms with a male CEO tend to engage in more overselling of GD performance. We also show that firms located in states with more social capital, more religious states, and more sexist states tend to engage in less GDT. Third, we evaluate whether GDT translates into stock performance around post-MeToo ECs and document a positive and significant effect of GDT on the cumulative market-adjusted return in the trading window surrounding the date of the post-MeToo conference calls. In our final test, we examine whether firms walk their GD talk. We show that post-MeToo female board representation, the net change in female board representation, and the likelihood of female CEO are not associated with GDT, suggesting that firms appear to engage in 'gender-diversity washing' by paying mere lip service to GD issues.

By turning scholarly attention to the extent to which firms manage stakeholders' impression about their GD performance and the valuation implications of such impression management, we depart from extant GD literature, the burden of which has been to establish the valuation effects of more female representation on corporate boards (e.g. Ahern and Dittmar 2012; Matsa and Miller 2013; Eckbo et al. 2022, among many others). We add to this literature by creating a comprehensive measure of GD talk, using the narrative content of disclosure in earnings

[21] This residual can also be viewed as a measure of abnormal GDT.

calls. In addition to adding to GD research, our study connects to three other strands of literature.

First, our study connects to a burgeoning line of inquiry that applies text-based analysis to measure tone-related characteristics in corporate documents. For instance, a dictionary-based approach was used to measure disclosure sentiment (Loughran and McDonald 2011), financial constraints (Bodnaruk et al. 2015), and sustainability hypocrisy (Attig 2021); supervised machine learning was recently used to measure credit risk (Donovan et al. 2021), the materiality of environmental and social disclosure (Chava et al. 2021), and financial constraints (Buehlmaier and Whited 2018).

Second, our study adds to the new yet burgeoning line of research that investigates the implications of the MeToo movement and public announcements of sexual harassment. To the best of our knowledge, only a handful of studies have made headway in examining the economic implications of MeToo; most focus on the market response. Billings et al. (2022) provide evidence on the role of corporate female-friendly culture, reflected by the absence (presence of a critical mass) of women directors in the board room, in shaping stock market reactions to #MeToo. Lins et al. (2023) document an increase in returns of firms with a female-friendly (i.e. non-sexist) corporate culture during the #MeToo movement. Cook and Luo (2022) show that #MeToo provided incentives for actively managed mutual funds to tilt their portfolios toward firms with greater C-suite female representation. Luo and Zhang (2022), however, focus on Hollywood producers and show that the #MeToo movement led to an increase in the likelihood of Hollywood producers working with female writers on new movie projects. Calder-Wang, Gompers, and

Sweeney (2021) show that the Ellen Pao v. Kleiner Perkins gender discrimination trial led to a significant increase in the rate of hiring female venture capitalists. Abeysekera and Fernando (2020) show that public announcements of sexual harassment are associated with negative market returns of social pressure. Gormley et al. (2022) provide evidence consistent with a relevant role of index investors in expanding women's participation in corporate leadership. Our work departs from these studies by focusing on the impact of MeToo on firm narrative selective disclosures.[22] As such, our study sheds light on the role of secondary stakeholders (e.g. Key 1999) in shaping corporate policies and outcomes.

Third, our study complements a recent line of inquiry on the extent to which firms 'walk the talk' of their sustainability. A handful of studies have made headway in suggesting that firms may oversell their ESG performance through communication of merely symbolic (rather than substantive) sustainability activities (Greenwashing)[23] to strengthen their legitimacy (e.g. Delmas and Burbano 2011; Du 2015; Khan, Serafeim, and Yoon 2016; Marquis, Toffel, and Zhou 2016; Cai, Xu, and Yang 2020; Attig, Rahaman, and Trabelsi 2021; Attig and Boshanna 2023). Our study also adds to the related strand of literature that examines the use of impression management to manage stakeholders' perceptions about a firm's performance (see Merkl-Davies and Brennan (2007) for a review). More broadly, our evidence lends credence to the line of inquiry that suggests that investors' tastes for ESG stocks can have valuation impact (e.g. Lins et al. 2023; Pástor,

[22] Our study connects to the sizeable literature on social movement (see King 2008a, 2008b), Arjaliès (2010), and Georgallis (2017) for a related discussion).

[23] Greenwashing refers to the practice of selectively communicating or disclosing positive information about a firm's environmental or social performance while withholding related negative information to frame activities as 'green' (Lyon and Maxwell 2011; Laufer 2003)

Stambaugh, and Taylor (2021); Pedersen, Fitzgibbons, and Pomorski (2021)) in which investor tastes for ESG stocks can impact valuation. However, our new evidence highlights the importance of communicating the firm ESG (i.e. in our case GD) performance in driving investors' responses.

The remainder of the paper is structured as follows. Section II discusses the theoretical background. Section III presents our data and summary statistics. In Section IV, we report our results. Section V concludes the paper.

2. Literature Background

Our work draws on insights from the following strands of literature:

2.1 Gender Diversity

The field of scholarship on GD has been guided by the perception of psychological and cognitive differences between genders. Dawson (1997), drawing on gender socialization theory, argues that men and women learn different sex roles, related values, and concerns in childhood, and these differences characterize masculine and feminine behavior. He posits that these differences lead men and women to exhibit psychological and cognitive differences in moral principles (Cumming et al. 2015, and references therein) and information processing (Meyers-Levy 1989; Meyers-Levy and Maheswaran 1991). As suggested by Carlson (1972), men are socialized to be guided by agentic goals that reflect achievement-oriented tendencies (e.g. Radtke 2000); women are socialized to attend to communal goals, leading them to put more emphasis on the development of interpersonal relationships and making them more sensitive to ethical issues.[24] These gender stereotypes as well as leadership stereotypes hold back women from obtaining senior leadership roles (Arnold and Loughlin 2019) and exacerbate the mismatch between the gender roles and leadership type (Eagly and Karau 2002).

Empirical research on the extent to which gender personality differences in psychology and experimental economics studies can be extrapolated to corporate leadership remains limited (e.g. Faccio et al. 2016). In a recent literature review, Teodósio et al. (2021, p. 1039) find that research on the effects of the GD of corporate leadership "is only approximately a decade old." The bulk of the extant literature focuses on the economic implications board GD, top management team (TMT) GD, and CEO gender and has yet to reach consensus.[25] We add to this strand of literature by providing one of the first pieces of evidence on using machine learning and textual analysis to construct a measure of firm GDT.

[24] Males tend to be more aggressive, whereas women are more caring (Radtke 2000). While the view that males and females are vastly different psychologically appears to dominate the popular culture, it is possibly overstating gender differences because such differences are more nuanced and complex than commonly believed. Hyde (2005) advances the gender similarities hypothesis, which holds that males and females are similar on most, but not all, psychological variables.

[25] Gender diversity on boards provides grounds for broader and more diverse skill sets resulting from adding female directors (Kim and Starks 2016; Bernile, Bhagwat, and Yonker 2018; Adams, Akyol, and Verwijmeren 2018). Adams and Feirreia (2009) find that female directors have better attendance records than male directors and are more likely to join monitoring committees. Cumming et al. (2015, and references therein) argue that gender diversity will likely result in increased scrutiny of board members (e.g. when members have less trust in each other because of conflicts among members of diverse boards), provide access to a better talent pool, and distinct leadership style. As such, more female representation on corporate boards may improve otherwise inefficient board elections (Agarwal, Qian, Reeb, and Sing 2016), improve monitoring (Adams and Feirreia 2009; Adams and Funk 2012), increase price informativeness (Gul et al. 2011), reduce the likelihood of financial restatement (Abbott et al. 2012), and increase effectiveness in mitigating both the presence and severity of fraud in male-dominated industries (Cumming et al. 2015). Ahern and Dittmar (2012) and Matsa and Miller (2013) show that gender quota law has a negative effect on corporate performance; Eckbo et al.'s (2022) evidence suggests a zero impact on firm value.

2.2 The #MeToo Movement and GDT

We posit that the #MeToo movement created incentives for managers to discuss the GD issues in the ECs that followed the MeToo movement, plausibly to communicate a positive image of their firm's GD performance. The crux of this prediction is that the actors of the #MeToo movement translate shared interests into collective action (Davis and Thompson 1994), mobilizing different stakeholders to exert pressure (King 2008a), thus making stakeholders' demands about gender equality more effective. It is important to note that collective action is a critical condition for stakeholders' demand to become effective (King 2008b). As stated in the outset, MeToo satisfies the factors that facilitate collective action and social movement's influence: mobilizing structures, corporate opportunities, and framing processes (e.g. King 2008b).

Indeed, MeeToo lay dormant for some time and gained traction only after Harvey Weinstein was accused of sexual misconduct (October 5, 2017) and Alyssa Milano tweeted the hashtag #MeToo, inviting victims of sexual harassment to share their experience (corporate/political opportunities). This incident presented an exogenous opportunity that inhibited "prospects for mobilization" and encouraged silenced voices of victims of sexual misconduct and GD advocates to take more risk and attempt to influence "mainstream institutional politics and policy" (Meyer and Minkoff 2004, p. 1457).[26] Collective action and resource mobilization of a social movement hinge on the extent to which the social movement activists strategically frame the issues (and use framing activities) to leverage the cognitive, emotional, cultural, and

[26] Corporate or political opportunities refers to stakeholders' response to exogenous opportunities (King 2008b, and references therein).

ideological reactions and orientations of potential supporters of the movement and create shared collective identities (Benford and Snow 2000; Snow and Benford 1988; Snow et al. 1986). MeToo has shaped collective identities of victims of sexual misconduct or gender-based frictions in the workplace and created shared understanding of their actions (Nissen 2000) and possibilities for social change (Campbell 1988). This has facilitated mobilizing structures to connect the movement with interests of "prospective constituents and actual or prospective resource providers" (Benford and Snow 2000, p. 624). To exert more influence on relevant social networks and societal institutions and "influence public discourse, and legitimize and motivate collective action" (Hipsher 2007, p. 246), mobilizing structures need to be deployed. These collective vehicles pool inputs of individuals and enable them to aggregate their opinions and efforts (King 2008b).[27]

The MeToo social media campaign (mobilizing structures) connected like-minded individuals and enabled the movement to gain extensive visibility across the globe as the hashtag "#MeToo" received over 500,000 responses in 24 hours (Abeysekera and Fernando 2020) and 1,595,453 tweets in the first week (Modrek and Chakalov 2019). It also spread to mainstream media and sparked an international social movement against sexual harassment in the workplace, causing the "silence breakers" to be named Time magazine's Person of the Year (Time 2017).

Building on these insights, and since managers may not be neutral in their presentation of narratives of their disclosures (Sydserff and Weetman 1999), they have incentives to use narrative techniques to gain the support of various stakeholders and maintain the legitimacy of their firms.

[27] Mobilizing structures refer to "collective vehicles, informal as well as formal, through which people mobilize and engage in collective action" (McAdam et al. 1996, p. 3).

Such narratives may also signal lower GD risks and reassure investors during the period of increased public attention on gender discrimination and sexual misconduct. Stakeholders (including shareholders) could penalize companies perceived to have gender abusive issues (Luo and Zhang 2022) and less than desirable GD image. Engaging is GD discussions to project a favorable GD image of the firm helps mitigate such risks.[28] Our first hypothesis is, thus, as follows:

H_1: Firms engaged in more GD 'Talk' after the MeToo event.

We next focus on the valuation effects of GD Talk. Two predictions guide our analysis. The first suggests that GD Talk can generate positive moral capital among the firm's stakeholders and thus provide insurance-like protection for a firm's relationship-based intangible assets (Godfrey 2005), which may result in more trust and support by stakeholders (i.e. social capital[29]). This in turn will likely translate into positive stock performance.[30] Alternatively, engaging in GDT during MeToo might have adverse effects due to additional public and political pressure for more GD initiatives to reduce gender-based frictions and the increased attention may induce investors to allocate more attention to firm-specific GD information. Relatedly, a company's GD can become

[28] Caution is merited in predicting a positive effect of MeToo on GDT. While we assume that (most) firm stakeholders value GD, one may argue that managers will not engage in GD Talk unless they think shareholders would value such narrative. Further, MeToo was criticized for being centered on sexual harassment experiences of white Western women (Gill and Orgad 2018) without questioning the socioeconomic and political structures that facilitate such discrimination against women (Sanín 2022). It also triggered some (short-lived) backlash movement (e.g. #HimToo) given men's heightened vulnerability to false accusation (e.g. Boyle and Rathnayake 2020). The MeToo movement made it harder for men to know how to interact with women in the workplace (Boyle and Cucchiara 2018).

[29] Social capital can be broadly ascribed to the quality of the firm's relationships with its stakeholders (Lins, Servaes and Tamayo 2017).

[30] This is plausible because the claimed GD performance is typically unobservable and unverifiable because of the lack of reporting standards. One might however argue that stakeholders could verify the extent of a firm's GD by determining whether its board is gender-diverse.

more publicly visible and therefore attract scrutiny from the media, regulators, analysts, and investors. Heightened scrutiny may associate overselling GD with distorted information in the firm's communicated GD performance, which could result in negative valuation effect.[31] It is also possible that investors know about the GD performance of the firm and, thus, GDT may not have an impact on the firm valuation.

The discussion above leaves the impact of GDT on financial performance (i.e. stock market return) during MeToo an open empirical question. For expositional convenience, however, we predict the effect to be positive and our second hypothesis is as follows:

H_2: GD Talk may result in positive short-term stock return performance (post-MeToo).

3. Data and Variables Construction

3.1. Sample Selection

To analyze the narrative of ECs, we start by downloading all quarterly ECs of U.S. firms during the period 2015–2019. We keep only R-readable ECs with .pdf format. We restrict our sample to calls of firms with available data in Compustat (quarterly) and other data sources as described in Appendix A. For all tests, we remove financials (SIC 6000−6999), utilities (SIC 4900−4999), and governmental and quasi-governmental entities (SIC 9000 and above). To ensure that the results of our empirical analyses are not driven by fundamental differences among firms with different firm-level variables, we include in our final sample firms with non-missing values

[31] Along this line, 'cheap talk' between firms and capital markets may attract the market's attention and result in valuation effects (Almazan et al. 2008).

of our main regression variables. These filters result in a main sample of 29,353 quarterly earnings calls for 2,411 unique firms.

3.2. Textual Construction of GDT: Collaborative Intelligence

3.2.1 Sources of GD bigrams

In developing our dictionary, we focus on bigrams because they are less ambiguous (Bloom et al. 2020) than unigrams and tend to convey more information than single-word keywords. To develop our preliminary list of bigrams we rely on various sources.

We first identified relevant books that can be used to extract the list of bigrams for our GD dictionary.[32] As an initial step, we contacted faculty members teaching GD-related courses in women and gender studies departments in the top 10 U.S. schools and requested the title of the main textbook used in their courses.[33] Among those who responded, *Feminist Frontiers* by Verta Taylor, Nancy Whittier, and Leila J. Rupp (2019, 10th edition), was recommended.[34] We also selected *#MeToo in the Corporate World: Power, Privilege, and the Path Forward* (2020) by Sylvia Ann Hewlett. Of note, both were published after the MeToo movement and are arguably expected to reflect MeToo-relevant GD bigrams.

[32] Using non-corporate disclosure to construct a domain-specific dictionary is common. Hassan et al. (2019) used textbooks (e.g., political and accounting textbooks) as well as newspapers from Factiva to develop a dictionary for their firm-level political risk proxy. Baker et al. (2016) used articles from leading U.S. newspapers to develop an economic policy uncertainty measure.
[33] Using "Best National University Rankings" from *US News*, available at https://www.usnews.com/best-colleges/rankings/national-universities
[34] Special thanks to Leila J. Rupp and Verta Taylor from the University of California Santa Barbara for granting us special access to a PDF copy of their textbook for use in our textual analysis.

Second, we supplement the above list of bigrams with GD bigrams from press articles that appeared in four major newspapers (i.e., *New York Times* and *USA Today* in the U.S.; *Hamilton Spectator* and *Toronto Star* in Canada) between January 2014 and December 2019. Building on Baker et al.'s (2016) approach, we use a list of keywords[35] to identify newspapers that may cover GD-relevant and MeToo-relevant topics.

Third, we use the Web of Science to identify the most-cited academic articles on GD published in the *Academy of Management Journal, Strategic Management Journal, Journal of Business Ethics, Corporate Governance: An International Review, Human Resource Management, American Sociological Review, Journal of Management,* or the *Human Resource Management Review*. We also consider two concurrent working papers on the MeToo movement: Calder-Wang et al. (2021) and Lins et al. (2023).[36] Finally, we use the following GD-relevant professional frameworks and documents: 2020 and 2022 Bloomberg Gender-Equality Index, 2020 European

[35] **GD keywords:** "gender parity" OR "gender diversity" OR "gender equality" OR "gender inequality" OR "women on board" OR "percentage of women" OR "women hold" OR "women gained" OR "women gain board seats" OR "women directors" OR "female directors" OR "women joining boards" OR "women's participation" OR "women represent" OR "presence of women" OR "representation of women" OR "gender diversity index" OR "empowerment of women" OR "women in the executive" OR "women in board committees" OR "female leaders" OR "women in CEO positions" OR "share of women" OR "women in leadership" OR "female chairs of the board" OR "female CEO" OR "female CFO" OR "chairwomen" OR "women in committees" OR "gender pay gap" OR "recruit women" OR "includes women" OR "retention of women" OR "gender equality in the workplace" OR "Women in the Workplace" OR "gender pay parity". **MeToo Keywords**: "me too movement" OR "Tarana Burke" OR "Harvey Weinstein" OR "sexual harassment" OR "sexually harassed" OR "sexually assaulted" OR "sexual abuse" OR "sexual violence" OR "support survivors" OR "community healing" OR "social justice" OR "rape culture" OR "sex discrimination" OR "sexual advances" OR "gender-based hostility" OR "Sexual misconduct" OR "victims of harassment" OR "sexual assailant" OR "gender discrimination" OR "sexual predators" OR "gender differences" OR "sexual victimization". The data are based on queries run on September 6, 2021.

[36] A list of the selected papers is provided in Appendix II. We exclude papers that are not in an R-readable format.

Women on Boards Gender Diversity Index, USA Women on Board: Gender Diversity Index over the period 2015–2020, and the 2019 MeToo Impact Report.[37]

We use these four resources (i.e. books, newspapers, research papers, and other resources) to create a corpus and perform the common pre-processing techniques to "make the textual analysis more precise by reducing unnecessary noise in the text" (Buehlmaier & Whited, 2018, p. 2697). We namely (i) remove punctuation, digits/numbers, and citations, (ii) convert all letters to lowercase and remove all stop words (stop-words listed in the R program using the tm R package). (iii) remove tokens that have less than three letters, and (iv) remove all whitespace left from the process above. In light of this procedure, the corpus is tokenized into 1,361,795 bigrams.

To better understand managers' language about GD in a firm's earnings calls, we develop our GD dictionary using a new approach (i.e. collaborative intelligence) that combines HI and AI to construct a textual feature that measures the extent to which managers discuss GD in ECs. The process of generating a GD dictionary has three phases. First, we rely on the expertise of humans with GD backgrounds to identify GD keywords. Second, we use machine learning algorithms to extract GD-related n-grams. Third, we apply a collaborative intelligence approach and include only bigrams that are agreed on by both human and machine learning.

3.2.2 Developing a GD dictionary: Human Intelligence

[37] Available at https://metoomvmt.org/wp-content/uploads/2020/01/2019-12-09_MeToo_ImpactReport_VIEW_4.pdf .

We rely on HI to identify keywords relevant to GD discussion since "no algorithm understands the context of human conversations better than human beings" (Li et al., 2022, p. 11). While it is possible for a human to inspect a large number of GD bigrams (e.g. 1,361,795 bigrams in our case) and identify the relevant ones, it is often impractical and ineffective (Li et al., 2022). That is why we select the most frequent 3,000 bigrams in each source (i.e. books, newspapers, research papers, and other resources) to compile a list of 12,000 bigrams. We then share this list with two graduate students, one enrolled in a Master's in gender and women's studies and the other in a Ph.D. program, specializing in GD, and with one professional English editor. They were asked to keep bigrams that only relate to GD, gender equality/equity, sexual harassment, gender disparities, discrimination against women, sexual misconduct, and MeToo.[38] The three participants identified and agreed on 1,683 bigrams. We (the co-authors of this study) reviewed their work and narrowed the list of bigrams to 1,200.

3.2.3 Developing a GD dictionary: Artificial Intelligence

In a second step, we apply an SML method to identify the GD-relevant bigrams. This approach requires a minor human intervention to train the machine by identifying GD and non-GD documents and libraries. For our GD library, we use (i) the two textbooks mentioned above (i.e. 10th edition of *Feminist Frontiers* (2019) and *#MeToo in the Corporate World: Power, Privilege, and the Path Forward* (2020)), (ii) the press articles in the selected newspapers from

[38] This draws on the notion of Amazon's Mechanical Turk service (MTurk) approach, which requires humans to perform some tasks. For example, Bochkay, Hales, and Chava (2020) applied MTurk in firms' earnings calls to develop a textual dictionary. They created a dictionary of 23,355 words and asked humans to rate them.

October 2017 to October 2018, using the GD keywords described in footnote 22, and (iii) Bloomberg Gender-Equality Index reports in 2020 and 2022, European women on board gender diversity index report in 2020, USA Women on Board: Gender Diversity Index reports over the period 2013–2020, and the MeToo Impact Report 2019. For our non-GD library (falsification exercise), we search for titles of press articles (in the same set of newspapers) using “accounting” and “performance” keywords (as in Hassan et al. 2019). We then create one corpus for all GD and non-GD documents. Each document is then divided into files, each with two pages, which is treated as a distinct document. This process results in 3,443 two-page documents: 1,881 GD documents (outcome =1) and 1,562 non-GD documents (outcome =0).

We apply the usual preprocessing techniques and, for text representation, we use term frequency (word count) to create a document term matrix (DTM) where each document represents a single row in DTM and each of the top bigrams in the entire corpus is a column. Each entry in the DTM is the bigram frequency, which is weighted by the number of times a bigram occurs in the whole corpus. We retain bigrams that occur more than ten times in the whole corpus (dimensionality reduction). Building on insights from Buehlmaier and Whited (2018), we use the bag-of-words approach and create a matrix (DTM) where on the left-hand side of the equation is an outcome variable (outcomes 1 = GD and 0 = non-GD) and on the right-hand side are the bigrams (mixed of GD and non-GD bigrams).

We use Random Forest (RF) model, one of the most powerful SML algorithms (Schonlau and Zou 2020; Frankel et al. 2022), highly performing in text classification, and "suitable for dealing with the high dimensional noisy data in text classification" (Islam et al. 2019, p. 1061).[39] We use RF classifier to create a bootstrapped dataset and decision trees (K =100). Decision trees classifiers are trained using bootstrapping by randomly subsampling bigrams and covariates at each node. We repeat this experiment 50 times (N = 50), and each time every decision tree will have training data (i.e. a subsample from the original) that has a set of features and variables. RF combines tree predictors, and the final outcome is the class that receives the majority of votes from the trees in the forest. In our validation test, we compare the performance of the RF model to Bagging, an alternative SML algorithm.[40] We apply bootstrapping techniques through repeated sampling with replacement to derive a 'training set.' The unselected samples of the data are used as a ‘testing/validation set (Aydede. 2023).

For model evaluation, we apply the area under the curve (AUC), which has been commonly used to compare the performance of the different models (e.g., Barboza et al. 2017; Jones et al. 2017; Nguyen and Huynh 2022; Siano and Wysocki 2021; Tian et al. 2015). The model with the largest mean of AUC is considered the best model. Using bigram-frequency, we ask the RF winner model to report the 500 most important bigrams (using bigram-frequency) used to achieve 99.9% performance in classifying documents into GD vs. non-GD documents. Similarly, we use bigram-

[39] RF is defined as "a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest" (Breiman 2001, p. 5).
[40] Bagging is also known as a "bootstrap aggregating of trees", a sampling technique by which observations are selected randomly, with replacement, to produce a random new subset of data (e.g. Srivastava et al. 2020). Bagging aims at reducing the variance and overfitting of a class within the model (Figini, Savona, and Vezzoli 2016).

frequency inverse document frequency; we ask the winner model (RF) to report the 500 most important bigrams (Aydede. 2023).

3.2.4 Developing a GD dictionary: Collaborative Intelligence

In the last step of developing our GD dictionary, we apply collaborative intelligence (CI) by matching the bigrams identified by HI to bigrams identified by artificial intelligence (i.e. SML) and keep only the agreed-upon bigrams by HI and SML approaches. CI resulted in 202 bigrams.

3.2.5 Bigram Frequency-Inverse Document Frequency

Loughran and McDonald (2011) stress that selecting the scheme of a term weighting is a critical first step when using a bag of words. Term frequency (bigram frequency, *bf*, in our study), counts the number of times a word (bigram) appears in a document. *bf* is a commonly used method to create the feature vectors for the representation of corporate documents. However, in addition to *bf*, we used an improved method: bigram frequency-inverse document frequency (*bf-idf*) to prioritize the important bigrams/unigrams specific to each row (e.g. Loughran and McDonald 2011; Mai, Tian, Lee, and Ma 2019).[41] *bf* describes only the word counts, without considering the relative importance of words, and thus suffers from the bias of granting "high weights to words that are frequent across the board but lacks discriminative power" (Mai et al. 2019, p. 751) and may not provide precise information. In contrast to word count (i.e. simple term frequency), which lacks discriminative power (Mai et al. 2019), *bf.idf* prioritizes the important words/bigrams

[41] This is a slightly modified approach of the term frequency-inverse document frequency used in Loughran and McDonald (2011).

specific to each document by accounting for bigram frequency and normalization while adjusting for impact across the entire collection of documents (whole corpus).

We follow Loughran and McDonald (2011) and define the weighted measure *tf.idf* as follows:

$$\omega_{ij} = \begin{cases} \dfrac{\left(1+\log\left(bf_{i,j}\right)\right)}{\left(1+\log(\alpha_i)\right)}\log\left(\dfrac{N}{df_i}\right) & if\ bf_{i,j} \geq 1 \\ 0 & otherwsie \end{cases}$$

where N represents the total number of documents in the corpus, df_i the number of documents containing at least one occurrence of the i^{th} bigram, $bf_{i,j}$ the raw count of the i^{th} bigram in the j^{th} the document, and α_i the average bigram count in the document. The log transformation attenuates the impact of high frequency words/bigrams and the term $\log\left(\frac{N}{df_i}\right)$ adjusts the impact of a term/bigram based on its commonality (Loughran and McDonald 2011).

In our analysis, we apply Principal Component Analysis (PCA) and use the first principal component (GDT-PCA) of GDT-BF and GDTT-BF-IDF.[42]

[42] While powerful and popular, the dictionary approach has recently attracted criticism because its performance depends on the (quality of the) dictionary. For instance, researcher-generated dictionaries to summarize qualitative disclosure content may be incomplete (Donovan et al. 2021) and may not reflect language change over time or across industries (Frankel et al. 2022). We recognize that caution is merited when using the dictionary-based method because such an approach may not consistently capture disclosure sentiment across time and managers might adjust the narratives in the firm documents to reflect what they believe investors perceive (Frankel et al. 2022). This caveat is, however, less likely to apply to our study because we are examining GDT in the narrative of ECs after an exogenous shock (MeToo). Further, when developing our word-list-based dictionary, we find it useful to use documents that cover different time periods (including post-MeToo period) to control, to some extent, for the potential change in GD vocabulary. We also identified keywords in different sources (i.e. books, newspapers, most cited research papers, and other resources) to control for language variation across industries and materiality of GD disclosure (e.g. GD indexes).

Before reporting our result, and as a first step of our investigation, we plot in Figure 1.A the number of *USA Today* and *New York Times* articles that contain GD and MeToo keywords.[43] Clearly, the number of press articles discussing GD issues and MeToo increased after the MeToo event. In Figure 1.B, we reproduce the same analysis using the *Toronto Star* and *Hamilton Spectator*, two leading Canadian newspapers. This figure also shows that the MeToo event resulted in increased attention to the issues of GD and sexual harassment. Figure 2 shows the numbers of articles discussing GD and MeToo in various regions across the globe (i.e. North America, Europe, Asia, Africa, Middle East, and Oceania).[44] One can easily notice that across the different regions, MeToo has provoked wide public attention and discussion, not only increasing awareness about the issue of sexual assault and gender inequality, but also possibly putting more pressure on firms to meet stakeholders' expectations about firms' GD performance.

Panel A of Table 1 presents descriptive statistics for all observations with available data. Our regression sample has 29,353 firm-quarter observations. The respective averages of GDT-BF, GDT-BF-IDF, and GDT-PCA are 0.015, 0.019, and -0.058. In Panel B, we show that GDT has trended upward over the 2015–2019 sample period. The pairwise correlation coefficients, reported in Panel C, suggest that multicollinearity issues can be safely ignored in our regression analysis.

[43] See footnote 22.
[44] We rely on Eureka database at Saint Mary's University (SMU), Halifax, Canada, which contains a wide range of newspapers from around the world. We select various regions using the "Search Domain". When we choose a region (e.g. Africa), Eureka displays a list of newspapers for that region, e.g. 197 newspapers and magazines for "Africa". We select all sources and apply the same procedure to the other regions.

4. Results

4.1. Regression Analysis: The effect of MeToo on GDT

To ground the results in Figure 1 with more formal statistical analysis, we run the following model:

$$GDT_{i,t} = \alpha_0 + \alpha_1 MeToo_{i,t} + FIRMCTRL_{i,t} + \varepsilon_{i,t},$$

where $GDT_{i,t}$ is our textual measure of gender diversity talk (GDT-PCA). MeToo is a dummy variable that takes the value 1 if EC was held after October 16, 2017, one day after the posting of the #MeToo hashtag. $FIRM\ CTRL$ is a set of firm controls. We control for firm size (Size) measured as the natural logarithm of total assets in year-quarter t, the ratio of total debt total assets (Leverage); the ratio of capital expenditure to total assets (CAPEX); the book-to-market ratio (BTM); the ratio of cash holdings to assets (Cash Holdings); a dummy variable that takes the value 1 if the firm pays dividends and 0 otherwise (Dividend); institutional ownership (IOWN); a dummy variable that takes the value 1 if the firm reports a negative earnings in the previous quarter (Negative earnings); and firm complexity (Complexity), measured by the number of business segments (Hay et al. 2006). We include firm-fixed effects (α_i) to control for time-invariant firm characteristics and the two-digit SIC industry- year-quarter pair fixed effects (δ_t) to control for innovation shocks that are specific to a given industry and year-quarter and unobserved heterogeneity. We also include day-of-the-week fixed effects (φ_d) to account for the possibility that different days may imply more or fewer investors' attention and information content of ECs.

While the firm-fixed effects subsume the state-fixed effects, we cluster the standard error at the state level. With these fixed effects, the coefficient on $MeToo$ captures the effect of the MeToo movement on GDT. Results are reported in Table 2.

We first present the regression results without time-variant firm characteristics (column 1) and report a positive and significant coefficient of MeToo on GDT-PCA. In column 2, we augment our regression model with the other controls. The estimated coefficient of MeToo remains positive and significant. As a robustness test, we reproduce the results of columns 1 and 2 after replacing GDT-PCA with its individual components: DGT-*bf* (columns 3 and 4) and DGT-*bf-idf* (columns 5 and 6).[45] Interestingly, the estimated coefficient of MeToo continues to load positively and significantly on GDT, irrespective of the way GDT is measured. This evidence is in accord with the prediction of our first hypothesis (H_1), suggesting that MeToo incentivized firms to overstate their GD performance in response to greater attention and pressure for more GD initiatives.

We now use our model to ascertain that MeToo incentivized firms to oversell their GD performance. One might argue that there is an overlap between GDT and broad corporate social responsibility (CSR) talk, and as such MeToo-estimated coefficients in Table 2 could be biased upward. To rule out this alternative, we orthogonalize GDT on a textual measure of CSR Talk (CSRT). To measure CSRT, we follow Attig and Boshanna (2023) and develop the CSR dictionary by identifying keywords in the Sustainability Accounting Standards Board (SASB) codified

[45] Our results do not change when use Baker, Bloom and Davis's (2016) measure of economic policy uncertainty (EPU) and Altman-Z score as additional controls. Results are available upon request.

standards, the 2021 Global Reporting Initiative (GRI) standards, the 2022 International Financial Reporting Standards (IFRS) climate-related disclosures, and Refinitiv MarketPsych ESG Analytics. We also use "Web of Science" to identify the most-cited CSR-related papers. We namely select the following five studies: "Corporate social responsibility theories: Mapping the territory" (Garriga and Melé 2004, *Journal of Business Ethics*), "Does doing good always lead to doing better? Consumer reactions to corporate social responsibility" (Sen and Bhattacharya 2001, *Journal of Marketing Research*), "Implicit and explicit CSR: A conceptual framework for a comparative understanding of corporate social responsibility" (Matten and Moon 2008, *The Academy of Management Review*), "Corporate social responsibility and financial performance: Correlation or misspecification?" (McWilliams and Siegel 2000, *Strategic Management*), and "What we know and don't know about corporate social responsibility" (Aguinis and Glavas 2012, *Journal of Management*). We also consider the wordlist of four existing dictionaries developed by Loughran, McDonald, and Yun (2009), Pencle and Mălăescu (2016), Moss, Renko, Block, and Meyskens (2018). After manual inspection of the CSR keywords, our disambiguation process resulted in 728 bigrams. We then use these bigrams and apply bigram-frequency and bigram frequency-inverse document frequency to measure CSRT-*bf* and CSRT-*bf-idf* . Here again we scale up these textual constructs by multiplying them by 100. We measure CSRT-PCA as the principal component of CSRT-*bf* and CSRT-*bf-idf* and use it in our GDT 'orthogonalization' regression. We then use the residual of this regression (GDT-Residuals) as the dependent variable and reproduce results of Table 3. As shown in columns 1 and 2 of Table 3, the estimated coefficient of MeToo loads positively and significantly on GDT PCA-Residuals, lending further credence to and supporting the validity of our first hypothesis GDT measure as a distinct textual proxy from CSRT.

In columns 3 and 4, we measure GDT PCA-Residuals from the regression of GDT-PCA on additional textual features of ECs. Namely, in addition to CSRT, we include: political risk (PRisk), and non-political risk (NPRisk) from Hassan et al. (2019), another textual measure of risk (TRisk), estimated by counting the total number of synonyms of risk and uncertainty in an earnings call divided by the number of words in the call ($TRisk_{it} \frac{\sum_{b}^{B_{it}} 1[b \in R]}{B_{it}}$), and a measure of sentiment (TSentiments), calculated by dividing the sum of positive and negative words in the earnings call by the total number of words in the call ($TSentiment_{it} = \frac{\sum_{b}^{B_{it}} S(b)}{B_{it}}$). One can see that the coefficient of PCA GDT-Residuals continues to load positively and significantly, supporting both the validity of our construct and our first hypothesis.

As an additional robustness check, we repeat the results of column 2 of Table 3 (i.e. main model using GDT-PCA) and control for potentially omitted variables. We sequentially and then concurrently control for the following additional variables: Roll's (1984) illiquidity proxy (*ILL1*), information asymmetry measured by the average effective bid-ask spread for the fiscal year (*AQBAS*), analyst forecast dispersion (*DISP*), intangible (INTANG), the ratio of the sum of income before extraordinary items, R&D, and depreciation and amortization to total assets. Results are reported in Table 5. Our main result remains unchanged, as the coefficient of MeToo continues to load positively and significantly at the 1% level, as shown in all specifications in Table 4.[46]

4.2 The Cross-sectional Variation of the MeToo-GDT Relationship

To take our new evidence one step further, we focus next on the degree to which different mechanisms might moderate the effect of MeToo on GDT. We report the results in table 5. In all specifications of Table 5 we control for an indicator variable that reflects our cross-sectional construct and its interaction with MeToo. We start by exploring the effect of female CEO (FemaleCEO) and report the results in column 1. The estimated coefficient of FemaleCEO is negative and significant (at 10%), suggesting that female CEO talk less gender diversity than their Male CEO counterpart. This is plausible because male CEOs appear to have more incentive to posture a GD socially desirable image. It is also possible that the presence of a female CEO may be viewed as a (visible) indicator of a female-friendly corporate culture. Alternatively, GDT can be viewed as diversity-valuing behavior, and female leaders tend to avoid engaging in diversity-valuing behavior (Hekman, Johnson, Foo and Yang 2017).[47] One can also borrow the argument of the stereotype threat, which occurs when a female leader is aware that she belongs to a group that is negatively stereotyped, to suggest that female CEOs may talk less about GD to avoid the impact

[46] Our conclusion does not change when we use GDT-*bf* and GDT-*bf-idf*. Results are available from the authors upon request.
[47] Engaging in diversity-valuing behavior may be perceived as a threat to “the existing status and power structure (Chattopadhyay et al. 2004, as cited in Hekman et al. 2017, p. 772)

of gender stereotype. The interaction variable FemaleCEO x MeToo does not bear any significant effect on GDT, suggesting that the CEO gender did not shape the effect of MeToo on GDT.

Relatedly, we examine in column 2 the effects of female board representation. Our indicator variable takes the value 1 when a firm has a 'critical mass' of female representation on its board (i.e., 3 female directors or more), and 0 otherwise. Both female directors and its interaction with MeToo do not load significantly on GDT. In columns 4 and 5 we examine the effects of institutional ownership and firm size. In both specifications the estimated coefficient of the interaction variable (Indicator x MeToo) is not significant. Importantly, MeToo continues to load positively and significantly on GDT in all specifications of Table 5.

In Table 6, we focus on the impact of a firm's geographic location. In column 1, we examine the impact of social capital. We measure social capital (*Social Capital* (*US Congress*) using the U.S. Congress overall index that captures family structure and stability, community cohesion, and trust and confidence in institutions of each state.[48] Interestingly, we find that firms headquartered in states with low social capital, and thus low trust, tend to oversell their GD performance around MeToo. We also find, in column 2, that firms located in less religious states tend to engage in more gender-diversity washing. We measure state religiosity (*Religious (PennState)*) using PennState's measure of the number of establishments in religious organizations (as in Ding, Levine, Lin, and Xie 2020). This evidence corroborates the findings reported in column 1, since all else equal, more religiosity is expected to be associated with more trust and

[48] Data available here: https://www.jec.senate.gov/public/index.cfm/republicans/socialcapitalproject

more social capital. In columns 3, we split our sample using the sample median of percentage of working women (*% Women-Workers*), measured by number of women workers in a state divided by sum of the number of women and men workers in that State.[49] The results do not suggest any significant effect of percentage of working women on GDT. In the last column of Table 6, following Giannetti, Mariassunta, and Wang (2022), we use Charles, Guryan and Pan's (2018) construct of state-level sexism.[50] This proxy reflects the extent of sexist culture in a firm's headquarters. Such a culture tends to reject the principle of gender equality and relegate women to secondary status (Pyle, 1976). We find that firms headquartered in more sexist states (i.e. Charles, Guryan and Pan's (2018) construct is above the sample median) appear to engage in more GDT. Stated differently, firms in states where stereotypical beliefs about a women's place in society are prevalent tend to oversell their GD performance. It is important to note that none of the interaction variable (Indicator x MeToo) bear a significant effect on GDT, suggesting that the impact of MeToo on GDT does not appear to vary with the selected geographic indicators. Taken together, the evidence in Table 6 continue to support our main hypothesis that MeToo incentivized firms to oversell their GD.

4.3. Stock Market Effects of GDT

In this section, we investigate the extent to which our GDT relates to conference call returns. To this end, we run the following model:

[49] Data available here: https://www.bls.gov/cps/demographics.htm
[50] Data available here: https://www.washingtonpost.com/business/2018/08/21/most-sexist-places-america/

$$CAR[0,t]_{i,q} = \alpha_0 + \alpha_1 GDT_{i,q} + \alpha_2 EARN\ SURP_{i,q} + \alpha_3 \log{(MVE)}_{i,q} + \alpha_4 BTM_{i,q} + \alpha_5 TURNOVER_{i,q} + \alpha_6 INSTOWN_{i,q} + \alpha_7 PRE\ FF\_ALPHA_{i,q} + \varepsilon_{i,q},$$

where $CAR[0,t]_{i,q}$ is equal to the cumulative abnormal (market-adjusted) return from trading day 0 to trading day t relative to the conference call date. We try different windows: [0,1], [0,2], [0,3], [0,4], and [0,5], where day 0 represents the days of the earnings calls during the first quarter after MeToo. To reduce the likelihood that GDT captures the information content of other observable firm characteristics on the conference call date, we follow Frankel et al. (2021) and control for firm earnings surprise (*Earnings Surprise*), calculated as the firm earnings per share in the current quarter less the median earnings per share forecast for the firm made prior to the current-quarter earnings announcement date scaled by the firm's stock price at the end of the quarter and based on the latest forecast prior to the current-quarter earnings announcement date;[51] the (log) of the market value of equity (MVE) for the firm in the current quarter or year calculated as the firm's stock price multiplied by the number of shares outstanding at the end of the quarter or year; the book to market ratio (BTM) calculated as the firm's book value of common equity at the end of quarter or year divided by MVE; the number of shares traded for the firm in the trading days [−252, −6] relative to the conference call date divided by the firm's shares outstanding at the conference call (*Turnover*); the percentage of shares of the firm held by institutional investors (*Institutional Ownership*); and the Fama–French alpha (*Pre-FF-Alpha*) based on the Fama–French three-factor model and using trading days [−252, −6] relative to the conference call date as the estimation

[51] We remove forecasts made more than 90 days prior to the earnings announcement date.

period.[52] We control also for firm-fixed effects (α_i), the two-digit SIC industry- year-quarter pair fixed effects (δ_t), and day-of-the-week fixed effects (φ_d). We report results in Table 7.

We present the results of the impact of GDT on the cumulative abnormal return without controls using GDT-PCA (in column 1), GDT-*bf* (in column 2), and GDT-*bf*-*idf* (in column 3). Importantly, and irrespective of the proxy used for GDT, the estimated coefficient of GDT is positive and statistically significant at the 5% level, suggesting that GDT bears positively on conference call short-term returns during the MeToo, in accord with the prediction of our second hypothesis.

4.4. Do managers walk the CSR talk?

In a final test, we ask whether managers walk their GD talk post-MeToo. Results are reported in Table 9. We use three proxies to measure gender diversity walk (GDW): percentage of female directors on the board (column 1), likelihood of having a female CEO (column 2), and net change in female board (column 3), calculated as the difference between female board representation in year t minus female board representation in year t-1 divided by female board representation in year t-1. We 'orthogonalize' GDT-PCA on the set of controls used in Table 2 (since we are using GDT as an explanatory variable). We namely run the following model (first step):

$$GDT_{i,t} = \alpha_0 + \alpha_1 MeToo_{i,t} + FIRMCTRL_{i,t} + \varepsilon_{i,t},$$

[52] We require firms to have at least 60 daily returns to be included in this analysis.

where GDT is measured using GDT-PCA and $FIRMCTRL$ is a set of firm control variables described above. We then recoup the residuals and run the following test:

$$GDW_{i,t} = \alpha_0 + \alpha_1 GDTResidual_{i,t} + \alpha_2 MeToo_{i,t} + \alpha_3 GDTResidual_{i,t} \times MeToo_{i,t} + FIRMCTRL_{i,t} + \varepsilon_{i,t},$$

To run this analysis we use annual data. MeToo is a dummy variable that takes the value 1 for the years 2018 and 2019, and zero otherwise. Importantly, in the three model specifications, as shown in Table 8, our coefficients of interest (i.e. α_1 and α_3) are not significant, suggesting that GDT is not associated with GDW. Stated differently, firms that engage in GD overselling are less likely to engage in substantive GD initiatives. To some extent, this new evidence indicates that firms do not walk their GD talk and appear to engage in gender-diversity-washing.

5. Conclusion

GD has recently moved to a central place in the corporate agenda as well as the agenda of policy makers. For instance, the United Nations Sustainable Development Goal #5 stresses that gender equality "is not only a fundamental human right, but a necessary foundation for a peaceful, prosperous and sustainable world".[53] In the 2020 Fortune/Deloitte CEO Survey, 96% of CEOs assert that diversity, equity and inclusion is a "personal strategic priority" (Deloitte 2021). Yet, the world is still crying out for more gender equality in the workplace. The United Nations (2017)

[53] The United Nations Development Programme (2021) stresses the importance of "removing the barriers that women and other marginalized groups face to access and thrive in the workplace, to progress in their careers and to reach decision-making levels in their organizations" (p. v).

Commission on the Status of Women (CSW61) indicates that the gender gap in average wages appears to persist in all countries and across all sectors. The United Nations (2020) World's Women report suggests that only 47% of women of working age participated in the labor market (compared to 74% of men), women held only 28% of managerial positions globally in 2019, and only 18% of surveyed enterprises had a female CEO in 2020.[54] In recent years, perhaps no other event has done more to raise consciousness about gender-based frictions in the workplace than MeToo. However, the extent to which firms engage in gender-diversity washing in response to social movement and the associated secondary stakeholders' pressure for more attention to gender-based frictions remain an almost-untapped empirical research area.

We add to the literature by employing a novel textual method, collaborative intelligence, which combines human and artificial intelligence to develop our construct of GDT. We then use the MeToo movement, an unequivocal social movement shock, and show that firms tend to oversell their GD performance, plausibly to posture a desirable image and manage stakeholders' impressions of their performance in reducing gender-based frictions in the workplace. Our new evidence indicates also that GDT is associated with positive short-term stock returns, possibly because overselling GD performance provides insurance-like protection for a firm's relationship-based intangible assets, which will likely translate into positive short-term stock performance given the lack of reporting standards and the average investor's lack of ability to verify the extent

[54] In the U.S., 74 female CEOs were running *Fortune* 500 businesses (*Fortune* 2022), compared to 41 (7) in June 2021 (2002), as of March 2022. While this suggests female talent has made some strides in breaking the glass ceiling, a significant imbalance in *Fortune* 500 leadership persists (15% female vs. 85% male).

of substantiality of firm GDT. We also document new evidence that firms do not walk their GD talk.

Our study offers fresh directions for future research. In particular, examining real economic implications of the MeToo movment and other social movments is a promising direction. Future research could usefully focus on the linkages of selective GD disclosure such as gender-diversity with corporate governance and firm financing frictions. We are confident that the general intuition drawn in this research on the nexus between the MeToo social movment and firms' gender-diversity washing is relevant for future academic works as well as policy initiatives to provide incentives for firms to engage in substantial GD initiatives rather than merely paying lip service to gender-based frictions in the workplace.

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Figure 1: Social Pressure of Gender Diversity and #MeToo Movement

Figure 1.A (1.B) shows the number of press articles that contain gender diversity and MeToo keywords and appeared in major U.S. (Canadian) newspapers: *USA Today*, *New York Times* (USA); *Toronto Star*, *Hamilton Spectator* (Canada). Keywords used in search the press articles are reported in footnote 22 of this study (page 14).

Figure 1.A

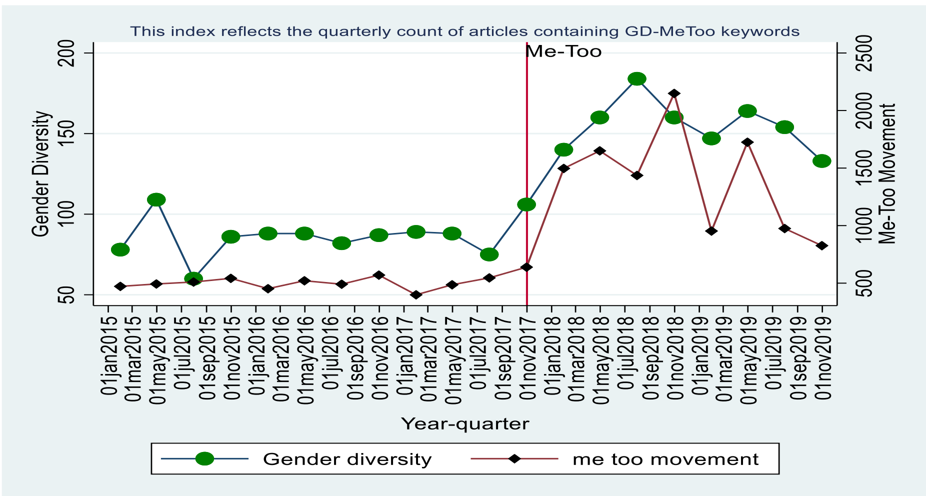

Figure 1.B

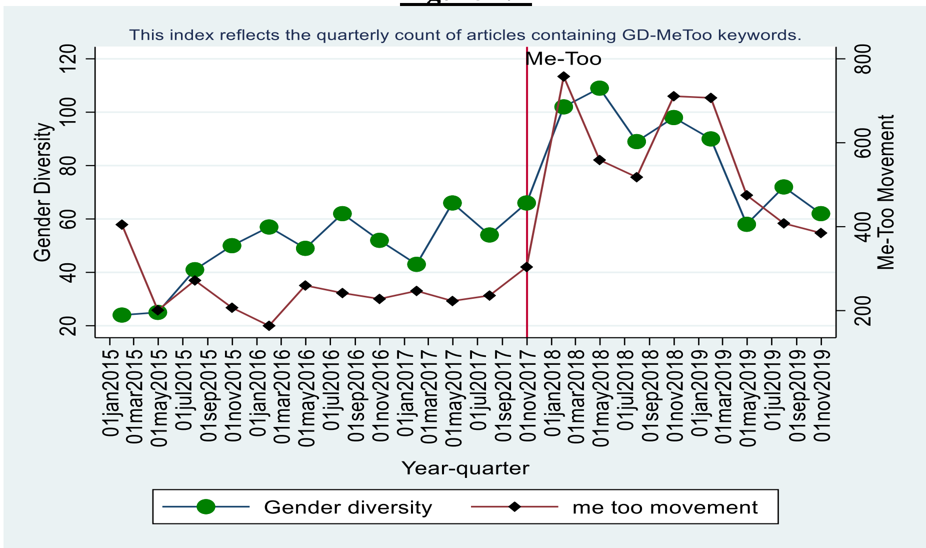

Figure 2: Social Pressure of Gender Diversity and MeToo Movement: International Evidence

This figure shows the number of press articles that contain gender diversity and MeToo keywords and appeared in major newspapers in different regions across the globe. Keywords used in the search of the press article are reported in footnote 22 of this study (page 14).

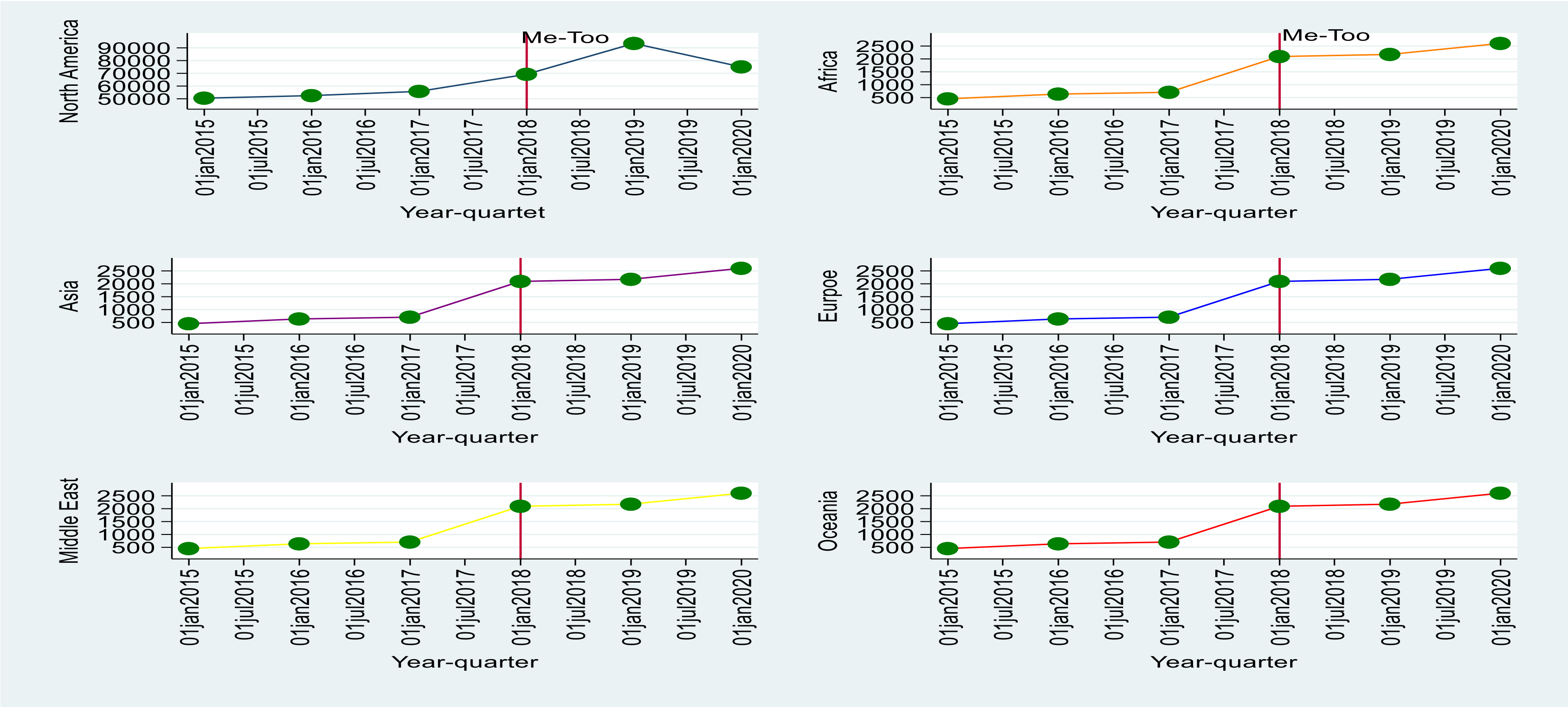

Table 1: Descriptive Statistics

Panel A of this table presents summary statistics of the variables used in the regression analysis during the sample period 2015–2019. We measure firm GD talk using different proxies: *% GDT BF*, bigram frequency scaled by the number of bigrams in the earnings call, GDT *BT_IDF* measured using bigram frequency-inverse document frequency. *GDT PCA* is the principal component analysis of the two measures (*% GDT BF* and *GDT DF-IDF*). *MeToo* is an indicator variable equal to 1 for the year-quarter after October 16, 2017, and zero otherwise. Panel E presents the time trend effect. Panel C reports the correlation matrix among our main variables. All continuous variables are winsorized at the 1% and 99% levels. Appendix A provides detailed definitions for all variables.

***Panel A:* Descriptive Statistics**

	GDT-BF	*GDT-BF-IDF*	*GDT-PCA*	*Size*	*Leverage*	*CAPEX*	*BTM*	*Cash Holdings*	*Dividend*	*Institutional Ownership*	*Negative Earnings*	*Complexity*
N	29353	29353	29353	29353	29353	29353	29353	29353	29353	29353	29353	29353
Mean	0.015	0.019	-0.058	7.317	0.292	0.027	0.402	0.599	0.403	0.78	0.333	5.791
SD	0.061	0.075	1.344	1.786	0.228	0.033	0.428	1.564	0.491	0.232	0.471	4.812

Panel E: Time Trend

VARIABLES	***Time Trend***	***FFE***	***Year-Q-FF***	***Days of the Week FE***	***Errors Clustered by State***	***Observations***	***R-squared***
GDT-PCA	0.004*** (3.893)	YES	NO	YES	YES	28,536	0.460

Panel C: Correlation Matrix

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
(1) GDT-BF	1.000											
(2) GDT-BF-IDF	0.998	1.000										
(3) GDT-PCA	0.998	1.000	1.000									
(4) Size	0.047	0.047	0.047	1.000								
(5) Leverage	-0.035	-0.035	-0.034	0.284	1.000							
(6) CAPEX	-0.004	-0.005	-0.005	0.052	0.055	1.000						
(7) BTM	0.002	0.002	0.002	0.031	-0.176	0.073	1.000					
(8) Cash Holdings	-0.025	-0.024	-0.024	-0.337	-0.207	-0.162	-0.120	1.000				
(9) Dividend	0.052	0.051	0.051	0.448	0.098	0.008	-0.028	-0.236	1.000			
(10) Institutional Ownership	0.033	0.033	0.033	0.321	0.041	-0.018	0.004	-0.115	0.075	1.000		
(11) Negative Earnings	-0.029	-0.028	-0.028	-0.376	-0.042	-0.030	0.068	0.334	-0.359	-0.202	1.000	
(12) Complexity	-0.007	-0.007	-0.007	0.268	0.032	-0.039	0.063	-0.178	0.235	0.097	-0.175	1.000

Table 2: #MeToo and GD Talk

In this table we examine the impact of the #MeToo social movement on firm GD talk. We measure GD talk using GDT-PCA (columns 1–2), the first component of the principal component analysis of GDT BF and GDT BF-IDF. Results using GDT BF and GDT BF-IDF are reported in columns 3–4 and 5–6, respectively. *MeToo* is an indicator variable equal to 1 for the year-quarter equal and after October 16, 2017, and zero otherwise. We control for *Size*, the natural logarithm of total assets in year t, firm age (*Log(Age)*), *Leverage*, the ratio of total debt to total assets, *CAPEX*, capital expenditures scaled by net assets, *BTM*, a firm's book value of common equity at the end of the year divided by MVE, *Cash Holdings*, calculated as the firm cash holding scaled by net assets, *Dividend*, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, *Institutional Ownership*, the percentage of shares of the firm held by institutional investors, *Negative Earnings*, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, *Complexity*, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sample		***Full Sample***				***Reduced Sample***	
VARABLES	***GD-PCA***	***GD-PCA***	***GD-BF***	***GD-BF-IDF***	***GD-PCA***	***GD-BF***	***GD-BF-IDF***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	
MeToo	0.257***	0.265***	0.012***	0.015***	0.385**	0.017**	0.021**
	(4.279)	(4.361)	(4.473)	(4.342)	(2.057)	(2.113)	(2.033)
Size		0.065***	0.003**	0.004***	-0.000	-0.000	0.000
		(2.766)	(2.690)	(2.782)	(-0.006)	(-0.131)	(0.013)
Log (Age)		0.004	0.000	0.000	-0.018	-0.001	-0.001
		(0.407)	(0.420)	(0.383)	(-0.677)	(-0.621)	(-0.731)
Leverage		-0.320***	-0.014***	-0.018***	-0.029	-0.001	-0.002
		(-3.490)	(-3.404)	(-3.535)	(-0.835)	(-0.555)	(-0.845)
CAPEX		-0.190	-0.009	-0.011	-0.921**	-0.042**	-0.052**
		(-0.894)	(-0.938)	(-0.891)	(-2.454)	(-2.469)	(-2.484)
BTM		-0.075***	-0.003***	-0.004***	-0.119***	-0.005***	-0.007***
		(-3.092)	(-2.786)	(-3.104)	(-4.230)	(-4.348)	(-4.262)
Cash Holdings		-0.007*	-0.000**	-0.000*	0.003	0.000	0.000
		(-1.840)	(-2.042)	(-1.854)	(0.527)	(0.564)	(0.511)
Dividend		0.106***	0.005***	0.006***	0.037	0.002	0.002
		(4.225)	(4.259)	(4.175)	(0.649)	(0.906)	(0.632)
Institutional Ownership		0.047	0.002	0.003	0.080	0.003	0.005
		(0.959)	(0.960)	(0.975)	(1.011)	(0.970)	(1.071)
Negative Earnings		0.019*	0.001*	0.001*	-0.014	-0.001	-0.001
		(1.902)	(1.885)	(1.921)	(-0.377)	(-0.441)	(-0.364)
Complexity		0.009*	0.000*	0.000*	0.010	0.000	0.001
		(1.780)	(1.858)	(1.833)	(1.066)	(1.114)	(1.035)
Firm FE	YES	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES	YES
Observations	27,085	27,085	27,085	27,085	10,994	10,994	10,994
R-squared	0.563	0.563	0.579	0.562	0.618	0.632	0.618

Table 3: #MeToo and GD Talk: Abnormal GDT Talk

In this table we use the residuals from orthogonalizing *GDT-PCA* on CSRT, our proxy for CSR talk to investigate the impact of MeToo on firm GD talk. Results are reported in columns 1 and 2. In columns 3 and 4, we measure (abnormal) GD talk by using the residuals from regressing GDT-*PCA* on various textual features. We namely include CSRT, *PRisk*, *NPRisk*, *COVIDRisk*, and *TRisk*, and *Tsentiment*. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARABLES	***GDT-PCA-CSRT-Residual***		***GDT-PCA-Risk-Residual***	
	(1)	(2)	(3)	(4)
MeToo	0.260***	0.268***	0.291***	0.298***
	(4.323)	(4.405)	(4.498)	(4.565)
Size		0.065***		0.056**
		(2.726)		(2.095)
Log (Age)		0.004		-0.001
		(0.397)		(-0.081)
Leverage		-0.320***		-0.319***
		(-3.488)		(-3.608)
CAPEX		-0.183		-0.245
		(-0.858)		(-0.883)
BTM		-0.075***		-0.057**
		(-3.106)		(-2.433)
Cash Holdings		-0.007*		-0.010***
		(-1.844)		(-3.816)
Dividend		0.105***		0.120***
		(4.186)		(4.640)
Institutional Ownership		0.047		0.076
		(0.955)		(1.573)
Negative Earnings		0.019*		0.025***
		(1.937)		(2.865)
Complexity		0.009*		0.006
		(1.781)		(1.136)
Firm FE	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES
Observations	27,085	27,085	26,116	26,116
R-squared	0.563	0.563	0.564	0.564

Table 4: #MeToo and GD Talk: Omitted important variables

In this table, we examine the effects of *MeToo* on GDT (*GDT-PCA*) after controlling for potentially omitted variables: illiquidity (*ILL1*, column 2), information asymmetry (*AQBAS*, column 3), analyst dispersion (*ADISP*, column 4), intangible (INTANG, column 5). *MeToo* is an indicator variable equal to 1 for the year-quarter post October 16, 2017, and zero otherwise. We control for *Size*, the natural logarithm of total assets in year t, firm age (*Log(Age)*), *Leverage*, the ratio of total debt to total assets, *CAPEX*, capital expenditures scaled by net assets, *BTM*, a firm's book value of common equity at the end of the year divided by MVE, *Cash Holdings*, calculated as the firm cash holding scaled by net assets, *Dividend*, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, *Institutional Ownership*, the percentage of shares of the firm held by institutional investors, *Negative Earnings*, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, *Complexity*, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES	***GDT-PCA***					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
MeToo	0.265***	0.265***	0.268***	0.268***	0.268***	0.268***
	(4.361)	(4.366)	(4.319)	(4.322)	(4.318)	(4.318)
ILL1		0.005	0.015	0.015	0.015	0.015
		(0.323)	(0.722)	(0.687)	(0.685)	(0.685)
AQBAS			-5.950	-5.911	-5.918	-5.918
			(-1.231)	(-1.223)	(-1.226)	(-1.226)
ADISP				0.081***	0.081***	0.081***
				(7.084)	(7.094)	(7.094)
INTANG					0.015	0.015
					(0.114)	(0.114)
Size	0.065***	0.066***	0.059**	0.053**	0.053**	0.053**
	(2.766)	(2.848)	(2.221)	(2.067)	(2.073)	(2.073)
Log (Age)	0.004	0.004	0.003	0.005	0.005	0.005
	(0.407)	(0.421)	(0.280)	(0.536)	(0.537)	(0.537)
Leverage	-0.320***	-0.320***	-0.313***	-0.312***	-0.311***	-0.311***
	(-3.490)	(-3.502)	(-3.266)	(-3.267)	(-3.345)	(-3.345)
CAPEX	-0.190	-0.189	-0.210	-0.191	-0.191	-0.191
	(-0.894)	(-0.892)	(-0.973)	(-0.884)	(-0.885)	(-0.885)
BTM	-0.075***	-0.075***	-0.073***	-0.074***	-0.074***	-0.074***
	(-3.092)	(-3.096)	(-3.038)	(-3.132)	(-3.112)	(-3.112)
Cash Holdings	-0.007*	-0.007*	-0.007*	-0.007**	-0.007**	-0.007**
	(-1.840)	(-1.856)	(-1.908)	(-2.051)	(-2.104)	(-2.104)
Dividend	0.106***	0.106***	0.106***	0.106***	0.106***	0.106***
	(4.225)	(4.221)	(4.212)	(4.230)	(4.237)	(4.237)
Institutional Ownership	0.047	0.048	0.030	0.036	0.036	0.036
	(0.959)	(0.965)	(0.587)	(0.689)	(0.686)	(0.686)
Negative Earnings	0.019*	0.019*	0.019*	0.019*	0.020	0.020
	(1.902)	(1.877)	(1.915)	(1.862)	(1.443)	(1.443)
Complexity	0.009*	0.008*	0.008*	0.008*	0.008*	0.008*
	(1.780)	(1.773)	(1.776)	(1.722)	(1.724)	(1.724)
Firm FE	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES

Days of the Week FE	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES
Observations	27,085	27,085	27,085	27,085	27,085	27,085
R-squared	0.563	0.563	0.563	0.563	0.563	0.563

Table 5: The Effects of Firm Characteristics

In this table, we examine the role of firm characteristics in altering the impact of the MeToo movement (*MeToo*) on firm GD talk (*GDT-PCA*). We examine the role of female CEOs (*FemaleCEO*, column 1), women directors using critical mass theory (*Women Directors*, column 2), institutional ownership (*Institutional Ownership*, column 3), firm size (*Firm Size*, column 4). We use the sample median of each of these variables to run our subsample analysis. We control for *Size*, the natural logarithm of total assets in year t, *Leverage*, the ratio of total debt to total assets, *CAPEX*, capital expenditures scaled by net assets, *BTM*, a firm's book value of common equity at the end of the year divided by MVE, *Cash Holdings*, calculated as the firm cash holding scaled by net assets, *Dividend*, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, *Institutional Ownership*, the percentage of shares of the firm held by institutional investors, *Negative Earnings*, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, *Complexity*, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES	***FemaleCEO*** **(1)**	***Women Directors*** **(2)**	***Institutional Ownership*** **(3)**	***Firm Size*** **(4)**
MeToo	0.215***	0.265***	0.261***	0.237***
	(3.270)	(4.341)	(4.129)	(3.998)
Indicator	-0.154*	0.015	-0.017	-0.003
	(-1.835)	(0.425)	(-0.687)	(-0.129)
Indicator x MeToo	0.067	0.010	0.011	0.058
	(0.663)	(0.208)	(0.454)	(1.651)
Size	0.075***	0.066***	0.065***	0.061**
	(3.841)	(2.799)	(2.808)	(2.293)
Log (Age)	0.007	0.004	0.004	0.007
	(0.728)	(0.435)	(0.409)	(0.782)
Leverage	-0.344***	-0.321***	-0.320***	-0.312***
	(-3.130)	(-3.544)	(-3.472)	(-3.286)
CAPEX	-0.203	-0.193	-0.194	-0.203
	(-0.887)	(-0.904)	(-0.912)	(-0.949)
BTM	-0.081***	-0.074***	-0.075***	-0.073***
	(-2.806)	(-3.068)	(-3.062)	(-3.115)
Cash Holdings	-0.006	-0.007*	-0.007*	-0.007**
	(-1.513)	(-1.872)	(-1.922)	(-2.194)
Dividend	0.097***	0.106***	0.106***	0.103***
	(3.420)	(4.199)	(4.187)	(4.003)
INSOWN	0.034	0.047	0.065	0.060
	(0.724)	(0.939)	(1.171)	(1.177)
Negative Earnings	0.017*	0.019*	0.019*	0.019*
	(1.754)	(1.907)	(1.873)	(1.882)
Complexity	0.010**	0.009*	0.009*	0.008*
	(2.250)	(1.859)	(1.824)	(1.691)
Firm FE	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES
Observations	25,767	27,085	27,085	27,085
R-squared	0.570	0.563	0.563	0.563

Table 6: The Effect of Firm Geographic Location

In this table, we examine the role of firm geographical location in altering the impact of the MeToo movement (*MeToo*) on firm GD talk (*GDT-PCA*). We examine the role of social capital (*Social Capital*, column 1), religion (*Religious*, column 2), % women-workers (*Women-workers)*, column 3), and the level of state sexism (*Sexism*, column 4). *MeToo* is an indicator variable equal to 1 for the year-quarter equal and after October 16, 2017, and zero otherwise. We control for *Size*, the natural logarithm of total assets in year t, *Leverage*, the ratio of total debt to total assets, *CAPEX*, capital expenditures scaled by net assets, *BTM*, a firm's book value of common equity at the end of the year divided by MVE, *Cash Holdings*, calculated as the firm cash holding scaled by net assets, *Dividend*, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, *Institutional Ownership*, the percentage of shares of the firm held by institutional investors, *Negative Earnings*, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, *Complexity*, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES	**Social Capital (1)**	**Religion (2)**	**% Women-Workers (3)**	**Sexism (4)**
MeToo	0.249***	0.264***	0.275***	0.259***
	(4.197)	(4.374)	(4.401)	(4.363)
Indicator	-0.267***	-0.247***	0.025	-0.222***
	(-4.204)	(-2.938)	(0.475)	(-3.227)
Indicator x MeToo	0.066	0.086	-0.092	0.038
	(1.229)	(0.509)	(-1.672)	(0.607)
Size	0.065**	0.066***	0.066***	0.066***
	(2.678)	(2.790)	(2.809)	(2.802)
Log (Age)	0.007	0.003	0.010	0.005
	(0.892)	(0.375)	(1.484)	(0.646)
Leverage	-0.322***	-0.320***	-0.322***	-0.322***
	(-3.536)	(-3.431)	(-3.519)	(-3.539)
CAPEX	-0.191	-0.198	-0.177	-0.190
	(-0.901)	(-0.932)	(-0.845)	(-0.901)
BTM	-0.073***	-0.074***	-0.074***	-0.075***
	(-3.122)	(-3.147)	(-3.125)	(-3.070)
Cash Holdings	-0.007*	-0.007*	-0.007*	-0.007*
	(-1.902)	(-1.954)	(-1.941)	(-1.910)
Dividend	0.106***	0.105***	0.106***	0.105***
	(4.228)	(4.148)	(4.173)	(4.169)
INSOWN	0.047	0.048	0.045	0.045
	(0.955)	(0.978)	(0.916)	(0.935)
Negative Earnings	0.019*	0.019*	0.019*	0.019*
	(1.848)	(1.895)	(1.895)	(1.856)
Complexity	0.008*	0.008*	0.008*	0.008*
	(1.724)	(1.715)	(1.700)	(1.768)
Firm FE	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES
Observations	27,085	27,085	27,085	27,085

R-squared	0.563	0.563	0.563	0.563

Table 7: Firm GD Talk and Short-Window Stock Returns around the Call

This table presents the regression results of the effects of *GDT-PCA* on the cumulative abnormal returns (CAR) over the trading window [0, 1] during the first post-MeToo quarter, where 0 is the conference call date. We control for the following variables: earnings surprise (*Earnings Surprise*), the difference between actual earnings and consensus analysts' forecast divided by the actual earnings, *Log (MVE)*, the firm in the current quarter calculated as the firm's stock price multiplied by the number of shares outstanding at the end of the quarter, *BTM*, the firm's book value of common equity at the end of quarter divided by MVE, *Turnover*, the number of shares traded for the firm in the trading days [−252, −6] relative to the conference call date divided by the firm's shares outstanding at the conference call date, *Pre_FFAlpha*, the Fama–French alpha based on a regression of their three-factor model using trading days [−252, −6] relative to the conference call date, *Institutional Ownership*, the percentage of shares of the firm held by institutional investors. Standard errors are double clustered by firm and earnings call date. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES	***CAR [0, 1]***	***CAR [0, 1]***	***CAR [0, 1]***
	(1)	**(2)**	**(3)**
GDT-BF	0.030**		
	(2.180)		
GDT-BF-IDF		0.022**	
		(2.040)	
GDT-PCA			0.001**
			(2.086)
Earnings Surprise	0.097	0.097	0.097
	(0.717)	(0.717)	(0.717)
Log (MVE)	0.100***	0.100***	0.100***
	(8.476)	(8.475)	(8.477)
BTM	-0.102***	-0.102***	-0.102***
	(-6.112)	(-6.115)	(-6.115)
Turnover	-0.003	-0.002	-0.003
	(-0.739)	(-0.733)	(-0.734)
Pre_FFAlpha	-32.988***	-33.002***	-32.998***
	(-24.260)	(-24.237)	(-24.228)
Institutional Ownership	-0.021	-0.021	-0.021
	(-0.507)	(-0.508)	(-0.508)
Firm FE	YES	YES	YES
SIC x Year-Quarter FE	YES	YES	YES
Days of the Week FE	YES	YES	YES
Errors Clustered by State	YES	YES	YES
Observations	2,066	2,066	2,066
R-squared	0.621	0.621	0.621

Table 8: Do Managers Walk their GD Talk?

This table addresses the question of whether firms walk their GD talk. We measure firm GD talk using textual features that measure the extent to which managers discuss gender diversity–related issues during earnings conference calls. We measure firm GD walk using a firm's actions regarding women on the board of directors. Column 1 reports the effects of GD talk (*GDT-PCA-Residual*), *Post2017*, and the interaction (*GDT-PCA-Residual xPost2017*) on the representation of women on board *(% Female Board*). In column 2, we replicate column 1, but with FemaleCEO as the dependent variable. In column 3, we replicate column 1, but with Net Board Female Change as the dependent variable. FemaleCEO is an indicator variable that takes the value of 1 if the CEO is female, and zero otherwise, and *Net Board Female Change* is the net increase in the number of females on the board relative to the previous year. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1**.**

VARIABLES	***% Female-Board***	***Female-CEO***	***Net-board-female-change***
	(1)	***(2)***	***(4)***
GDT-PCA-Residual	0.004	0.000	-0.142
	(0.274)	(0.016)	(-0.988)
Post2017	-0.006	-0.015*	-0.011
	(-1.334)	(-1.687)	(-0.202)
GDT-PCA-Residual xPost2017	-0.024	-0.004	0.207
	(-1.214)	(-0.115)	(0.993)
Size	0.006*	0.004	0.054
	(1.750)	(0.719)	(1.473)
Leverage	-0.014*	-0.010	-0.083
	(-1.663)	(-0.609)	(-0.889)
CAPEX	-0.002	0.019*	0.054
	(-0.333)	(1.947)	(0.936)
BTM	-0.006	-0.009	-0.027
	(-1.421)	(-1.185)	(-0.617)
Cash Holdings	0.001	-0.003	0.004
	(0.783)	(-1.382)	(0.277)
IOWN	0.037	0.254	0.161
	(0.127)	(0.477)	(0.052)
Negative Earnings	-0.003	0.005	0.015
	(-0.975)	(1.011)	(0.492)
Complexity	-0.000	0.000	-0.003
	(-0.330)	(0.184)	(-0.485)
Firm FE	YES	YES	YES
SICxYear FE	YES	YES	YES
Errors Clustered by State	YES	YES	YES
Observations	7,081	7,081	6,859
R-squared	0.875	0.878	0.319

Appendix A: Variable definitions

Variable definitions

Variables	Definition	Source
Dependent Variables		
CAR [0, 1]	The cumulative market-adjusted return for the firm in the [0,1] trading window surrounding the current-quarter conference call date.	CRSP
FemaleCEO	An indicator variable that takes the value of 1 if the CEO is female, and zero otherwise.	BoardEx
Female-Board	The percentage of women directors on board.	As above
GDT-BF	Counting the number of GD bigrams and scaled by the total number of bigrams in the earnings call.	Corporate earnings conference calls from Capital IQ
GDT-BF-IDF	GD bigram frequency inverse document frequency.	As above
GDT-PCA	The principal component analysis of the two measures (GDT-BF and GDT-BF-IDF).	As above
GDT-PCA-CSRT-Residual	Obtained by orthogonalizing GDT PCA on CSRT PCA.	As above
Net-board-female-change	The net increase in the number of females on the board relative to the previous year.	BoardEx
GDT-PCA-Risk-Residual	Obtained by orthogonalizing GDT PCA on CSRT PCA, PRisk, NPRisk, COVIDRisk, and TRisk, Tsentiment.	As above
Social Capital	An overall index captures family structure and stability, community cohesion, and trust and confidence in institutions of each county.	The U.S. Congress (Joint Economic Committee)
% Women-workers	Number of women workers in a State divided by sum of the number of women and men workers in that State.	BoardEx
Women Directors	An indicator variable equal to 1 if a firm has 3 or more women on the board (Critical Mass Theory).	As above
Sexism	A dummy variable that equals 1 if a state's sexism ranking is in the highest categories based on Figure 2 of Charles et al. (2018).	Charles et al. (2018).
Main Independent Variables		
MeToo	An indicator variable equal to 1 for the year-quarter equal and after October 16, 2017, and zero otherwise.	CRSP + Authors' calculation
Post2017	Indicator variable equal to 1 for years after 2017, and zero otherwise.	CRSP + Authors' calculation
Control Variables		
ADISP	Dispersion of analyst forecasts defined as the coefficient of variation of one-year-ahead analyst forecasts of earnings per share.	Authors' calculations
ANAN	Analyst coverage, measured by number of equity analysts following a firm; equals the logarithm of 1 plus the number of one-year-ahead earnings forecasts.	I/B/E/S
INTANG	The ratio of the sum of income before extraordinary items, R&D, and depreciation and amortization to total assets.	Authors' calculations
BTM	The firm's book value of common equity at the end of quarter divided by MVE.	As above
CAPEX	Capital expenditures scaled by total assets.	As above
Cash holdings	Ratio of cash holding to net assets.	As above
Complexity	The number of business segments.	Compustat
COVID_Risk	COVID risk measure from Hassan et al. (2022)	

Dividend	An indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise.	As above
Earnings Surprise	The difference between actual earnings and consensus analysts' forecast divided by the actual earnings.	Authors' calculations and I/B/E/S
ILL	Roll's (1984) illiquidity proxy measured as the average effective bid-ask spread over the fiscal year.	Authors' calculations
Institutional Ownership	The percentage of shares of the firm held by institutional investors.	Thomson 13-F data
Leverage	Measured by the ratio of total debt to total assets.	CRSP
Log (Age)	Computed as one plus the difference between the year under investigation and the firm's year of birth, which is the first year the firm appears in CRSP	As above
Log (MVE)	Market value of equity for the firm in the current quarter calculated as the firm's stock price multiplied by the number of shares outstanding at the end of the quarter.	As above
Negative Earnings	An indicator variable equal to 1 if the firm has negative earnings in that quarter, and 0 otherwise.	As above
NPRisk	Non-political risk measure from Hassan et al. (2019).	
Pre-FF-Alpha	It is the Fama–French alpha based on a regression of their three-factor model using trading days [−252, −6] relative to the conference call date. At least 60 observations of daily returns must be available to be included in the sample.	CRSP + Corporate earnings conference calls from Capital IQ + Fama and French Three-Factor Model.
PRisk	Political risk measure from Hassan et al. (2019).	
ROA	A firm's total net income scaled by total assets.	CRSP
Kaplan-Zingales Index	Kaplan and Zingales' (1997) index	Authors' calculations
Size	Natural logarithm of total assets in year-quarter t.	As above
Time Trend	The time-series trends of our main variables by regressing SCR PCA on a linear trend variable, which takes the value of 0 in 2007Q1, 1 in 2007Q2, 3 in 2007Q3, etc.	As above
TRisk	Total number of synonyms for risk and uncertainty divided by the total number of words in an earnings call.	
TSentiment	The sum of positive and negative words, scaled by the total number of words in an earnings call.	
Turnover	The number of shares traded for the firm in the trading days [−252, −6] relative to the conference call date divided by the firm's shares outstanding at the conference call date.	CRSP + Corporate earnings conference calls from Capital IQ.

Chapter 3: Cheap Talks Is Not Cheap: Evidence from CSR Talk and Greenwashing During Hard Times

Abstract

Using industry-relevant documents and the most-cited CSR/ESG papers to develop a new CSR dictionary, we then show that the COVID-19 pandemic incentivized firms to engage in overselling of their CSR. This effect is more pronounced in small and financially unconstrained firms. We find that more CSR talk during COVID translates into value depression, indicating that investors, on average, do not perceive CSR overselling as value-relevant. Our evidence suggests that firms do not walk their CSR talk and that CSR Talk is positively (negatively) associated with the use of positive (negative) words. Our evidence suggests that 'cheap talk is not cheap'.

1. Introduction

Having explored how firms' gender diversity response to the #MeToo social movement in the previous chapter, the focus now shifts towards investigating how firms' ESG response to the mounting pressure for increased corporate social responsibility.

"The world cries out for repair" (Margolis Walsh 2003, p. 268) more than ever before, recognition of environmental, social, and governance (ESG) issues have been on the rise for decades. However, these issues have gained more prominence in the wake of the COVID-19 pandemic, emphasizing the need for a more socially responsible corporate agenda. While society has some expectations for corporate social responsibility (CSR) because business and society are intertwined (Wood, 1991), firms may resort to symbolic CSR reporting and communication without engaging in substantive CSR initiatives. This practice of paying mere lip service to CSR issues by posturing a socially desirable image to manage impressions of stakeholders and gain social legitimacy, usually termed greenwashing (GW),[55] has recently taken central place in the agenda of policymakers, practitioners, and the public at large. [56]

Displaying symbolic compliance and overselling CSR reporting to promote the appearance of conformity with societal expectations can be sufficient to attain legitimacy (Oliver, 1991). This

[55] GW refers to the practice of selectively communicating or disclosing positive information about a firm environmental or social performance while withholding related negative information to frame activities as 'green' (Lyon & Maxwell, 2011; Laufer, 2003). CSR refers to a firm's "actions that appear to further some social good, beyond the firm's interests and that which is required by law" (McWilliams & Siegel, 2001, p. 117). ESG refers to integrating sustainability and other non-financial goals in a firm's and investor's decisions. Sustainability refers to the integration of non-financial goals (e.g., social and environmental concerns) in firm policies and operations to promote shareholders' and stakeholders' long-term well-being. Given the overlap in CSR, ESG, and sustainability definitions, we use them interchangeably.

[56] The CFA Institute, in its reports on the integration of ESG in the Americas (2018) and Europe, the Middle East, and Africa (2019, p. 6), concludes that ESG investing is "often used as a marketing slogan." The Center for Corporate Citizenship at Boston College (2013) reveals that over 70% of surveyed companies cite 'enhanced reputation' among the top three business goals of their sustainability efforts. Greta Thunberg, the environmental activist, whose campaigning has gained international recognition, drew attention to the issue of GW at the United Nations Climate Change Conference COP25, held December 2–13, 2019, in Madrid.

is plausible given the unobservability of CSR investments and the lack of reporting standards. A handful of studies have indeed made headway in suggesting that firms engage in GW and documenting its economic implications.[57] However, notably missing from extant literature is explicit attention to the extent to which firms use selective CSR communication in response to growing pressure for more CSR in the aftermath of COVID. Our study fills this void by addressing three new questions.

We first investigate whether COVID provided incentives for firms to engage in more CSR talk. To address this question, we perform a textual analysis to measure the share of CSR talk (CSRT) in the narrative of the transcripts of earnings conference calls (ECs). Since CSR issues are multifaceted, the textual analysis presents a unique opportunity for adding value to the process of capturing the nuances of measuring the CSRT (e.g. Loughran and McDonald, 2022, p. 1). A distinctive feature of our study is that to extract CSRT from ECs we develop a new and comprehensive CSR/ESG dictionary that likely captures (at least partially) the materiality of CSR reporting. When developing our word list–based dictionary, we identify keywords from both academic and industry sources and cover different time periods.[58] We focus our textual analysis on bigrams because they are less ambiguous (Bloom, Hassan, Kalyani, Lerner, and Tahoun, 2020) than unigrams and tend to convey more information than single-word keywords. We use ECs to extract the textual feature of CSR Talk (CRST) because they are an unaudited medium for voluntary disclosure and interactive verbal communications (e.g., Bushee, Matomoto, & Miller, 2003; Bowen, Davis, & Matsumoto, 2002; Frankel, Johnson, & Skinner, 1999), providing

[57] See, for example: Pucker (2021), Attig, Rahaman, and Trabelsi (2021), Tashman, Marano, and Kostova (2019), Khan, Serafeim, and Yoon (2016), Marquis, Toffel, and Zhou (2016), Marquis and Qian (2014), Walker and Wan (2012), Delmas and Burbano (2011), Lyon and Maxwell (2011), Laufer (2003), Tolbert and Zucker (1983), and Meyer and Rown (1977), among others.
[58] A detailed discussion of our approach in developing our dictionary is provided in Section 3.

managers with more discretion in the narrative of their communications. Hail, Kim, and Zhang (2022) argue that ECs are an important channel of direct communication between a company's top management team and various stakeholders (e.g., investors, equity analysts, and the business press). Matsumoto, Pronk, and Roelofsen (2011) suggest that, during conference calls, managers are less constrained in providing information and analysts play an important role in uncovering information during the question-and-answer session, making ECs incrementally informative. Further, conference call disclosures can be particularly useful as they are held quarterly and contain senior management's direct responses to questions from analysts and market participants (Hassan Hollander, van Lent, & Tahoun, 2019; Hassan, Hollander, van Lent, Schwedeler, & Tahoun, 2021), and thus may represent a timely source of information (Donovan et al., 2021; Frankel, Jennings, and Lee, 2021).[59]

After identifying the most frequent bigrams, we review them manually to ensure that each bigram is CSR-relevant. Manually inspecting the word list is important to mitigate false positive cases since "no algorithm understands the context of human conversations better than human beings" (Li et al., 2020, p. 11). As an additional step of this disambiguation approach, we identified sentences associated with 10% of randomly selected bigrams in 10% of randomly selected ECs and verify their meaning and their context manually. Our disambiguation process enabled us to integrate an explicit understanding of the context when identifying our world list, resulting in 782 bigrams. Importantly, in our analysis, we use the bigram frequency-inverse document frequency (*bf-idf*) approach to extract CSRT. In contrast to word count (i.e., simple term frequency), which lacks discriminative power (Mai, Tian, Lee, and Ma, 2019), *bf.idf* prioritizes the important

[59] Campbell, Zheng, and Zhou (2021) argue that ECs draw significant investor attention because they are one of the first disclosures released by firms.

words/bigrams specific to each document by accounting for bigram frequency and normalization, while adjusting for impact across the entire collection of documents (whole corpus).

We expect CSRT to be more pronounced in the aftermath of COVID. This is because COVID has deepened social inequalities and other social ills, and increased pressure for more CSR. While this may offer an opportunity for firms to shift towards "more genuine and authentic genuine CSR" (He & Harris, 2020, p. 176), the increased societal and institutional pressures from various constituencies may lead the firms to engage in CSRT and develop sustainability façades. The lack of verifiability could not only limit the downside risk for a company claiming unsubstantiated CSRT but may also enhance its social capital.[60] In line with this expectation, we document a positive and significant effect of COVID on CSRT. This result remains unchanged when we restrict our sample to firms with non-zero CSRT and measure CSRT using managers' abnormal level of CSR discussion (e.g. Bushee, Gow, & Taylor, 2018; Hail et al., 2022). We also show that the effect of COVID on CSRT is more pronounced in small and less financially constrained firms.

For our second question, we investigate the impact how CSRT relates to conference call returns during the pandemic and document a negative impact of CSRT on firm abnormal returns around the conference call dates during the first quarter of COVID. We also show that CSRT—during COVID—bears negatively on future corporate performance, measured by the firm's future Tobin's Q and industry-adjusted Tobin's Q. This fresh evidence indicates that investors, on average, do not perceive CSR overselling as value-relevant.

In our third question, we investigate the extent to which firms walk the talk of their CSR. Stated differently, we investigate the effect of COVID on GW. We address the challenge of

[60] One could argue that engaging in CSRT may inflict reputational damage on the managers and their firms, if such talk is not associated with a 'CSR walk'. It is costly for stakeholders to gather and verify the materiality of the firms' CSR information.

measuring GW by proposing a new and intuitive measure that captures the distance between a firm's CSRT and its 'CSR walk' (CSRW). We use Refinitiv's (Thomson Reuters Asset4) ESG rating to measure CSRW. Refinitiv rating is particularly relevant as a proxy for CSRW because it reflects firm performance in the environmental and social areas (Baldini, Dal Maso, Liberatore, Mazzi, & Terzani, 2018). Refinitiv uses an ESG materiality matrix that determines the relative importance of each theme to each individual industry group and has the most individual indicators and the lowest values for scope divergence (Berg, Koelbel, & Rigobon, 2022). It has enjoyed a growing popularity in recent academic CSR research (e.g., Bae, El Ghoul, Gong, & Geudhami, 2021; Jackson, Bartosch, Avetisyan, Kinderman, & Knudsen, 2020; Aouadi & Marsat, 2018; Benlemlih, Shaukat, Qiu, & Trojanowski, 2018; Al-Shaer & Zaman, 2019; Hawn & Ioannou, 2016; Rathert, 2016; Cheng, Ioannou, & Serafeim, 2014; Eccles, Ioannou, & Serafeim, 2014; Ioannou & Serafeim, 2012, among many others). Our new measure of GW is the difference between the decile rank transformed CSRT and CSRW (GW=Rank CSRT – Rank CSRW), which may reflect the extent to which firms try to greenwash their CSR performance to present a socially responsible public image. We use rank transformation (by year and industry) to mitigate potential (i) measurement error in our proxies, (ii) change in CSR rating standards over time, (iii) differences in industry-specific standards and materiality in CSR reporting, and (iv) to allow comparison between CSRT and CSRW.

We show that COVID does not have a significant effect on CSRW and loads positively and significantly (at 10%) on GW. In a final and related test, we show CSRT is positively (negatively) related to the use of positive (negative) words in ECs and the net tone, measured by the ratio of the difference between positive and negative words to the total number of words. This evidence becomes more pronounced during COVID. All else equal, the link between CSRT and the use of positive words indicates that CSRT is likely to be associated with overselling of CSR performance or framing ESG/CSR concerns.[61] It is possible that managers, when talking CSR/ESG, resort to the use of positive words to favorably shape investors' (and other stakeholders') impressions about the social image of their firms.

Our study is timely given the increasing interest in CSR by managers, investors, and the public at large. Deloitte (2016), for instance, suggests that 87% of the surveyed Millennials believe that "the success of a business should be measured in terms of more than just its financial performance." The SEC (2020) states that "ESG is no longer a fringe concept. It is an integral part of the larger investment ecosystem of our modern, global, interconnected world". KPMG (2020) documents that over 90% of the world's 250 largest companies report on sustainability. The 2016 PWC Global CEO Survey shows that 64% of CEOs believe that CSR "is core to [their] business rather than being a stand-alone program". Importantly, 3,826 institutional investors—with more than US$121 trillion of assets under management (as of 31 March 2021)—signed the United Nations Principles for Responsible Investment (UN PRI), pointing to escalating pressures and demand for CSR.[62] However, our new evidence indicates that firms, in response to growing pressure to conform to stakeholders' CSR expectations, tend to engage in CSR selective disclosure to promote the appearance of conformity.

Our findings may inform managers on the economic (negative) implications of displaying symbolic societal compliance and policymakers on the importance of incentivizing business to engage in more genuine and substantial CSR. Our evidence suggests that 'cheap talk is not cheap'

[61] Loughran and McDonald (2011, 2016) suggest managers frequently use positive words to frame negative statements.
[62] An increase from US$103.4 trillion in 2020. The UN PRI is an UN-supported global initiative promoting the integration of environmental, social, and governance (ESG) factors into institutional investing practices.

as we find that overselling CSR, during COVID, comes at the direct expense of firm shareholders. With this fresh evidence, our study connects to different strands of empirical work. The first examines the impact of COVID on various corporate outcomes (see Goldstein, Koijen, and Mueller (2021) for a discussion). Goldstein et al. conclude that the COVID-19 pandemic has opened up new directions for future research, and many remain unexplored. While we respond to this call, we think that a direction of research ripe for exploration is the linkage between CSRT and supply chains, and the extent to which socially responsible supply chains contributed to the resilience of firms to disruptions and lockdowns imposed by the pandemic. In addition, empirical analysis of the real effects of CSRT seems warranted.

Our study connects to a burgeoning strand of inquiry that applies text-based analysis to measure tone-related characteristics in corporate documents. For instance, a dictionary-based approach was used to measure disclosure sentiment (Loughran & McDonald, 2011), financial constraints (Bodnaruk, Loughran, & McDonald, 2015), and sustainability hypocrisy (Attig 2021), supervised machine learning was recently used to measure credit risk (Donovan et al., 2021), the materiality of environmental and social disclosure (Chava et al., 2021), and financial constraints (Buehlmaier & Whited, 2018). Hail et al.'s (2022) study is particularly germane to the focus of our work. The authors use textual analysis to investigate the extent to which firms greenwash their underlying climate change activities and conclude that GW is prevalent in regular communication between managers and investors and that it occurs at the top management team's discretion. More broadly, our evidence lends credence to the line of inquiry that suggests that investors' tastes for ESG stocks can have valuation impact (e.g. Lins et al., 2017; Pastor, Stambaugh, & Taylor 2021; Pedersen, Fitzgibbons, & Pomorski 2021).

The remainder of the paper is structured as follows. Section 2 presents the theoretical background of our analysis. Section 3 discusses our data, variables construction, and summary statistics. In Section 4, we report our results and Section 5 concludes the paper.

2. Theoretical Background

There has been a long tradition of academic interest in the implications of CSR, mostly predicated on the ubiquitous view that CSR plays a non-negligible role in creating and preserving a firm's competitive advantage by serving its stakeholders' interests (e.g., Davis, 1973; Freeman, 1984).[63] Recent evidence suggests that a firm can enhance its social capital through CSR investments (e.g., Jha & Cox, 2015) because it builds trust with its stakeholders, which pays off when the level of trust suffers a negative shock (Lins, Servaes, & Tamayo, 2017; Amiraslani, Lins, Servaes, & Tamayo, 2022).

A related but much less studied topic is the extent to which firms use CSR communication and selective disclosure to promote the societal appearance of conformity. Meyer and Rowan (1977) introduced the concept of decoupling through which organizations conform their visible structures, but not their core activities, to social norms. Nystrom and Starbuck (1984) suggest that managers construct organizational facades to conceal activities or results they want to hide and mislead stakeholders. A growing line of inquiry studies impression management, which refers to the behavioral strategies used to create desired social images or identities (Tetlock & Manstead, 1985) to control or manipulate the reactions of others (e.g., Leary & Kowalski, 1990).

[63] The alternative view builds on Berle's (1931) shareholder primacy, advocating that CSR initiatives are at the expense of shareholders and that firms fulfill their societal obligations by increasing their profits and complying with applicable laws and regulations (Friedman, 1970).

Since managers may not be neutral in their presentation of accounting narratives (Sydserff & Weetman, 1999), they have incentives to use narrative techniques to obscure the actual CSR performance of their firms[64] and conceal negative outcomes, thus reducing the adverse impact on stakeholders' perceptions (Courtis, 2004) of the firm's actual CSR performance.[65] As such, managers can use CSR narrative as a voluntary disclosure (Kim & Verrecchia, 1994) to distort stakeholders' perceptions of the firm's actual CSR performance. This view is grounded in the idea that CSR discretionary disclosures are largely voluntary and corporate narratives are largely unregulated (Merkl-Davies & Brennan, 2007). In a recent study, Hail et al. (2022) show that top management teams have discretion in overstating their environmental performance, particularly when responding to difficult questions.

Of relevance to the focus of our study, COVID has provided incentives for managers to oversell the CSR of their firms. Indeed, as stated in the outset, COVID has urged firms to shift towards more CSR agenda to help address the pressing global social and environmental challenges. In response to this increased demand for CSR, managers may selectively communicate positive information about the CSR of their firms to decrease the incongruence between desired and actual CSR images (Tata & Prasad, 2015). This is because it is easier to manage stakeholders' impression of a firm's CSR image through communication and selective disclosure than by changing the firm's operations and policies (e.g., Neu, Warsame, & Pedwell, 1998) and promoting the appearance of

[64] This argument parallels, to some extent, the insights of theoretical models predicting that managers, in the presence of disclosure frictions, will strategically withhold bad news and disclose good news (e.g., Dye, 1985; Beyer & Dye, 2012). Further, firms may have incentives in concealing their actual CSR performance as this can be viewed as proprietary information that needs to be protected from competitors.
[65] This is plausible because the perception of a firm's CSR practices is a key driver of how individuals feel about a company (Flammer & Kacperczyk, 2019, and references therein). Merkl-Davies and Brennan (2007) discuss two main approaches to concealment: obfuscating bad news or emphasizing good news through thematic manipulation.

conformity can be sufficient to attain legitimacy (Oliver, 1991). They can do that by overselling their CSR to enhance their social legitimacy.[66] Accordingly, our first hypothesis:

H_1: The COVID-19 pandemic is associated with increased CSR Talk.

A priori, it is unclear whether, during hard times (e.g. COVID), overselling CSR will build social capital and thus enhance financial performance (positive view) or translate into social liability and result in value destruction (negative view). The positive view rests on the assumption that CSRT is not de facto fraudulent (when done within the allowances of investor protection regulations). As stated above, CSRT might help the firm posture a socially desirable image and gain the trust and support of stakeholders, which may enhance corporate financial performance. It is possible that CSRT serves as a signal of lower ESG risks or more socially responsible initiatives in the future.[67] This, in turn, can generate positive moral capital among the firm's stakeholders and thus provide insurance-like protection for a firm's relationship-based intangible assets (Godfrey, 2005). This is because communicating symbolic aspects of CSR can reduce the incongruity between the firm's real social performance and the information perceived by stakeholders, which in turn may mitigate the adverse capital (and labor) market consequences of missing such expectations.[68] The extent of market response hinges on stakeholders' assessment of the materiality of the disclosed CSR performance. However, it would be difficult for stakeholders to make meaningful assessments of firms' CSR claims—even if they are false or misleading—

[66] Arguably, the pandemic (and other bad times) tend to be associated with volatile aggregate shocks that may distract the attention of shareholders (e.g., Loh & Stulz, 2018) and other stakeholders, thereby rendering their impressions about corporate policies and initiatives more open to interpretation.
[67] Christensen, Morsing, and Thyssen (2013) suggest that discrepancies between CSR talk and actions have the potential to stimulate CSR improvements.
[68] While the Sustainability Accounting Standards Board (SASB) has recently developed 77 industry-specific standards to assist companies in disclosing material nonfinancial sustainability issues (SASB, 2020), managers have complete discretion over their sustainability reports and there are no mandates or third-party validation of the firm's sustainability report.

because they lack sufficient information to evaluate these claims (Busch & Hoffmann, 2009; Lyon & Maxwell, 2011) and because of the lack of objective standards.[69]

Alternatively, one could argue that overselling CSR can be associated with disclosure of symbolic CSR, which may create distrust and social liability. This, in turn, can bear negatively on firm performance. This alternative prediction suggests that overselling CSR during COVID might have adverse effects due to additional public and political pressure for more substantive CSR initiatives.[70] Further, attention may increase with the level of uncertainty (Kacperczyk, Van Nieuwerburgh, & Veldkamp, 2016; Andrei & Hasler, 2020; Gargano & Rossi, 2018), which will likely induce investors to allocate more attention to firm-specific information in general (Andrei, Friedman, & Ozel, 2022), and firm-specific CSR information in particular. Activists may optimally allocate their limited resources to search for, collect, and process information about a firm’s environmental and social performance. For instance, given the growing importance of CSR/ESG reporting in the allocation of assets and effective investment analysis, investment advisors, asset managers, and institutional investors may build their own scoring systems to verify the materiality and veracity of the disclosed sustainability information.[71] Relatedly, a company's environmental and social footprint can become more publicly visible and, therefore, more subject

[69] ISO COPOLCO (2002): “in the absence of credible, verifiable information concerning the CR activities of firms—the type of information which can be obtained through use of practical, globally accepted management systems standards—it is difficult for all of these parties to make meaningful assessments and decisions about a firm’s corporate responsibility practices” (p. 5).

[70] For instance, such pressures could increase litigation risks for firms that issue misleading environmental reports. Peters and Romi (2014) suggest that carbon disclosures may create adverse consequences by leading to potentially negative attention from environmental advocacy groups, providing information that invokes costly litigation (e.g., the investigation by government agencies).

[71] State Street Global Advisors (2019, p. 1) states that "ESG data has increasing importance for investors' ability to allocate capital most effectively" and recognizes that the lack of standardization and transparency in ESG reporting and scoring presents major challenges for investors. In response, State Street Global Advisors (2019) has built its own scoring system that uses data from multiple providers and leverages SASB’s transparent materiality framework.

to scrutiny from the media, regulators, analysts, and investors. Heightened scrutiny may associate CSRT with distorted information in corporate disclosures.[72]

The foregoing discussion leaves the impact of CSRT on financial performance, during COVID, an open empirical question. For expositional convenience, however, we predict the effect to be negative, which leads to our second hypothesis:

H_2: CSR Talk hinders financial performance during COVID.

3. Data and Research Design

3.1. Sample Selection

We start by downloading all ECs published as PDF files from Capital IQ. From these PDFs we extract firm information, such as the name, ticker, date and time of the call, speaker's name and title, type of speaker, and whether the text is in the presentation or the question-and-answer section. We apply fuzzy name matching[73] to match firms' names to the Compustat database (quarterly). We remove financials (SIC 6000−6999), utilities (SIC 4900−4999), and governmental and quasi-governmental entities (SIC 9000 and above). To ensure the results of our empirical analysis are not driven by fundamental differences among firms with different firm-level variables, we restrict our sample to firms with non-missing values of our regression variables, including CRSP and institutional ownership data (13f) variables. These filters result in a final sample of 72,411 firm-quarter observations, representing 3,386 unique firms and covering the period January 2007 to December 2020. To minimize the influence of outliers, non-categorical control variables

[72] Along this line of sight, 'cheap talk' between firms and capital markets may attract the market's attention and result in valuation effects (Almazan, Banerji, & de Motta, 2008).

[73] We use the R program to conduct fuzzy name matching (Hassan et al., 2019). The method looks for words/phrases with a percentage of common characters. The fuzzy-name-matching score ranges from 0 to 1, with a 0 score if there is no similarity between the two names by considering their common characters and 1 if the names are identical. We match by name, keeping matching scores of more than 0.95.

are winsorized at the 1% level at each tail of our sample. All variables and their sources are described in **Appendix** A.

3.2. Text extraction and pre-processing

Loughran and McDonald (2016, p. 1192) state that "most textual analysis papers in accounting and finance provide vague statements about how a document is parsed and then produce results from a software package where the driving forces behind the results are opaque". Drawing on this criticism, we provide below relevant details of our text extraction process.

We perform structured text extraction using R programming and create an algorithm that reads ECs (.PDFs) and splits them into paragraphs using the newline escape character (\n).[74] Our algorithm extracts the company name, company ticker, event (in our case, ECs), day, call date, and time using the description in the top of the first page of the ECs and then creates a new column for each item for the output. The .PDFs are then crawled to locate a table of contents that contains two columns. The first column shows the sections of the document—call participants, presentation, and question-and-answer (Q&A) section—and the second shows the number of pages assigned to each section (e.g., call participants 3, presentation 4, and question and answer 10).

The algorithm uses the title and page number of each section in the table of contents of the EC to detect and trace the pages. It identifies the text/narrative associated with the presentation and Q&A sections. This allows us to analyze the whole transcript of the earnings call, the presentation section, or the Q&A section. The algorithm also crawls the call participants section, which contains the executives, analysts, and other participants (in this order), and identifies their names, titles, and roles (e.g., speaker name, speaker title, and speaker type) using the newline

[74] When the algorithm sees a backslash and the letter [n], it breaks the text from that line and creates a new line. The letter [n] is an escape character if it has the backslash [\] in front of it (Thompson, 1984).

escape character (\n). The algorithm saves their names, titles, and roles. We exclude unknown names (e.g., unknown speakers, unknown participants, unknown callers, and unknown firm analysts, as well as the operator) and focus on the conversation between call participants and firm management on the conference call.

We read the presentation and Q&A sections of ECs to identify the typical starting and ending marks to the algorithm in order to retrieve the text associated with each speaker. Each section starts with the speaker's name and title (e.g., *Gabrielle Rabinovitch, Vice President of Corporate Finance & Investor Relations*), and their narratives come immediately below their names and roles. To identify the narrative of each speaker in either section (e.g., presentation or Q&A), we use the first speaker's name as the starting phrase mark and the second speaker's name as the ending phrase (e.g., *Daniel H. Schulman President, CEO & Director*). The text between these two names (*Gabrielle Rabinovitch* and *Daniel H. Schulman*) is devoted to the narrative of the first name (*Gabrielle Rabinovitch*), while the text between the second and third names is dedicated to the second name narrative, and so on. Since each name has been saved in an earlier stage in either the executives' or analysts' section, our algorithm provides us with four more columns: speaker name, title, speaker type, and which part of the narrative (presentation vs. question-and-answer).

After identifying each section, we create a corpus and tokenize it into bigrams using all earning calls over our sample period. We then perform the common pre-processing techniques to "to make the textual analysis more precise by reducing unnecessary noise in the text" (Buehlmaier & Whited, 2018, p. 2697).[75] We namely remove punctuations, digits/numbers, and citations,

[75] Pre-processing is the cleaning and preparation of the text for textual analysis. Skipping the text pre-processing stage increases the dimensionality problem, which makes the classification more difficult because every single n-gram is treated as one dimension (Haddi, Liu, & Shi, 2013), and introduces unnecessary noise into the documents, which

convert all letters to lowercase, remove all stop words (stop-words listed in the R program using the tm R package) and remove tokens that have fewer than three letters as well as all whitespaces left from the process above.

3.3. Creating the CSR dictionary

To measure CSRT from ECs, we first need to develop a CSR dictionary comprising n-grams (phrases) relevant to CSR topics. As stated above, we focus on bigrams because they are less ambiguous and tend to convey more information than unigrams. To construct our CSR keywords list, we employ several data sources. First, we review the literature and identify existing CSR dictionaries. We consider the bigrams of four existing dictionaries developed by Loughran, McDonald, and Yun (2009), Pencle and Mălăescu (2016), Moss, Renko, Block, and Meyskens (2018), and Baier, Berninger, and Kiesel (2020). Second, we add CSR keywords that we extract from several industry guidelines and documents from practitioner-oriented institutions. We find it useful to rely on industry-related sources as they may provide industry experts' insights, which are relevant in identifying n-grams that capture CSR discussions more effectively (e.g., Loughran and McDonald, 2016). For the purpose of our study, we use the following sources:

- Global Reporting Initiative (GRI) Standards Glossary 2021 report:[76] We manually read the report and extract n-grams using all the highlighted GRI glossary and the examples.

makes the textual analysis less precise (Buehlmaier & Whited, 2018). Jianqiang and Xiaolin (2017) study the impact of text pre-processing methods on performing sentiment analysis and show that applying pre-processing improves the accuracy of the machine learning algorithms.

[76] file:///C:/Users/Bosha/Downloads/GRI%20Standards%20Glossary%202022.pdf

- International Financial Reporting Standards (IFRS) Climate-related Disclosure:[77] It contains Appendix A–defined terms and Appendix B–Industry disclosure requirements. Appendix A–defined terms are in two columns: term and definition. We focus on the keywords listed in the term section and manually read and extract all of them. Appendix B–Industry disclosure requirements presents keywords across different industries and contains four columns. We use the keywords included in the disclosure topic section across different industries.
- Refinitiv Marketpsych ESG Analytics:[78] It provides three pillar scores for each asset: environmental, social, and governance. It uses natural language processing (NLP) and score calculation techniques to provide more than 100 RM-ESG scores. We use the available RM-ESG scores section, which contains key phrases for environmental, social, and governance.
- Directors' Guide to the SASB Standards 2021:[79] we tokenize this document into bigrams using the document-bigram-matrix and identify 8,716 bigrams that we add to our list.

Importantly, we supplement the above list of bigrams with CSR bigrams identified in the most-cited academic published studies. We use the Web of Science to identify the most-cited CSR and consider the following five studies: [80]

[77] https://www.ifrs.org/content/dam/ifrs/groups/trwg/trwg-climate-related-disclosures-prototype.pdf
[78] https://resourcehub.refinitiv.com/443870globalsustainablefinanceesg/443870-ESG-PaperMarketPsychSustainability?utm_source=Eloqua&utm_medium=email&utm_campaign=443870_2021GlobalSustainableFinanceESG&utm_content=443870_2021GlobalSustainableFinanceESG+Email6MarketPhychQuantAMERSEMEA
[79] https://ccli.ubc.ca/wp-content/uploads/2021/11/SASBVRF-Directors-eng-Guide-110821.pdf
[80] The numbers of citations are as of October 24, 2022 in Google Scholar.

- “Corporate Social Responsibility Theories: Mapping the Territory” (Garriga & Mele, 2004, *Journal of Business Ethics*): 6,861 citations.
- “Does Doing Good Always Lead to Doing Better? Consumer Reactions to Corporate Social Responsibility” (Sen & Bhattacharya, 2001, *Journal of Marketing Research*): 6,628 citations
- “Implicit and Explicit CSR: A Conceptual Framework for a Comparative Understanding of Corporate Social Responsibility (Matten and Moon, 2008, *The Academy of Management Review*): 5,603 citations.
- “Corporate social responsibility and financial performance: Correlation or misspecification?” (McWilliams and Siegel, 2000, *Strategic Management Journal*): 5,417 citations
- “What We Know and Don’t Know About Corporate Social Responsibility” (Aguinis and Glavas, 2012, *Journal of Management*): 4,174 citations.

We create a corpus using the five research papers and tokenize the corpus into bigrams using document-bigram-matrix. We identify 29,525 bigrams which we add to our wordlist of bigrams. While we recognize that caution is merited when using the dictionary-based method because such an approach may not consistently capture disclosure sentiment across time and managers might adjust the narratives in the firm documents to reflect what they believe investors perceive (Frankel et al., 2021), this caveat is less likely to apply to our study for at least two reasons. First, we are examining CSRT after an exogenous shock (COVID). Second, as detailed above, when developing our word list-based dictionary, we identify keywords from both academic and industry sources that cover different time periods.

After identifying the most frequent bigrams, we review them manually to ensure that each is CSR/ESG relevant. As discussed in the outset, our disambiguation[81] process enables us to integrate an explicit understanding of the context when identifying our world list, resulting in 782 bigrams. In Appendix B, we provide a sample of our CSR bigrams.

3.4. Measuring firm-level CSR talk

We use three proxies to measure CSRT: The first proxy (*CSRT BF*) measures the frequency of CSR bigrams in ECs, calculated by dividing the total number of CSR bigrams by the total number of bigrams in the EC. The second proxy is measured using the bigram's frequency-inverse document frequency (*CSRT BF-IDF*). This method prioritizes the important words/bigrams specific to each document by accounting for bigram frequency and normalization, while adjusting for impact across the entire collection of documents (whole corpus).[82] Stated differently, bigram frequency-inverse document frequency approach prioritizes the important bigrams relevant to each row in our study (e.g., Mai et al., 2019). We apply Loughran and McDonald's (2011) equation of term frequency-inverse document frequency after adjusting it for the use of bigrams:

$$\omega_{ij} = \begin{cases} \dfrac{\left(1 + \log\left(bf_{i,j}\right)\right)}{\left(1 + \log(\alpha_i)\right)} \log\left(\dfrac{N}{df_i}\right) & if\ tf_{i,j} \geq 1 \\ 0 & otherwsie \end{cases}$$

[81] Applying a disambiguation technique is essential in improving detection accuracy and minimizing the effect of Type 1 errors. A Type I error occurs when the null hypothesis is rejected when it's true. In textual analysis, it refers to misclassification errors. It is common and can "do more than add noise to the data and can unintentionally create latent measures of other firm attributes such as size or industry" (Loughran & McDonald, 2016, p. 1192). McKenny, Aguinis, Short, and Anglin (2018) suggest conducting a manual textual analysis of at least 10% of the data to ensure that the concept measures what it is supposed to measure (validity) by verifying the context of the bigrams.

[82] Loughran and McDonald (2011) suggest that selecting a term weighting scheme is a critical first step when using a bag of words. Relying on the term frequency—counting the number of times a word appears in a document—has the drawback of granting "high weights to words that are frequent across the board but lack discriminative power" (Mai et al., 2019, p. 751). Loughran and McDonald (2016) add that "*in most instances, we do not want to use the raw count, since this is obviously strongly tied to document length*" (p. 1207).

where N represents the total number of documents in the corpus, df_i the number of documents containing at least one occurrence of the i^{th} bigram, $tf_{i,j}$ the raw count of the i^{th} bigram in the j^{th} document, and α_i the number of bigrams' count in the document. The log transformation attenuates the impact of high-frequency words/bigrams and the term $\log\left(\frac{N}{df_i}\right)$ adjusts the impact of a bigram based on its commonality (Loughran & McDonald, 2011). In Appendix C, we provide an example to illustrate the implementation of this approach.

For our third proxy of CSRT (*CSRT PCA*), we apply Principal Component Analysis and use the first principal component of *CSRT BF* and *CSRT BF-IDF*.

4. Empirical results

4.1. Descriptive statistics and validation tests

We start by plotting *CSRT BF* over our sample period. Figure 1 shows an upward-sloping trend, reaching an all-time high during the first quarter of COVID. Figure 2 presents the 100 most frequently used words within 10 words (i.e., before and after) of the term "CSR" or "ESG".

Panel A of Table 1 provides descriptive statistics of our key regression variables. The average of *CSR BF*, *CSR BF-IDF*, and *CSR PCA* is, respectively, 0.241, 0.03, and 0.007. The pairwise correlation coefficients, reported in Panel B, suggest that multicollinearity issues can be safely ignored in our regression analysis.

4.2. Do Firms Oversell their CSR during the COVID19 Pandemic?[83]

To answer our first question, we run the following model:

[83] In our analysis, we assume that managers' interests are aligned with those of the firm.

$$CSR\ Talk_{i,t} = \alpha_0 + \alpha_1 COVID_t + FIRM\ CTRL_{i,t} + \alpha_i + \delta_t + \varphi_d + \varepsilon_{i,t},$$

Where $CSR\ Talk_{i,t}$ is our dictionary-based construct of CSR narrative in EC of a firm I in quarter t. COVID is a dummy variable that takes the value 1 if EC was held after March 20, when the World Health Organization declared COVID-19 a pandemic. $FIRM\ CTRL$ is a set of firm controls. We control for firm size (Size) measured as the natural logarithm of total assets in year-quarter t, the ratio of total debt total assets (Leverage); the ratio of capital expenditure to total assets (CAPEX); the book-to-market ratio (BTM); the ratio of cash holdings to assets (Cash); a dummy variable that takes the value 1 if the firm pays dividends and 0 otherwise (Dividend); institutional ownership (INSOWN); a dummy variable that takes the value 1 if the firm reports a negative earnings in the previous quarter (Negative earnings); and firm complexity (Complexity), measured by the number of business segments (Hay, Knechel, & Wong, 2006). We include firm-fixed effects (α_i) to control for time-invariant firm characteristics and the two-digit SIC industry-year-quarter pair fixed effects (δ_t) to control for innovation shocks that are specific to a given industry and year-quarter and unobserved heterogeneity. We also include day-of-the-week fixed effects (φ_d) to account for the possibility that different days may imply more or fewer investors' attention and information content of ECs. While the firm-fixed effects subsume the state-fixed effects, we cluster the standard error at the state level. With these fixed effects, the coefficient on COVID captures the effect of the COVID-19 pandemic on SCR. Results are reported in Table 2.

In Panel A of Table 2 we report the results based on our entire sample period (2007–2020). We start by running our regressions without time-variant firm characteristics. We namely examine the effect of COVID on *CSRT BF*, *CSRT BF-IDF*, and *CSRT PCA* and report the results in, respectively, columns (1), (2), and (3) of Panel A. In line with our first hypothesis, the coefficient of COVID is positive and statistically significant at the 1% level, suggesting that firms increased their CSRT in response to COVID. We then augment the regression model with firm-specific controls and report the results in columns (4)–(6). Interestingly, the coefficients of COVID remain positive and significant and of comparable scale to those reported in columns (1)–(3). To test the robustness of our new evidence, we restrict our sample to the period 2018–2020 to have a balanced period on each side of COVID and report the results in Panel B. Interestingly, the results of Panel B confirm the evidence reported in Panel A.

As an additional robustness test, we restrict our sample to firms with non-zero CSRT and report the results in Panel A (entire period) and Panel B (reduced period) of Table 3. Here again the estimated coefficient of COVID is positive and significant, lending further support to our first hypothesis. Taken together, the evidence of Tables 2 and 3 suggests that CSR overselling in the regular communication between managers and investors is more pronounced during COVID.

Since our evidence is robust to the choice of the method of constructing our CSR Talk (*CSRT BF, CSRT BF-IDF,* and *CSRT PCA*), we will focus on *CSRT PCA* in the rest of the paper. In Table 4, we test the stability of our findings to the inclusion of additional variables to curtail the effect of the potential bias of omitted variables. We sequentially[84] and then concurrently control for the following additional variables: (ILL1), Roll's (1984) illiquidity proxy measured as the average effective bid-ask spread over the fiscal year (AQBAS), number of analysts (ANAN), analyst dispersion (DISP) and intangible (INTANG), the ratio of the sum of income before extraordinary items, R&D, and depreciation and amortization to total assets. Results of using the entire (reduced) sample period, reported in column (1) ((2)) of Table 4, continue to lend credence to our hypothesis that the COVID-19 pandemic incentivizes firms to oversell their CSR. Although these variables

[84] Our evidence remains unchanged when we sequentially control for the potentially omitted variables. Results are not reported in the text but available upon request.

certainly cannot capture every potential source of omitted variables bias, the stability of our new evidence suggests that ILL1, AQBAS, ANAN, DISP and INTANG are driver of the effect of COVID on CSR.

In an additional robustness test, we examine the impact of COVID on a firm-quarter measure of abnormal CSR discussion (CSRT_abnormal), measured by the residual from regressing *CSRT PCA* on our set of main controls. We then run our regression analysis using the full-sample period (column (3) of Table 4) and the reduced sample period (column (4)). Our results indicate that COVID loads positively and significantly on *CSRT PCA*, suggesting that CSR discussion during COVID was above the predicted norm for ECs.

4.3. The cross-sectional variation of the COVID-CSR narrative relationship

In this section, we investigate whether our new evidence on the effect of COVID on CSRT varies across types of firms. We consider five firm characteristics: number of analysts, institutional ownership, operating performance, financial constraints,[85] and firm size. We use a dummy variable (indicator) that distinguishes firms with values of the firm characteristic above the sample median from those with values below the sample median. We then run the following regression:

$$CSR\ Talk_{i,t} = \alpha_0 + \alpha_1 COVID_t + \alpha_2 indicator_{i,t} + \alpha_3 COVID_t \times indicator_{i,t} + FIRM\ CTRL_{i,t} + \alpha_i + \delta_t + \varphi_d + \varepsilon_{i,t},$$

Our coefficient of interest is α_3 as it indicates the extent to which the effect of COVID on CSRT is mediated by some firm characteristics. We report the results in Table 5. Results on the effects of number of analysts, institutional ownership, operating performance, financial constraints, and firm size are reported in, respectively, columns 1, 2, 3 4 and 5. We first note that

[85] We use the Kaplan–Zingales Index as our measure of financial constraint.

the coefficient of COVID continues to be positive and significant across all specifications. We also note that the coefficient of interaction variable ‘number of analysts (ANA) x COVID’ is negative and significant, suggesting that the presence of more analysts reduces managers’ incentives to oversell the CSR of their firms during uncertain times (i.e. COVID). The negative and significant coefficient ‘financial constraint x COVID’ suggests that financially constrained firms do appear to engage less in overselling their CSR performance during COVID, whereas small firms appear to talk more CSR during COVID.

One might also argue that financially constrained firms are less inclined to engage in overselling of their CSR performance during COVID because such CSR initiatives tend to be associated with short-term costs (and uncertain long-term profits) and the COVID outbreak and associated lockdowns have adversely affected firm financial constraints. It is thus possible that investors and other stakeholders will associate discussions of CSR issues during COVID by financially constrained firms with GW behavior. Results reported in column (5) indicate that small firms are more likely to discuss CSR issues in the narratives of their ECs during COVID. This is possible because large firms tend to have better information quality (e.g., more analyst following). Large firms that disclose CSR are likely to attract more investors/traders that are CSR conscious. As such, the costs associated with misleading CSR disclosure can be more pronounced for large firms.[86]

4.4. How is the Market Response to CSR Talk?

In this section, we examine the extent to which our CSRT relates to conference call returns. To this end, we run the following model:

[86] The marginal benefit of increased disclosure for large firm is higher than that for small firms (Diamond & Verrecchia, 1991)

$$CAR[0,t]_{i,q} = \alpha_0 + \alpha_1 CSR\,Talk_{i,q} + \alpha_2 EARN\,SURP_{i,q} + \alpha_3 \log(MVE)_{i,q} + \alpha_4 BTM_{i,q} + \alpha_5 TURNOVER_{i,q} + \alpha_6 INSTOWN_{i,q} + \alpha_7 PRE\,FF\_ALPHA_{i,q} + \varepsilon_{i,q},$$

where $CAR[0,t]_{i,q}$ is equal to the cumulative abnormal (market-adjusted) return from trading day 0 to trading day t relative to the conference call date. We try different windows: [0,1], [0,2], [0,3], [0,4], and [0,5], where day 0 is the day of earning call. To reduce the likelihood that GD Talk captures the information content of other observable firm characteristics on the conference call date, we follow Frankel et al. (2021) and control for (i) firm earnings surprise (*EARN SURP*), calculated as the firm earnings per share in the current quarter less the median earnings per share forecast for the firm made prior to the current-quarter earnings announcement date scaled by the firm's stock price at the end of the quarter and based on the latest forecast prior to the current-quarter earnings announcement date;[87] the (log) of the market value of equity (MVE) for the firm in the current quarter or year calculated as the firm's stock price multiplied by the number of shares outstanding at the end of the quarter or year; the book to market ratio (BTM) calculated as the firm's book value of common equity at the end of quarter or year divided by MVE; the number of shares traded for the firm in the trading days [−252, −6] relative to the conference call date divided by the firm's shares outstanding at the conference call (*Turnover*); the percentage of shares of the firm held by institutional investors (*INSTOWN*); and the Fama–French alpha (Pre_FFAlpha) based on a regression of their three-factor model using trading days [−252, −6] relative to the conference call date.[88] Results are reported in Table 6.

Consistent with our expectations, we find that the coefficient of the impact of CSR talk (*CSRT BF*, *CSRT BF-IDF*, and *CSRT PCA*) on short-term cumulative abnormal returns around the

[87] We remove forecasts made more than 90 days prior to the earnings announcement date.
[88] We require firms to have at least 60 daily returns to be included in this analysis.

conference calls (days 0 and 1) is negative and significant at the 1% level. This new finding suggests that firms with higher CSR talk experienced a larger decrease in stock conference call returns during the first quarters of COVID.

In a related test, we try to examine whether CSR Talk hinders firm future performance by running the following regression:

$$FFP_{i,t} = \alpha_0 + \alpha_1 CSRT\_residual_{i,t} + \alpha_2 COVID + \alpha_3 CSRT\_residual_{i,t} \times COVID + \alpha_3 FIRMCTRL_{i,t} + \varepsilon_{i,t}$$

where FFP is our measure of firm performance, measured using Tobin's Q (TOBINSQ) and industry-adjusted TOBINSQ, calculated by subtracting the industry median from the sample firm value for each year and firm. Following McLean, Zhang, and Zhao (2012), Rauh (2006), and Baker, Stein, and Wurgler (2003), we estimate TOBINSQ as the market value of equity, minus the book value equity, plus the book value of assets, all scaled by the book value of assets. We focus on TOBINSQ because it is a market-based forward-looking measure of firm performance that is risk-adjusted, less susceptible to changes in accounting practices (Fauver, Hung, Li, & Taboada, 2017; Bharadwaj, Bharadwaj, & Konsynski, 1999; Montgomery & Wernerfelt, 1988) and captures the outcome of various potential channels through which CSRT can affect firm value. Importantly, TOBINSQ is an appropriate measure of firm performance in the context of CSR because it captures investors' expectations of the present value of a firm's future profitability (Jo & Harjoto, 2011; Cai, Jo, & Pan, 2012; Jayachandran, Kalaignanam, & Eilert, 2013; Manchiraju & Rajgopal, 2013; Rassier & Earnhart, 2015; Buchanan, Cao, & Chen, 2018; Bu, Chan, Choi, & Zhou, 2021, among many others).

We report the results in Table 7. In column (1), we use CSRT PCA without time-variant firm characteristics, whereas in column (2), we measure CSR Talk by the residual of our main regression (CSRT PCA Residual) and augment our regression model with firm-characteristics. The results reported in these two columns indicate that CSR Talk bears a negative and significant effect on future (i.e., next quarter) Tobin's Q. In columns (3) and (4), we reproduce the analysis of columns (1) and (2) after replacing future Tobin's Q with future industry-adjusted Tobin's Q. The results are in line with the evidence reported in columns (1) and (2). Importantly, the interaction variable between COVID and CSRT PCA Residual loads negatively and significantly on both Tobin's Q and industry-adjusted Tobin's Q, during COVID. To a large extent, this result corroborates the findings reported in Table 6, suggesting that overselling CSR may hinder firm financial performance.

4.5. Do managers walk the CSR talk?

Our evidence so far indicates that firms appear to engage in overselling their CSR during COVID and that such behavior may come at the expense of shareholders. In this section, we ask whether firms walk the talk of their CSR during COVID. Results are reported in Table 8. In column (1), we reproduce our core evidence that COVID incentivizes managers to overstate the CSR performance of their firms. In column 2, we examine the effect of COVID on CSR walk (CSRW). We measure CSRW using Refinitiv's (Thomson Reuters Asset4) ESG rating. Refinitiv rating, as a proxy for CSRW, is particularly relevant because it reflects a firm's performance in the environmental and social spheres (Baldini et al., 2018). Refinitiv uses an ESG materiality matrix that identifies the relative importance of each theme to each individual industry group and has the most individual indicators and the lowest values for scope divergence (Berg et al., 2022). It has enjoyed growing popularity in recent academic CSR research (e.g., Bae, El Ghoul, Gong, & Guedhami, 2021; Jackson et al., 2020; Aouadi & Marsat, 2018; Benlemlih et al., 2018; Al-Shaer

& Zaman, 2019; Hawn & Ioannou, 2016; Rathert, 2016; Cheng et al., 2014; Eccles et al., 2014; Ioannou & Serafeim, 2012, among many others).

We note that there is no association between COVID and CSRW. This evidence should be viewed with caution because most of the Refinitiv ratings for 2020 are from 2019.[89] This should not represent a major caveat because we are not claiming that COVID led to more or less CSR actions. In addition, CSR actions /investments entail some financial costs and are inherently long term. So it is less likely that COVID had immediate (i.e., short-term) effects on firms' "investments" in substantive CSR initiatives.

Most importantly, we use CSRW to propose a novel measure of GW as difference between the decile rank transformed CSRT and CSRW (GW=Rank CSRT – Rank CSRW), which indicates the extent to which firms attempt to greenwash their CSR performance to appear socially responsible. We use rank transformation (by year and industry) to mitigate potential (i) measurement error in my proxies, (ii) change in CSR rating standards over time, (iii) differences in industry-specific standards and materiality in CSR reporting, and (iv) to allow comparison between CSRT and CSRW. When constructing GW, we restrict our sample to firms with non-zero CSRT.[90] We do not include the 'pillar' of governance in our CSR Walk score and use the average of the environment and social scores.

We report the impact of COVID on GW in column (3) of Table 8. Interestingly, we document a positive and significant effect (at 10%) of COVID on GW, lending further credence to our

[89] We populated the missing data for 2020 with data from 2019.
[90] Because we are interested in greenwashing, when CSR Talk is zero, we end up measuring the (opposite) effect of CSR Walk (rating). In addition, caution is merited when using CSR/ESG ratings since ratings from different sources have fairly low correlations with each other (Chatterji, Durand, Levine, & Touboul, 2016; Berg, Fabisik, & Sautner, 2021; Berg et al., 2022) and may lead to different conclusions. We are unable to use KLD data because it has not been produced since 2018.

hypothesis that managers are more likely to greenwash the CSR performance of their firms in response to increased demand for and attention to CSR/ESG issues. Our evidence indicates that GW became more pronounced in regular communication between managers and investors during COVID. Stated differently, firms do not appear to walk the talk of their CSR during COVID.

In a final test, we investigate the linkage between CSR Talk and various textual features (as in Hail et al., 2022) and report the results in Table 9. We use CSRT PCA Residual as our proxy for CSR Talk (since we are using it as an independent variable). In column (1), we investigate the effect of CSRT PCA Residual and its interaction effect with COVID on the frequency of positive words in the document (% positive), measured as the ratio of positive keywords to the total number of words in the EC. We use Loughran and McDonald's (2011) list of positive words and measure their frequency in the ECs. Both CSRT PCA Residual and its interaction effect with COVID (i.e., CSRT PCA Residual x COVID) load positively and significantly on % positive.

In column (2), we reproduce the analysis of column (1) after replacing % positive with % negative, where % negative is the ratio of negative keywords to the total number of words in the EC. The list of negative keywords is from Loughran and McDonald's (2011) dictionary. We note that the effect of CSRT PCA Residual on "% negative" is negative, whereas the coefficient of CSRT PCA Residual x COVID has no significant effect. In column (3), we use the net tone (Net Tone) as the dependent variable. We measure Net Tone as the ratio of the difference between positive and negative words to the total number of words in the EC. In accord with the results reported in columns (1) and (2), both variables CSRT PCA Residual and CSRT PCA Residual x COVID load positively and significantly on Net Tone. The evidence in Table 9 should not surprise us because managers frequently use positive words to frame negative statements (Loughran & McDonald, 2011, 2016). It is thus possible that managers, when talking CSR/ESG, resort to the use of positive words to favorably shape investors' (and other stakeholders') impression about the social image of their firms. As such, all else equal, the link between CSRT and the use of positive words indicates that CSRT is likely to be associated with overselling of CSR performance or framing ESG/CSR concerns.

5. Conclusion & Discussion

In a recent *Harvard Business Review* article, Pucker (2021) sheds light on the overselling of sustainability reporting, pointing to the discrepancy between sustainability reporting and sustainable investing. Stephen Hahn-Griffiths, chief reputation officer of the Reputation Institute, commented on the sustained increase—since 2011—in CSR reputation of U.S. firms, as revealed by the Institute's corporate responsibility index: "It's not necessarily that companies have done anything dramatically different, but they're doing a better job of providing reasons to believe that they have good intentions" (Forbes, 2019). The claim by Tariq Fancy, former chief investment officer for sustainable investing at the world's largest asset manager (BlackRock), that ESG is a 'dangerous placebo' (e.g., CNBC, 2021) is echoing a wave of skepticism that has recently fueled the debate on the growth of ESG investments and the materiality of their disclosures. More broadly, a simple perusal of recent headlines in major newspapers highlights concerns about GW.[91]

Despite the growing concerns about GW, little attention has been paid to the drivers of,

[91] "Biden administration faces increasing calls to stop companies from greenwashing" (ABC News, 2021), "It's time to bring greenwashing under control" (Forbes, 2021), "Former BlackRock executive blows the whistle on greenwashing" (Bloomberg, 2021b), "UK legislators call for action on financial greenwashing" (Reuters, 2021), "Greenwashing in finance: Europe's push to police ESG investing" (Financial Times, 2021), "How to tell if a company's claim of ethical practices is true" (New York Times, 2021), "FTC proposes crackdown on greenwashing" (New York Times, 2010). The World Wildlife Fund notes that "the private sector is making a lot of verbal progress—while real deforestation results are evasive" (Fortune, 2021). Anne Simpson, the director for Board Governance & Sustainability at CalPERS, the California Public Employees' Retirement System, also expressed skepticism about the green marketing pitch fueling the rise of ESG funds (Bloomberg, 2021a). Terrachoice's (2010) report indicates that more than 95% of consumer products claiming to be green committed at least one of Terrachoice's "seven sins" of greenwashing.

and how to detect, such corporate behavior and to its economic implications. This study adds to the literature by documenting that firms, in response to pressure to conform to their stakeholders' expectations for more CSR, turn to selective disclosure in the narratives of their earning calls to oversell the CSR performance of their firms. We further show that firms tend to engage in more GW during COVID. Importantly, our findings indicate that the market responds negatively to such CSR overselling. We also show that firms with less analysts coverage, financially unconstrained firms and small firms tend to engage in more CSR overselling during COVID and that firms that oversell their CSR are less likely to walk their CSR talk. This is important as it exposes the potential for firm deceptive practices and highlights the need for transparency and genuine commitment to societal well-being in times of crisis. Arguably, our fresh evidence suggests that overselling CSR can lead to social liability that translates into value depression when the economy faces an unexpected crisis of trust (COVID).

By turning scholarly attention to the extent to which firms manage stakeholders' impressions about their CSR and the valuation implications of such CSR overselling, we add to, yet depart from, extant CSR literature, much of which has been to establish the valuation effects of CSR ratings. As such, our findings relate to the ongoing debate in the academic literature on the performance relevance of CSR. Much of the debate centers on the effect of firm CSR initiatives, as revealed by third-party scores, overlooking the extent to which the disclosed information is material to the firm CSR performance. Our study adds to the literature because little is known about the economic implications of quality CSR communication and reporting (e.g., Christensen, Hail, & Leuz, 2021). It also suggests that at least a partial explanation for the mixed evidence on the effect of CSR on corporate performance lies in lack of materiality of the disclosed information on firm environmental and social initiatives.

Our study is among the first steps necessary to gain a deeper understanding of the impact of greenwashing on other corporate outcomes and the factors that lead to different CSR and environmental disclosures over time and across countries. More broadly, our evidence appears to converge with the ongoing regulatory discussions on "whether ESG disclosures are material and should be incorporated into its integrated disclosure regime" (SEC, 2020).[92] Further, the Sustainability Accounting Standards Board (SASB) has recently developed 77 industry-specific standards to assist companies in disclosing material nonfinancial sustainability issues (SASB, 2020). The evidence of this study echoes the calls for policymakers to accelerate the design of policies and standards so that firms accurately disclose verifiable social and environmental performances.

[92] The SEC (2020) points out that "For close to 50 years, the SEC has periodically contemplated whether ESG disclosures are material and should be incorporated into its integrated disclosure regime for SEC-registered Issuers", adding that "The point is that, despite a great deal of information being in the mix, there is a lack of consistent, comparable, material information in the marketplace and everyone is frustrated – Issuers, investors, and regulators".

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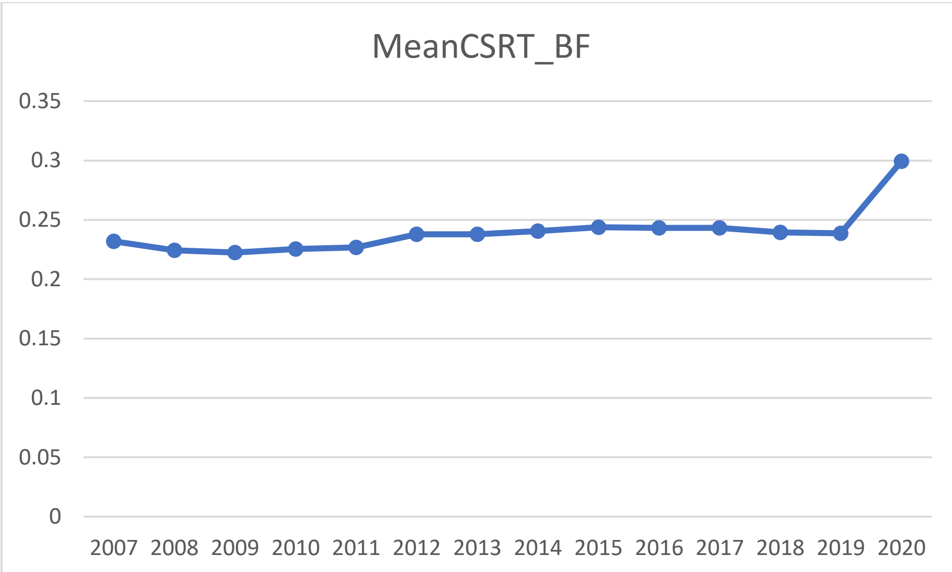
Figure1: The Average of CSRT-BF over our sample period

This figure depicts the average of CSRT-BF over our sample period.



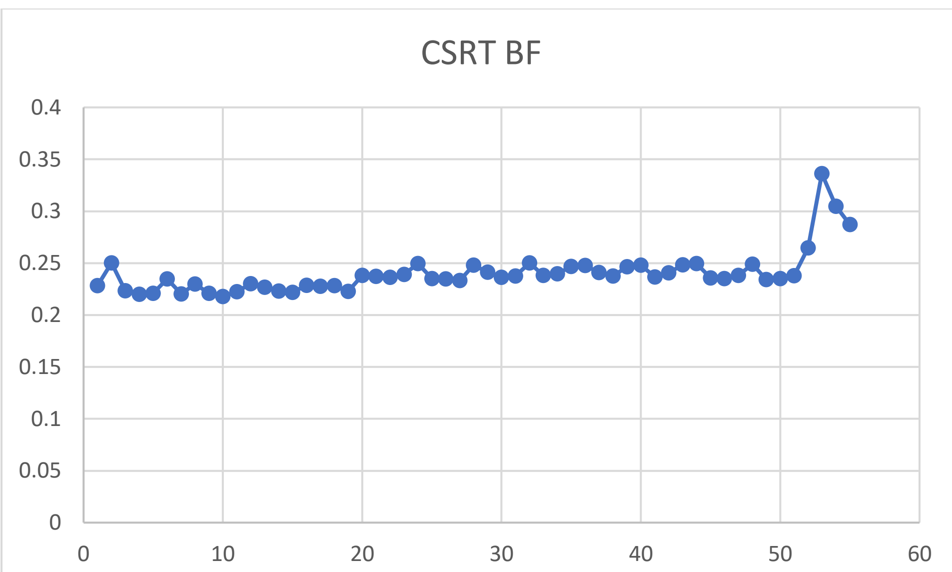


Figure 2: CSR and ESG Word Cloud

This figure displays the 100 most frequently used words within ten words before or after the word "CSR" or "ESG" in all 2020 ECs.

Table 1: Descriptive Statistics for Key Variables

Panel A of this table presents the descriptive statistics of our key regression variables. We measure firm CSR talk using different proxies: CSRT BF measured by using CSR bigram frequency scaled by the total number of bigrams in the earnings call while CSRT BT-IDF measured using CSR bigram frequency inverse document frequency. CSRT-PCA is the principal component analysis of the two measures (CSRT-BF talk and CSRT-DF-IDF). In Panel B reports the correlation matrix among our main variables. All continuous variables are winsorized at the 1% and 99% levels. Appendix A provides detailed definitions for all variables. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

Panel A: Descriptive Statistics

	CSRT BF	CSRT BF-IDF	CSRT PCA	Size	Leverage	CAPEX	BTM	Cash Holdings	Dividend	IOWN	Negative Earnings	Complexity
N	72,411	72,411	72,411	72,411	72,411	72,411	72,411	72,411	72,411	72,411	72,411	72,411
Mean	0.241	0.03	0.007	7.213	0.259	0.028	0.45	0.583	0.382	0.772	0.3	5.755
SD	0.149	0.019	1.391	1.742	0.224	0.034	0.428	1.581	0.486	0.229	0.458	4.825

Panel B: Correlation Coefficients of Our Key Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) CSRT BF	1.000											
(2) CSRT BF-IDF	0.949	1.000										
(3) CSRT PCA	0.987	0.987	1.000									
(4) Size	0.168	0.149	0.161	1.000								
(5) Leverage	0.056	0.011	0.034	0.296	1.000							
(6) CAPEX	0.044	0.064	0.055	0.051	0.046	1.000						
(7) BTM	0.002	0.009	0.005	0.003	-0.166	0.032	1.000					
(8) Cash Holdings	-0.152	-0.162	-0.159	-0.327	-0.186	-0.151	-0.143	1.000				
(9) Dividend	0.086	0.088	0.089	0.434	0.091	0.008	-0.044	-0.220	1.000			
(10) INSOWN	0.041	0.032	0.037	0.298	0.035	-0.027	-0.032	-0.099	0.054	1.000		
(11) Negative Earnings	-0.056	-0.091	-0.075	-0.321	0.027	-0.032	0.082	0.311	-0.305	-0.181	1.000	
(12) Complexity	0.069	0.100	0.085	0.256	0.015	-0.040	0.068	-0.177	0.219	0.073	-0.165	1.000

Table 2: Corporate Social Responsibility and COVID

Panel A reports the results of multiple regression analysis examining the impact of the COVID-19 pandemic (COVID) on firm CSR talk (CSR Talk) using a full sample. Firm CSR talk is measured using three proxies: CSRT BF (columns 1 and 4) measured by using bigram frequency scaled by the number of bigrams in the earnings call; CSRT BF-IDF (columns 2 and 5) measured using bigram frequency-inverse document frequency; and CSRT PCA (columns 3 and 6) is the first component of the principal component analysis of the CSRT BF and CSRT BF-IDF. COVID is an indicator variable that takes the value of 1 for a date equal to and after March 20, 2020, and 0 otherwise. In Panel B, we repeat the analysis of Panel A after restricting our sample period to a shorter window (2018–2020). We control for firm (Size), Leverage (leverage), capital expenditure (CAPEX), book-to-market ratio (BTM), ratio of cash holding to net assets, where net asset is total asset minus cash holding, Dividend, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, Institutional Ownership (INSOWN), the percentage of shares of the firm held by institutional investors, Negative Earnings, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, Complexity, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Full Sample

	BF	BF-IDF	PCA	BF	BF-IDF	PCA
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
COVID	0.067***	0.004***	0.447***	0.068***	0.004***	0.456***
	(13.555)	(4.547)	(8.935)	(13.642)	(4.551)	(8.891)
Size				0.017***	0.002***	0.158***
				(14.216)	(18.376)	(16.249)
Leverage				-0.004	-0.001	-0.037
				(-0.886)	(-0.959)	(-0.913)
CAPEX				-0.007	-0.001	-0.063
				(-0.440)	(-0.365)	(-0.414)
BTM				-0.004***	-0.001***	-0.040***
				(-2.994)	(-2.931)	(-2.946)
Cash Holdings				-0.001***	-0.000***	-0.012***
				(-3.164)	(-4.827)	(-4.042)
Dividend				0.001	-0.000	0.001
				(0.276)	(-0.205)	(0.045)
INSOWN				0.002	0.000	0.025
				(0.275)	(0.561)	(0.421)
Negative Earnings				0.002**	0.000	0.012*
				(2.267)	(1.670)	(1.931)
Complexity				-0.000	-0.000	-0.004
				(-1.352)	(-1.361)	(-1.384)
Firm FE	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES
Observations	70,562	70,562	70,562	70,562	70,562	70,562
R-squared	0.402	0.399	0.388	0.403	0.400	0.389

Table 2 (continued):

Panel B: Reduced Sample						
VARIABLES	**BF**	**BF-IDF**	**PCA**	**BF**	**BF-IDF**	**PCA**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
COVID	0.069***	0.004***	0.474***	0.071***	0.004***	0.487***
	(10.628)	(5.570)	(8.535)	(11.061)	(5.779)	(8.868)
Size				0.009***	0.001***	0.078***
				(4.607)	(3.504)	(4.081)
Leverage				0.025***	0.004***	0.248***
				(3.427)	(3.979)	(3.729)
CAPEX				-0.032	-0.007	-0.393
				(-0.707)	(-1.394)	(-1.035)
BTM				-0.002	-0.000	-0.022
				(-0.630)	(-1.516)	(-1.054)
Cash Holdings				-0.002***	-0.000***	-0.020***
				(-3.576)	(-2.788)	(-3.123)
Dividend				-0.000	-0.000	-0.014
				(-0.121)	(-0.682)	(-0.392)
INSOWN				0.002	0.001	0.053
				(0.370)	(1.531)	(0.952)
Negative Earnings				0.003	0.000	0.017
				(1.599)	(0.853)	(1.276)
Complexity				0.000	0.000**	0.007
				(0.018)	(2.383)	(1.088)
Firm FE	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES
Observations	17,965	17,965	17,965	17,965	17,965	17,965
R-squared	0.505	0.507	0.479	0.505	0.507	0.480

Table 3: Corporate Social Responsibility and COVID (non-zero CSRT)

In this table we reproduce the analysis of Table 2 after restricting our sample to firms with non-zero CSR talk (CSR BF). Panel A reports the results of multiple regression analysis examining the impact of COVID on firm CSR talk (CSR Talk) using a full sample. In Panel B, we repeat the analysis of Panel A after restricting our sample period to a shorter window (2018–2020). We control for firm (Size), Leverage (leverage), capital expenditure (CAPEX), book-to-market ratio (BTM), ratio of cash holding to net assets, where net asset is total asset minus cash holding (Cash Holdings), Dividend, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, Institutional Ownership (INSOWN), the percentage of shares of the firm held by institutional investors, Negative Earnings, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, Complexity, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

Panel A: Full Sample

	BF	**BF-IDF**	**PCA**	**BF**	**BF-IDF**	**PCA**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
COVID	0.036***	0.002***	0.235***	0.036***	0.002***	0.240***
	(9.722)	(4.106)	(8.102)	(10.045)	(4.232)	(8.360)
Size				0.007***	0.001***	0.063***
				(12.520)	(12.997)	(14.032)
Leverage				-0.006***	-0.001**	-0.054***
				(-2.714)	(-2.699)	(-2.708)
CAPEX				-0.007	-0.001	-0.084
				(-0.705)	(-1.028)	(-0.909)
BTM				-0.002***	-0.000***	-0.018***
				(-3.061)	(-2.971)	(-3.007)
Cash Holdings				-0.001**	-0.000***	-0.006**
				(-2.180)	(-2.788)	(-2.515)
Dividend				0.000	0.000	0.003
				(0.319)	(0.182)	(0.281)
INSOWN				-0.000	0.000	-0.001
				(-0.188)	(0.053)	(-0.072)
Negative Earnings				0.003***	0.000***	0.022***
				(3.386)	(2.799)	(3.026)
Complexity				-0.000	-0.000	-0.002
				(-1.213)	(-0.934)	(-1.124)
Firm FE	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES
Observations	53,741	53,741	53,741	53,741	53,741	53,741
R-squared	0.440	0.570	0.456	0.441	0.571	0.457

Table 3 (continued):

Panel B: Reduced Sample						
VARIABLES	**BF**	**BF-IDF**	**PCA**	**BF**	**BF-IDF**	**PCA**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
COVID	0.040***	0.002***	0.272***	0.040***	0.003***	0.275***
	(6.750)	(5.220)	(6.418)	(6.846)	(5.301)	(6.519)
Size				0.002*	0.000	0.019**
				(2.018)	(1.602)	(2.042)
Leverage				-0.005	-0.000	-0.026
				(-0.621)	(-0.002)	(-0.388)
CAPEX				0.024	0.001	0.129
				(1.580)	(0.293)	(0.875)
BTM				0.000	-0.000	0.001
				(0.128)	(-0.000)	(0.094)
Cash Holdings				-0.001	-0.000*	-0.008*
				(-1.414)	(-1.990)	(-1.785)
Dividend				-0.001	-0.000	-0.012
				(-0.792)	(-0.929)	(-0.850)
INSOWN				0.005	0.001*	0.050
				(1.421)	(1.901)	(1.625)
Negative Earnings				0.002**	0.000	0.015
				(2.196)	(1.069)	(1.643)
Complexity				-0.001	0.000	-0.003
				(-1.547)	(0.227)	(-0.867)
Firm FE	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES
Observations	14,278	14,278	14,278	14,278	14,278	14,278
R-squared	0.547	0.746	0.576	0.547	0.746	0.576

Table 4: Corporate Social Responsibility and COVID (Additional Robustness Checks)

In this table we examine the stability of our results to potentially omitted variables. In column 1 we use the entire sample period (2007–2020) and in column 2 we use the reduced sample period (2018–2020). We then use CSRT PCA Abnormal, measured by the residual from regressing CSRT PCA on our set of controls. Results using the full (reduced) sample are reported in column 3 (4). In addition to our main explanatory variables used in Tables 2 and 3, we control for the following variables: Roll's illiquidity (ILL1), average bid-ask spread (AQBAS), analyst coverage (ANAN), analyst dispersion (ADISP), Intangible (INTANG), and accruals (Accruals). COVID is an indicator variable that takes the value of 1 for a date equal to and after March 20, 2020, and 0 otherwise. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	**CSRT PCA**		**CSRT PCA Abnormal**	
	Full Sample	**Reduced Sample**	**Full Sample**	**Reduced Sample**
COVID	0.453***	0.484***	0.453***	0.484***
	(8.971)	(8.643)	(8.971)	(8.643)
ILL1	0.001	-0.018	0.001	-0.018
	(0.047)	(-0.879)	(0.047)	(-0.879)
AQBAS	-2.276	1.053	-2.276	1.053
	(-0.812)	(0.356)	(-0.812)	(0.356)
ANAN	0.005***	0.005*	0.005***	0.005*
	(3.824)	(1.742)	(3.824)	(1.742)
ADISP	0.060***	0.067***	0.060***	0.067***
	(6.048)	(4.716)	(6.048)	(4.716)
INTANG	-0.558***	-0.148	-0.558***	-0.148
	(-3.343)	(-0.924)	(-3.343)	(-0.924)
Accruals	0.000	0.000	0.000	0.000
	(0.375)	(0.476)	(0.375)	(0.476)
Size	0.143***	0.066***	0.047***	-0.031*
	(12.721)	(3.651)	(4.164)	(-1.714)
Leverage	-0.049	0.236***	0.143***	0.428***
	(-1.100)	(3.215)	(3.219)	(5.821)
CAPEX	-0.056	-0.289	-1.437***	-1.670***
	(-0.350)	(-0.696)	(-8.938)	(-4.023)
BTM	-0.038***	-0.023	0.030**	0.045**
	(-2.818)	(-1.170)	(2.245)	(2.262)
Cash Holdings	-0.013***	-0.020***	0.102***	0.095***
	(-4.298)	(-3.297)	(33.189)	(15.788)
Dividend	-0.002	-0.012	-0.020	-0.030
	(-0.113)	(-0.346)	(-0.983)	(-0.843)
INSOWN	0.016	0.055	0.081	0.120**
	(0.270)	(1.086)	(1.389)	(2.375)
Negative Earnings	-0.010	0.016	-0.045***	-0.019
	(-1.606)	(0.966)	(-7.531)	(-1.151)
Complexity	-0.003	0.008	-0.013***	-0.003
	(-1.161)	(1.180)	(-5.172)	(-0.430)
Firm FE	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES

Observations	69,995	17,882	69,995	17,882
R-squared	0.390	0.481	0.364	0.449

Table 5: The Effects of Firm Characteristics

In this table, we examine the role of firm characteristics in altering the impact of COVID on CSR Talk (*CSRT PCA*). We focus on the role of the number of analysts (*ANAN*, column 1), institutional ownership (*Institutional Ownership*, column 2), operating profitability (*Operating Profitability*, column 3), financial constraint (Kaplan–Zingales Index, in column 4), and firm size (Firm Size, column 5). *COVID* is an indicator variable that takes the value of 1 for a date equal to and after March 20, 2020, and 0 otherwise. We control for firm (Size), Leverage (leverage), capital expenditure (CAPEX), book-to-market ratio (BTM), ratio of cash holding to net assets, where net asset is total asset minus cash holding (Cash Holdings), Dividend, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, Institutional Ownership (INSOWN), the percentage of shares of the firm held by institutional investors, Negative Earnings, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, Complexity, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	**ANAN**	**Institutional Ownership**	**Operating Profitability**	**Kaplan–Zingales Index**	**Firm Size**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
COVID	0.514***	0.494***	0.497***	0.545***	0.523***
	(12.235)	(11.447)	(10.810)	(12.111)	(12.377)
Indicator	0.021**	0.032*	-0.006	-0.007	0.020
	(2.649)	(1.816)	(-0.675)	(-0.614)	(1.298)
IndicatorxCOVID	-0.039**	0.014	0.003	-0.048**	-0.040**
	(-2.028)	(0.616)	(0.070)	(-2.040)	(-2.050)
Size	0.157***	0.158***	0.158***	0.158***	0.154***
	(15.757)	(16.123)	(16.422)	(16.047)	(15.600)
Leverage	-0.035	-0.035	-0.038	-0.031	-0.039
	(-0.877)	(-0.892)	(-0.894)	(-0.825)	(-0.974)
CAPEX	-0.072	-0.059	-0.063	-0.062	-0.061
	(-0.475)	(-0.386)	(-0.411)	(-0.407)	(-0.400)
BTM	-0.040***	-0.039***	-0.041***	-0.040***	-0.041***
	(-2.916)	(-2.896)	(-2.976)	(-2.928)	(-2.971)
Cash Holdings	-0.012***	-0.012***	-0.013***	-0.012***	-0.012***
	(-3.957)	(-4.060)	(-3.974)	(-3.960)	(-3.993)
Dividend	0.000	0.000	0.001	0.000	0.001
	(0.021)	(0.021)	(0.049)	(0.022)	(0.038)
INSOWN	0.018	-0.025	0.025	0.023	0.024

	(0.301)	(-0.462)	(0.437)	(0.389)	(0.401)
Negative Earnings	0.013*	0.012*	0.009	0.013*	0.012*
	(1.985)	(1.929)	(1.589)	(1.956)	(1.906)
Complexity	-0.004	-0.004	-0.004	-0.004	-0.004
	(-1.364)	(-1.390)	(-1.380)	(-1.396)	(-1.386)
Firm FE	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES
Observations	70,562	70,562	70,562	70,562	70,562
R-squared	0.389	0.389	0.389	0.389	0.389

Table 6: Corporate Social Responsibility and Market reactions

This table presents the regression results of the effects of firm CSR Talk on the cumulative abnormal return (CAR) during the [0, 1] trading window surrounding the earnings conference call filing date using risk-adjusted return model (RAR). We set our estimation window to be [-252, -6] before March 20, 2020, when the World Health Organization declared COVID-19 a pandemic. We constrained our sample to the period March 20, 2020–September 30, 2020, which is the two quarters after COVID hits. In columns 1, 3, and 5, we examine the effects of CSRT PCA, CSRT BF, CSR BFT-IDF, and on CAR respectively. In columns 2, 4, and 6, we augment the regression model with the firm-specific controls. We control for the following variables: earnings surprise (Earnings Surprise), the difference between actual earnings and consensus analysts' forecast divided by the actual earnings, Log (MVE), the firm in the current quarter calculated as the firm's stock price multiplied by the number of shares outstanding at the end of the quarter, BTM, the firm's book value of common equity at the end of the quarter divided by MVE, Turnover, the number of shares traded for the firm in the trading days [−252, −6] relative to the conference call date divided by the firm's shares outstanding at the conference call date, Pre_FFAlpha, It is the Fama–French alpha based on a regression of their three-factor model using trading days [−252, −6] relative to the conference call date (at least 60 observations of daily returns must be available to be included in the sample), Institutional Ownership (INSOWN), the percentage of shares of the firm held by institutional investors. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES	**CAR [0,1]**	**CAR [0,1]**	**CAR [0,1]**	**CAR [0,1]**	**CAR [0,1]**	**CAR [0,1]**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CSRT_PCA	-0.053***	-0.043***				
	(-3.996)	(-3.169)				
CSRT BF			-0.783***	-0.628***		
			(-4.035)	(-3.205)		
CSRT BF-IDF					-0.008***	-0.006***
					(-4.010)	(-3.181)
Earnings Surprise		0.133***		0.133***		0.133***
		(6.601)		(6.601)		(6.601)
Log (MVE)		0.180***		0.180***		0.180***
		(9.812)		(9.810)		(9.811)
BTM		-0.001		-0.001		-0.001
		(-0.026)		(-0.024)		(-0.025)
Turnover		-0.005**		-0.005**		-0.005**
		(-2.666)		(-2.664)		(-2.665)
Pre_FFAlpha		-13.142***		-13.144***		-13.142***
		(-10.882)		(-10.880)		(-10.881)
INSOWN		-0.243***		-0.243***		-0.243***
		(-3.991)		(-3.991)		(-3.991)
Firm FE	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES
Observations	2,624	2,624	2,624	2,624	2,624	2,624
R-squared	0.508	0.562	0.508	0.562	0.508	0.562

Table 7: Corporate Social Responsibility and Firm Performance (Tobin's Q)

In this table, we report the results of the effects of CSR talk on firm performance, measured by Tobin's Q (TOBINSQ), estimated as the sum market value of equity, preferred stock, total debt, all scaled by the book value of assets, and industry-adjusted Tobin's Q (TOBINSQ adjusted) calculated by subtracting the industry median from the sample firm value for each year and firm. In columns 1 and 3, we use CSRT PCA to measure CSR Talk. In columns 2 and 4, we use CSR PCA Residual to measure CSR Talk. We control for firm (Size), Leverage (leverage), capital expenditure (CAPEX), book-to-market ratio (BTM), ratio of cash holding to net assets, where net asset is total asset minus cash holding (Cash Holdings), Dividend, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, Institutional Ownership (INSOWN), the percentage of shares of the firm held by institutional investors, Negative Earnings, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, Complexity, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES	**Lead-TOBINSQ**		**Lead-TOBINSQ-Adjusted**	
	(1)	**(2)**	**(3)**	**(4)**
CSRT PCA	-0.008**		-0.010**	
	(-2.550)		(-2.668)	
CSRT PCA Residual		-0.003		-0.003
		(-1.282)		(-1.306)
COVID		0.129*		0.129*
		(1.797)		(1.803)
CSRT PCA ResidualxCOVID		-0.040***		-0.039***
		(-2.893)		(-2.814)
Size		-0.383***		-0.383***
		(-23.466)		(-23.526)
Leverage		-0.472***		-0.466***
		(-8.508)		(-8.742)
CAPEX		0.731***		0.725***
		(4.835)		(4.847)
BTM		-0.760***		-0.757***
		(-22.497)		(-22.363)
Cash Holdings		0.091***		0.091***
		(10.370)		(10.383)
Dividend		0.058**		0.056**
		(2.434)		(2.352)
INSOWN		0.289***		0.287***
		(3.514)		(3.527)
Negative Earnings		-0.167***		-0.165***
		(-14.038)		(-13.996)
Complexity		0.001		0.001
		(0.281)		(0.278)
Firm FE	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES
Observations	67,316	67,316	63,758	67,316
R-squared	0.775	0.797	0.789	0.786

Table 8: Do Managers Walk the CSR talk?

In this table, we examine whether managers walk the talk of CSR. In column 1, we report the effect of COVID on CST talk (CSRT PCA), while in column 2, we report the effect of COVID on CSR walk (CSRW). In column 3, we examine the effects of COVID on greenwashing (GW). We measure CSRW using Refinitiv's (Thomson Reuters Asset4) ESG rating. GW is the difference between the decile rank transformed CSRT and CSRW (GW=Rank CSRT – Rank CSRW), which indicates the extent to which firms attempt to greenwash their CSR performance to appear socially responsible. We control for firm (Size), Leverage (leverage), capital expenditure (CAPEX), book-to-market ratio (BTM), ratio of cash holding to net assets, where net asset is total asset minus cash holding (Cash Holdings), Dividend, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, Institutional Ownership (INSOWN), the percentage of shares of the firm held by institutional investors, Negative Earnings, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, Complexity, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	**CSRT PCA**	**CSRW**	**GW**
	(1)	**(2)**	**(3)**
COVID	0.456***	1.980	1.784*
	(8.891)	(0.884)	(1.809)
Size	0.158***	2.162***	-0.166
	(16.249)	(6.146)	(-0.723)
Leverage	-0.037	-0.512	0.398
	(-0.913)	(-0.950)	(1.373)
CAPEX	-0.063	-11.391***	3.595***
	(-0.414)	(-7.698)	(2.819)
BTM	-0.040***	-0.643**	0.063
	(-2.946)	(-2.426)	(0.416)
Cash Holdings	-0.012***	0.073	-0.160**
	(-4.042)	(1.079)	(-2.678)
Dividend	0.001	1.478***	0.055
	(0.045)	(4.725)	(0.192)
INSOWN	0.025	-1.100**	-0.990***
	(0.421)	(-2.155)	(-2.882)
Negative Earnings	0.012*	-0.402***	0.144**
	(1.931)	(-4.859)	(2.134)
Complexity	-0.004	-0.086**	-0.069**
	(-1.384)	(-2.488)	(-2.595)
Firm FE	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES
Days of the Week FE	YES	YES	YES
Errors Clustered by State	YES	YES	YES
Observations	70,562	31,857	25,233
R-squared	0.389	0.903	0.547

Table 9: CSR talk and other textual features

In this table, we examine the effects of the interaction between CSRT PCA Residual and COVID (*CSRT PCA ResidualxCOVID)* on several textual features. We report the impact of the interaction variable *CSRT PCA ResidualxCOVID* on positive tone (% Positive), measured as the total number of positive words in an earnings call divided by the total number of words in the call (column 1); negative tone (% Negative), measured as the total number of negative words in an earnings call divided by the total number of words in the call (column 2); and net tone (Net Tone), measured by the ratio of the difference between positive words and negative words to the total number of words in the EC (column 3). Positive and negative are from Loughran and McDonald's (2011) dictionary.

VARIABLES	**% Positive**	**% Negative**	**Net Tone**
	(1)	**(2)**	**(3)**
CSRT PCA Residual	0.020***	-0.008***	0.000***
	(12.317)	(-6.038)	(15.211)
COVID	0.231***	0.299***	-0.001
	(3.659)	(10.166)	(-0.740)
CSRT PCA ResidualxCOVID	0.021**	0.001	0.000*
	(2.218)	(0.076)	(1.827)
Size	-0.056*	-0.020***	-0.000
	(-1.792)	(-2.970)	(-1.058)
Leverage	0.037	0.195***	-0.002***
	(1.242)	(10.091)	(-4.721)
CAPEX	-1.520***	-0.029	-0.015***
	(-11.769)	(-0.271)	(-6.956)
BTM	-0.121***	0.192***	-0.003***
	(-9.858)	(32.035)	(-21.462)
Cash Holdings	-0.009***	0.006***	-0.000***
	(-6.418)	(2.786)	(-6.465)
Dividend	-0.040***	-0.024**	-0.000
	(-2.992)	(-2.606)	(-1.156)
INSOWN	-0.002	0.045	-0.000
	(-0.090)	(1.651)	(-0.920)
Negative Earnings	-0.085***	0.094***	-0.002***
	(-13.230)	(16.080)	(-21.680)
Complexity	0.001	-0.006***	0.000***
	(0.741)	(-3.730)	(3.065)
Firm FE	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES
Days of the Week FE	YES	YES	YES
Errors Clustered by State	YES	YES	YES
Observations	70,583	70,583	70,583
R-squared	0.554	0.532	0.557

Appendix A: Variable definitions

Variable definitions

Variables	Definition	Source
Dependent Variables		
CAR [0, 1]	The cumulative market-adjusted return for the firm in the [0,1] trading window surrounding the current-quarter conference call date.	CRSP
CSRT-BF	Counting the number of CSR bigrams and scaling by the total number of bigrams in the earnings call.	Corporate earnings conference calls from Capital IQ
CSRT-BF-IDF	CSR bigram frequency inverse document frequency.	Corporate earnings conference calls from Capital IQ
CSRT-PCA	The principal component analysis of the two measures (CSR-BF and CSR-DF-IDF).	Corporate earnings conference calls from Capital IQ
CSRT PCA Residual (Abnormal)	The residual of the fitted value after regress CSRT PCA on Size, Leverage, CAPEX, BTM, Cash Holding, Dividend, Institutional Ownership, Negative Earnings, and Complexity.	Corporate earnings conference calls from Capital IQ
CSRW	Average of the environment and social scores at the end of 2019 from the Refinitiv ESG database.	Thomson Reuters Asset4
GW	The proxy for greenwashing, measured as the difference between CSRT and CSRW.	Authors' calculation
ROA	A firm's total net income scaled by total assets.	CRSP
Lead-TOBINSQ	One year-quarter ahead firm Tobin's Q calculated over the period following the release of the earnings call. Tobin's Q, estimated as the sum market value of equity, preferred stock, total debt, all scaled by the book value of assets.	CRSP
Lead-TOBINSQ-adjusted	One year-quarter ahead firm Tobin's Q Adjusted calculated over the period following the release of the earnings call. It is calculated by subtracting the industry median from the sample firm value for each year and firm.	CRSP
Main Independent Variables		
Covid	An indicator variable that takes the value of 1 for date equal and after March 20, 2020, and 0 otherwise.	Authors' calculation
Control Variables		
Accruals	Defined as earnings before extraordinary items less cash flow from operations.	Compustat
ADISP	Dispersion of analyst forecasts defined as the coefficient of variation of one-year-ahead analyst forecasts of earnings per share.	IBES
ANAN	Analyst coverage, measured by number of equity analysts following a firm; equals the logarithm of 1 plus the number of one-year-ahead earnings forecasts.	As above
AQBAS	Average effective bid-ask spread over the fiscal year	Compustat
BTM	The firm's book value of common equity at the end of quarter divided by MVE.	CRSP
CAPEX	Capital expenditures scaled by total assets.	CRSP
Cash flow	The sum of income before extraordinary items, R&D, and depreciation and amortization, and divided by total assets.	CRSP
Cash holdings	Ratio of cash holding to net assets	CRSP
Complexity	The number of business segments.	Compustat

Dividend	An indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise.	As above
Earnings Surprise	The difference between actual earnings and consensus analysts' forecast divided by the actual earnings.	CRSP
INSOWN	The percentage of shares of the firm held by institutional investors.	Thomson 13-F data
Kaplan–Zingales Index	Kaplan and Zingales' (1997) index (as implemented by Lamont, Polk, and Saá-Requejo (2001)).	
Leverage	Measured by the ratio of total debt to total assets.	CRSP
Log (MVE)	Market value of equity for the firm in the current quarter calculated as the firm's stock price multiplied by the number of shares outstanding at the end of the quarter.	As above
Negative Earnings	An indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise.	As above
Pre-FFAlpha	It is the Fama–French alpha based on a regression of their three-factor model using trading days [−252, −6] relative to the conference call date. At least 60 observations of daily returns must be available to be included in the sample.	CRSP + Corporate earnings conference calls from Capital IQ + Fama and French Three-Factor Model.
ROA	A firm's total net income scaled by total assets.	CRSP
Size	Natural logarithm of total assets in year-quarter t.	As above
Turnover	The number of shares traded for the firm in the trading days [−252, −6] relative to the conference call date divided by the firm's shares outstanding at the conference call date.	CRSP + Corporate earnings conference calls from Capital IQ.
% Positive	Total number of positive words scaled by the total number of words in an earnings call.	Corporate earnings conference calls from Capital IQ
% Negative	Total number of negative words scaled by the total number of words in an earnings call.	Corporate earnings conference calls from Capital IQ
Tone	The difference between positive and negative scores (Positive – Negative), divided by the total number of words in an earnings call.	Corporate earnings conference calls from Capital IQ
CSRSentiment	Firm-level CSR sentiment measure constructed from earnings calls	Corporate earnings conference calls from Capital IQ

Appendix B: A sample of (98) CSR keywords

health care	climate change	environmentally friendly	energy policy	energy source	customers receiving	environmental concerns
customer satisfaction	storage capacity	fuel cells	storage facilities	environmental stewardship	wood fiber	infrastructure energy
energy efficiency	energy management	human resource	wind power	hazardous waste	air filtration	number cycles
renewable energy	time employees	water supply	social governance	assume responsibility	global warming	product lifecycle
workers compensation	air quality	water management	quality safety	corporate social	health risk	social issues
health safety	local communities	environmental social	efficiency efforts	diesel engines	greenhouse gases	socially responsible
clean energy	team work	diversity inclusion	management employees	surface water	product safety	environmental safety
food safety	environmental impact	local community	carbon dioxide	collective bargaining	full coverage	affected customers
minimum wage	human health	turnover rate	corporate responsibility	environmental performance	flexible work	environmental management
product quality	waste management	environmental regulations	natural resource	efficiency initiative	emissions reduction	career development
wind energy	produced water	management processes	employee turnover	efficiency measures	efficiency product	skilled workforce
greenhouse gas	natural disasters	fuel consumption	african american	water purification	hybrid vehicles	water consumption
energy efficient	mental health	business community	safe environment	total energy	cubic meters	economic social
alternative energy	gas emissions	social responsibility	protection agency	environmental footprint	safety risk	human rights

Appendix C: Examples to illustrate the construct.

In Panel A of this Appendix, we use two examples to illustrate how we construct CSR-BF and CSRT BF-IDF using the equation below:

$$\omega_{ij} = \begin{cases} \dfrac{\left(1+\log\left(tf_{i,j}\right)\right)}{\left(1+\log(\alpha_i)\right)} \log\left(\dfrac{N}{df_i}\right) & if\ tf_{i,j} \geq 1 \\ 0 & otherwsie \end{cases}$$

where N represents the total number of documents in the corpus, df_i is the number of documents containing at least one occurrence of the i^{th} bigram, $tf_{i,j}$ the raw count of the i^{th} bigram in the j^{th} document, and α_i the total bigram count in the document. The log transformation attenuates the impact of high-frequency words/bigrams and the term $\log\left(\frac{N}{df_i}\right)$ adjusts the impact of a bigram based on its commonality (Loughran & McDonald, 2011).

For the purpose of understanding the examples, in the first example, we assume that our CSR library contains only one unigram, which is "**environment**", and we use unigrams to extract CSR term-frequency (CSRT TF) and CSR term-frequency inverse document frequency (CSRT TF-IDF).

In the second example, we assume that our CSR library contains only one bigram, which is "**environment responsibility**", and we use bigrams to extract CSR bigram-frequency (CSRT BF) and CSR bigram frequency-inverse document frequency (CSRT BF-IDF). Let's also assume that we have two texts (Text 1 and Text 2).

Text 1: "Until we see confidence return in the economy, the business environment will remain very dangerous for many firms."

Text 2: "Corporate environment responsibility creates value."

The table below shows how bigrams, such as "environment responsibility", have distinctive properties and can be used to identify that Text2—in contrast to text 1—talks about CSR.

Text 1							
Term	**Count**	**If $tf_{i,j} \geq 1$**	**TF**			**IDF**	**TF-IDF= TF * IDF**
			$(\mathbf{1 + log(tf_{i,j})})$	$(\mathbf{1 + log(\alpha_i)})$	$(\mathbf{1 + log(tf_{i,j})) / (1 + log(\alpha_i)})$	$\log\left(\frac{N}{df_i}\right)$	
Until see	1	NO					0
See confidence	1	NO					0
Confidence return	1	NO					0
Return economy	1	NO					0
Economy business	1	NO					0
Business environment	1	NO					0
Environment remain	1	NO					0
Remain very	1	NO					0
Very dangerous	1	NO					0
Dangerous many	1	NO					0
Many firms	1	NO					0
Total	11	NO					0
Text 2							
Term	**Count**	**If $tf_{i,j} \geq 1$**	**TF**			**IDF**	**TF-IDF= TF * IDF**
			$(\mathbf{1 + log(tf_{i,j})})$	$(\mathbf{1 + log(\alpha_i)})$	$(\mathbf{1 + log(tf_{i,j})) / (1 + log(\alpha_i)})$	$\log\left(\frac{N}{df_i}\right)$	
Corporate environment	1	NO					0
Environment responsibility	**1**	**YES**	**(1 + log (1)) = 1**	**(1 + log (4)) = 1.602**	**= (1 / 1.602) = 0.624**	**= log (2/1) = 0.301**	**0.301**
Responsibility creates	1	NO					0
Creates value	1	NO					0
Total	4	NO					0

Chapter 4: Supply Chain Risk: Measurement and Real Effects

Abstract

We use Natural Language Processing to measure supply chain risk (SCR) faced by US firms, as expressed in narratives of quarterly earnings conference calls. We show that exposure to SCR reached unprecedented levels during COVID-19. The effect of COVID-19 on SCR is more pronounced in firms with a greater dispersion of analyst forecasts, increased complexity, more financial constraints and those in industries more vulnerable to supply chain disruptions. We document a negative effect of SCR on conference call short-term returns and future profitability. High-SCR firms are also associated with longer cash conversion cycles and more ESG overselling.

Keywords: Supply chain, supply chain risk, textual analysis, earnings calls, corporate social responsibility, disclosure.

1. Introduction

Since the dawn of time, the world has experienced major natural and man-made events, such as earthquakes, floods, tsunami, global economic and financial crises, SARS, strikes, armed conflicts, and terrorist attacks that increased the vulnerability of supply chains. The coronavirus pandemic (COVID-19) is perhaps the latest example of the risks arising from supply chain disruptions. Against this backdrop, the increasingly globalized operating models (World Economic Forum, 2012) and the complex interconnectedness of flows of materials, funds, and information (Bode & Wagner, 2015 and references therein) have made resilience and risk management of supply chains top priorities on managers' agendas. For instance, over 90% of supply chain and transport experts[93] surveyed by the World Economic Forum (2012) reported that supply chain and transport risk management have become greater priorities in their organizations. Further, top executives of the surveyed Global 1,000 companies in North America and Europe view supply chain disruptions as the leading threat to top revenue sources (Elkins et al., 2007).

In academia, while a sizable literature has examined managing supply chain risks,[94] extant literature has not given much consideration to an aggregate measure of the supply chain risk that reflects the extent of a firm's vulnerability to supply chain shocks This study attempts to address this important gap in the literature by operationalizing a supply chain risk (SCR) measure. SCR can help identify firms that are prone to supply chain disruptions and, thus, inform investment decisions.[95] An SCR proxy can also be useful to managers in addressing appropriate strategic responses to supply chain

[93] From business, government, and academia across various regions and sectors.
[94] See Ho et al. (2015) and Fahimnia et al. (2018) for a review.
[95] This is important since supply chain disruptions can bear negatively and heavily on returns to shareholders (Hendricks & Singhal, 2005).

vulnerability and to researchers who are interested in examining the linkage between SCR and corporate and economic outcomes.

The paucity of research is unsurprising because measuring supply chain risk is not straightforward and academic research faces the daunting challenge of bringing an empirical proxy to bear on the extent to which firms are exposed to supply chain disruptions. The fact that supply chain risk is a multifaceted and complex concept[96] is not observable, and there are no reporting standards in this regard, further compounds the challenge of measuring supply chain risk. We address this challenge by performing a textual analysis of the transcripts of earnings conference calls to measure the extent of supply chain risk faced by individual US firms. We rely on the methodology introduced by Hassan et al. (2019), used to quantify firm-level political risk, to measure the share of supply chain risk in the quarterly earnings conference calls (ECs) narrative(Hassan et al., 2019). Borrowing Loughran and McDonald’s (2022) argument, we posit that using textual analysis presents a unique opportunity to add value in capturing the nuances of measuring SCR.

Our work is one of the first studies using textual analysis to measure SCR and investigate its economic implications. To be sure, and to the best of our knowledge, the concurrent study of Ersahin et al. (2022) is the only work that uses textual analysis of ECs to quantify firms' SCR. We, however, depart from their work in many important aspects. Perhaps most importantly, in developing our dictionary, we find it useful to rely on industry experts' insights, as Loughran and McDonald (2016) recommended, to identify n-grams that capture supply chain discussions more

[96] Supply chain risk can be defined as “the likelihood and impact of unexpected macro and/or micro level events or conditions that adversely influence any part of supply chain leading to operational, tactical, or strategic level failures or irregularities” (Ho et al., 2015, p. 5035).

effectively. We use the list of supply chain keywords developed by Rob O'Byrne, a renowned supply chain expert with over 42 years of experience in managing, advising, and teaching on the supply chain.[97] O'Byrne's list of supply chain keywords is relevant because of his extensive expertise in the field. While O'Byrne's list contains unigrams, bigrams, and trigrams, we transform the trigrams into bigrams and focus on bigrams because they are less ambiguous (Bloom et al., 2020) and tend to convey more information than unigrams.

We then supplement O'Byrne's list of bigrams with bigrams extracted from the most-cited published studies on supply chain. We use "Web of Science" to identify the most-cited supply chain–related papers and consider the following eight studies: "Information distortion in a supply chain: The bullwhip effect" (2004, *Management Science*); "Supply chain management with guaranteed delivery" (2003, *Management Science*); "A comparative literature analysis of definitions for green and sustainable supply chain management" (2013, *Journal of Cleaner Production*); "Quantitative models for sustainable supply chain management: Developments and directions" (2014, *European Journal of Operational Research*); "Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future" (2015, *European Journal of Operational Research*); "Green supply chain management: A review and bibliometric analysis" (2015, *International Journal of Production Economics*); "Corporate innovation along the supply Chain" (2018, *Management Science*) and "Blockchain technology and its relationships to sustainable supply chain management" (2018, *International Journal of Production Research*).[98]

[97] Rob O'Byrne is the founder and CEO of Logistics Bureau (https://www.logisticsbureau.com/rob-obyrne). This consulting firm provides advice on supply chain/logistics at strategic and operational levels to more than 500 companies across 25 countries. https://www.logisticsbureau.com/supply-chain-glossary/

[98] While we used the "Web of Science" to select the most-cited studies with "supply chain" as key words, we exercise some judgment in selecting studies so that our supply chain dictionary covers different periods.

We then manually inspect our wordlist of bigrams to mitigate false positive cases. Manually inspecting the wordlist is an important disambiguation step since "no algorithm understands the context of human conversations better than human beings" (Li et al., 2022, p. 11). Our disambiguation approach resulted in a dictionary of 474 bigrams. We also manually inspected O'Byrne's list of unigrams and retained 22 unigrams.

Our approach is distinct from Ersahin et al. (2022) who relied on the textbook *Supply Chain Management: Strategy, Planning, and Operation* (6th edition; Chopra & Meindl, 2016) to extract 70,820 bigrams associated with supply chain discussion. This large number of bigrams increases the risk of false positive cases and is much more prone to error when compared to fewer unambiguous targeted words or phrases (Loughran & McDonald, 2016).[99] From the discussion of their methodology, it is unclear whether Ersahin et al. (2022) have manually inspected their wordlist and the extent to which their wordlist reflects insights from supply chain experts (as recommended by Loughran and McDonald, 2016). Equally important, the discussion of their methodology does not indicate whether pre-processing techniques were used. Yet, a full text pre-processing is a necessary step to improve the accuracy of textual analysis and reduce “unnecessary noise in the text” (Buehlmaier & Whited, 2018, p. 2697).[100] For instance, inspecting Ersahin et al.’s (2022) top 100 bigrams, reported in Table 2 of their manuscript (p. 44), one could notice that

[99] Manually inspecting the list is an essential step of the disambiguation process because using unrelated bigrams can mislead the results across firms and industries and are likely to proxy for a specific industry. For example, arguably, the bigram "milk runs", included in Ersahin’s e al (2022) top 100 bigrams of the supply chain dictionary, may suggest an increased exposure of supply chain risk of the dairy product industry if "milk runs" is found associated with risk synonyms.

[100] Pre-processing is the process of cleaning and preparing the text for textual analysis. Skipping the text preprocessing stage increases the dimensionality problem, which makes the classification more difficult because every single n-gram is treated as one dimension (Haddi et al., 2013), as well as introduces unnecessary noise in the documents, which makes the textual analysis less precise (Buehlmaier & Whited, 2018). Jianqiang and Xiaolin (2017) study the impact of text pre-processing methods on performing sentiment analysis and show that applying pre-processing improves the accuracy of the machine learning algorithms. See also (Babanejad et al., 2020).

stop words were not removed.[101] If stop words were removed, about 33% of their top 100 bigrams become unigrams, which may decrease the accuracy of their algorithm (Jianqiang & Xiaolin, 2017). Our study also departs from Ersahin et al. (2022) by providing the first evidence on (i) the short-term stock market reaction to SCR during COVID-19 and (ii) the association between SCR and ESG talk during COVID-19.[102]

We start our analysis by constructing SCR using ECs of US firms from 2007 to 2020 for a total of 65,577 firm-quarter observations. We use ECs to extract the textual SCR because ECs are an unaudited medium for voluntary disclosure and interactive verbal communications (e.g., Bushee et al., 2003; Bowen et al., 2003; Frankel et al.,1999), providing managers with more discretion in the narrative of their communications. Matsumoto et al. (2011) suggest that, during conference calls, managers are less constrained in providing information and analysts play an important role in uncovering information during the question-and-answer (Q&A) session, making ECs incrementally informative (Matsumoto et al., 2011). Further, the disclosures made during conference calls are particularly useful because they are held quarterly and contain senior management's direct responses to questions from analysts and market participants (Hassan et al., 2019, 2022), and thus may represent a timely source of information (Donovan et al., 2021; Frankel et al., 2022). Campbell et al. (2021) argue that ECs draw significant investor attention because they are one of the first disclosures released by firms.

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[101] For example, the following are among Ersahin et al.'s (2022) top 100: "*the supply", " a supply", "the retailer", "the manufacturer", "the optimal", the demand", "the supplier", "of supply", "an order", "a mean", " a standard", "the season", "and demand", "the forecast", "of safety", "the goal", "to order", "of scale", " if demand", "the aggregate", "to improve", "the lot", "time is", "is obtained"* and *"the lead"*.

[102] ESG stands for Environmental, Social, and Governance and refers to integrating sustainability and other non-financial goals in a firm's (and investor's) decisions. Corporate social responsibility (CSR) refers to a firm's "actions that appear to further some social good beyond the interests of the firm and that which is required by law" (McWilliams and Siegel 2006, p. 117). Given the overlap in the definitions of CSR and ESG, we use them interchangeably. We, however, opted for the acronym ESG to minimize the confusion between the acronyms CSR and SCR.

As the first step in our empirical analysis, we carry out a series of validation tests to examine whether our SCR proxy is relevant and captures independent sources of risk. Specifically, we show that SCR is more pronounced in firms operating in industries that are more vulnerable to supply chain disruptions and has a positive and significant effect on future volatility of stock returns. This result remains valid even after controlling for other textual risk measures, such as Hassan et al.'s (2019) measures of political risk (*PRISK*) and non-political risk (*NPRISK*), Hassan et al.'s (2022) proxy of COVID risk (*COVIDRisk*) as well as a textual measure of risk (*TRisk*). The effect of SCR on future volatility remains positive and significant after replacing SCR with 'SCR Residuals', obtained by orthogonalizing SCR on *PRisk*, *NPRisk*, *COVIDRisk*, and *TRisk*. This result is important as it indicates that our proxy SCR is capturing a distinct source of risk.

We show that SCR varies intuitively over time, soaring to unprecedented high levels during COVID-19.[103] Further, the analysis of the unconditional time-series trends in SCR indicates that SCR has trended up over the 2007–2020 sample period. To ground these results with more formal statistical analysis, we conduct a multivariate analysis and control for many covariates, firm, year-quarter, days of the week fixed effects and clustered errors by state, and document a positive and significant effect of COVID on SCR. This result holds whether we measure SCR with bigrams (SCRB), unigrams (SCRU), or the principal component (SCR PCA) of SCRB and SCRU. We next investigate whether our new evidence of the positive effects of COVID on SCR varies across types of firms. We find that the effect on SCR of COVID is more pronounced in firms with higher

[103] The effect of the 2008–2009 global financial crisis on SCR appears less pronounced than that of COVID-19, plausibly because both shocks are of different nature: one is demand-driven (the financial crisis) and the other is supply driven (COVID-19).

analyst forecast dispersion, increased complexity, more financial constraints, and those operating in industries that are more vulnerable to supply chain disruptions.

We then explore the real effects of SCR. We start by studying the stock market reaction to SCR during COVID-19 and show that high-SCR firms experience a larger decrease in short-window stock returns around the earnings call. We also document a negative effect of SCR on future profitability. Relatedly, high-SCR firms appear to have larger inventories and longer cash conversion and operating cycles. Since these metrics are important to gauging “the effectiveness of a firm's management and intrinsic need for external financing” (Wang, 2019, p. 472), this new evidence suggests that SCR decreases the effectiveness of a firm's management operations, which may negatively impact shareholder value. We also find that high-SCR firms invest less in research and development (R&D).

In a final test, we investigate the impact of SCR on the extent of ESG talk in the narratives of ECs (ESG overselling). It is possible that high-SCR firms engage in ESG selective disclosure to promote the appearance of conformity with stakeholders' expectations of corporate social performance and alleviate the adverse impact of increased SCR. We expect this to happen during the COVID-19 pandemic because of increased pressure for more corporate ESG performance. As in Attig and Boshanna (2022), we develop an ESG dictionary by identifying key words in the Sustainability Accounting Standards Board (SASB) codified standards, the 2021 Global Reporting Initiative (GRI) standards, the 2022 International Financial Reporting Standards (IFRS)-climate-related disclosures, and Refinitiv MarketPsych ESG Analytics. We also use “Web of Science” to identify the most-cited CSR-related papers. We also consider the wordlist of four existing dictionaries developed by Loughran et al. (2009), Pencle and Mălăescu (2016), Moss et al. (2018), and Baier et al. (2020). After manual inspections of the keywords, our disambiguation process resulted in 728 bigrams. Interestingly, and in line with our expectation, our results indicate that firms experiencing a surge in SCR tend to engage in more 'ESG overselling', measured using ESG bigrams frequency (*ESG-BF*), bigrams frequency inverse document frequency (*ESG-BF-IDF*), or the principal components of these two measures (*ESG-PCA*).[104]

With this fresh evidence, our study connects to different strands of empirical work. The first examines the impact of COVID-19 on various corporate outcomes. Goldstein et al. (2021) conclude that the COVID-19 pandemic has opened new directions for future research, and many remain unexplored. Our study is a response to this call. It connects to a handful of studies that have made headway in using textual analysis to quantify political risk (Hassan et al., 2019), cyber risk (Florackis et al., 2023), climate risk (Sautner et al., 2022), ESG risk (Attig & Boshanna, 2022a), and geopolitical risk (Caldara & Iacoviello, 2022). More broadly, this study relates to the burgeoning strand of inquiry that applies text-based analysis to measure tone-related characteristics in corporate documents. For instance, a dictionary-based approach was used to measure disclosure sentiment (Loughran & McDonald, 2011), financial constraints (Bodnaruk et al., 2015), and CSR talk (Attig & Boshanna, 2022b).[105]

The remainder of the paper is structured as follows. Section 2 presents research design, Section 3 discusses the empirical results, and Section 4 concludes the paper.

2. Research Design

[104] We multiply these textual variables by 100.

[105] Supervised machine learning was recently used to measure credit risk (Donovan et al., 2021), the materiality of environmental and social disclosure (Chava et al., 2021), and financial constraints (Buehlmaier & Whited, 2018), among others.

2.1. Date and sample selection

We start by downloading from Capital IQ all ECs published as PDF files, from which we extract firm information, such as the name, ticker, date and time of the call, speaker's name and title, type of speaker, and whether the text is in the presentation or the Q&A section. We apply fuzzy name matching[106] to match firms' names to the Compustat database. We consider firms with available transcripts of ECs in Capital IQ and accounting data in Compustat (quarterly). We remove financials (SIC 6000−6999), utilities (SIC 4900−4999), and governmental and quasi-governmental entities (SIC 9000 and above). We restrict our sample to firms with enough data to run tests on conference call returns (CRSP data and other firm characteristics) and with institutional ownership data (13f). To ensure the results of our empirical analysis are not driven by fundamental differences among firms with different firm-level variables, we keep firms with non-missing values of our regression variables. These additional filters result in a final sample of 64,099 firm-quarter observations, representing 3,132 unique firms and covering the period January 2007 to December 2020. To minimize the influence of outliers, non-categorical control variables are winsorized at the 1% level at each tail of our sample. All variables and their sources are described in Appendix A.

2.2. Text extraction and pre-processing

Following Loughran and McDonald's (2016) critique that "most textual analysis papers in accounting and finance provide vague statements about how a document is parsed and then

[106] We use the R program to conduct fuzzy name matching (Hassan et al., 2019). The method looks for words/phrases with a percentage of common characters. The fuzzy-name-matching score ranges from 0 to 1, with a 0 score if there is no similarity between the two names by considering their common characters and 1 if the names are identical. We match by name, keeping matching scores of more than 0.95.

produce results from a software package where the driving forces behind the results are opaque" (p. 1192), we provide below relevant details of our text extraction and pre-processing techniques.

We perform structured text extraction using R programming and create an algorithm that reads .pdf reports (i.e., ECs), and splits them into paragraphs using the newline escape character (\n). When the algorithm sees a backslash and the letter [n], it breaks the text from that line and creates a new line.[107] Our algorithm extracts the company name, company ticker, event (in our case, ECs), day, call date, and time using the top of the first page of the ECs and then creates a new column for each item for the output.[108] Next, as part of the algorithm, .pdf files are crawled to locate a table of contents that contains two columns. The first column shows the sections of the document—call participants, presentation, and Q&A section—and the second shows the number of pages assigned to each section. (e.g., call participants 3, presentation 4, Q&A 10). Utilizing the title and page number of each section presented in the table of contents in the ECs, the algorithm detects and traces the pages. It identifies the text/narrative associated with the presentation and Q&A sections. This allows us to analyze the whole transcript of the earnings call, the presentation section, or the Q&A section. Relatedly, the algorithm crawls the call participants section, which contains the executives, analysts, and other participants (in this order), and identifies their names, titles, and roles (e.g., speaker name, speaker title, and speaker type) using the newline escape character (\n). The algorithm saves their names, titles, and roles. Our study excludes unknown names, such as unknown speakers, participants, callers, and firm analysts, as well as the operator, and focuses on the conversation between participants and firm management on the conference call.

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107 The letter [n] is an escape character if it has the backslash [\] in front of it (Thompson, 1984).

108 Example: *PayPal Holdings, Inc. NasdaqGS:PYPL FQ2 2021 Earnings Call Transcripts Wednesday, July 28, 2021, 9:00 PM GMT.*

We need to provide starting and ending marks to the algorithm to retrieve the text associated with each speaker. As a result of the manual reading of the presentation and Q&A sections of ECs from the Capital IQ database, our algorithm was developed based on its textual structures. Both sections start with the speaker's name and title (e.g., *Gabrielle Rabinovitch, Vice President of Corporate Finance & Investor Relations*),[109] with their narratives immediately below. As such, to identify the narrative of each speaker in either presentation or Q&A sections, we use the first speaker's name as the starting phrase mark and the second speaker's name as the ending phrase (e.g., *Daniel H. Schulman President, CEO & Director*). The text between these two names (*Gabrielle Rabinovitch* and *Daniel H. Schulman*) is devoted to the narrative of the first name (*Gabrielle Rabinovitch*), while the text between the second and third names is dedicated to the second name narrative, and so on. Since each name has been saved in an earlier stage in either the executives or analysts section, our algorithm provides us with four more columns: speaker name, title, speaker type, and which part of the narrative (presentation vs. Q&A).

After identifying each section, we create a corpus using all earnings calls over the period 2007–2020. We apply NGramTokenizer in the RWeka package to tokenize the corpus into bigrams (unigrams) to generate bigram-based (unigram-based) SCR, i.e., SCRB (SCRU). Then, we perform the common pre-processing techniques "to make the textual analysis more precise by reducing unnecessary noise in the text" (Buehlmaier & Whited, 2018, p. 2697). To this end, we remove punctuation, digits/numbers, and citations. Next, we convert all letters to lowercase and remove all stop words (stop words listed in the R program using R text mining package) and remove tokens with fewer than three letters as well as all whitespace left from the process above.

[109] PayPal Holdings, Inc's EC for 2021q3.

2.3. Creating the supply chain dictionary

In developing our dictionary, we began with a list of keywords developed by Rob O'Byrne, well-known industry expert in the field of supply chain and transportation. This is important since Loughran and McDonald (2016) stress the role of industry experts in identifying n-grams that capture the subject matter (i.e., supply chain in our case) discussions more effectively. O'Byrne's list contains unigrams, bigrams, and trigrams. We transform the trigrams into bigrams and focus on bigrams because they are less ambiguous. We supplement this list with bigrams extracted from the most-cited papers, as discussed at the outset. We then manually inspect our world-list of bigrams to minimize the likelihood of false positives. Our disambiguation approach resulted in a dictionary of 474 bigrams. We also inspect O'Byrne's list of unigrams and retain 22 of them. A sample of our supply chain bigrams and unigrams is presented in Appendix B.

2.4. Measuring firm-level SCR

Following Hassan et al. (2019), we start by decomposing each conference-call transcript of firm i in quarter t into n-grams (bigrams) contained in the transcript b = 1, …., β_{it}. Generating supply chain risk using bigrams, we collapse earnings calls into documents-bigrams-matrix, where each column represents a bigram, and each row represents an earnings call. We count the number of occurrences of bigrams, indicating discussion of the supply chain, using their locations (positioning) in the text, with the set of 10 words surrounding a synonym (unigram) for "risk" or "uncertainty" on either side and divided by the total number of bigrams in the transcript.[110] We namely use the following equation:

[110] The list of synonyms of risk is provided in Appendix 4. In Appendix 5, we use three hypothetical examples to illustrate how we construct SCR.

$$\text{SCRB}_{it} = \frac{\sum_{b}^{B_{it}}(1[b \in S\backslash N] \times 1[|b-r| < k] \times \frac{f_{b,S}}{B_S})}{B_{it}}$$

where $SCRB_{it}$ is our proxy of bigram-based SCR, *b* is the given bigram contained in the transcript, where we decompose each transcript of firm i in quarter t into a list of bigrams contained in the transcript b = 1,…. B_{it}. B_{it} is the total number of bigrams in an earnings call transcript. 1[•] is the indicator function, *S* is the supply chain dictionary, and *N* is the non-supply chain dictionary. *S/N* is the set of bigrams contained in *S* but not *N*. *r* is the positioning of the nearest synonym of risk or uncertainty. The distance between *S* or *N* n-grams (bigrams) and the synonym of risk or uncertainty is set to be 10 unigrams. $f_{b,S}$ is counting the number of frequencies of each S bigram in an earnings call transcript. B_S is the total number of supply chain n-grams (bigrams) found in a transcript. For the non-supply-chain dictionary, we use the financial accounting textbook *Financial Accounting* (10th edition; Libby et al., 2020).[111] In Appendix C, we report excerpts of transcripts with highest SCRB and the associated risk keywords.

It is important to note that we repeat the analysis above with our dictionary of supply chain unigrams to obtain our measure of unigram-based SCR (SCRU).[112] In our main analysis, however, we apply a principal component analysis (PCA) to offer a reliable measure SCR as a combination of SCRB and SCRU (SCR PCA).

3. Empirical Results

[111] Available at: https://www.firmlevelrisk.com/download
[112] To generate SCRU, we collapse earnings calls into a documents-term-matrix where each column represents a unigram, and each row represents an earnings call.

3.1. Descriptive statistics and validation tests

As a first step in our investigation, we plot -in Figure 1- the time trend of *SCR PCA* and notice an obvious change in *SCR PCA* during the pandemic. This is plausible because COVID-19 has massively disrupted supply chains. Figure 2 presents the 300 most frequently used words in the 10 words before or after the word "supply" in all 2020 earnings calls. Interestingly, Figure 2 indicates that the word COVID was frequently used in the context of supply chain.

Figure 3A depicts the relationship between all words used in earnings calls and the word "supply" in the year 2020. To better understand the context of the supply chain, we used a computational linguistic technique called word association, which is used in psycholinguistic literature. It is commonly used "in linguistics to classify words not only on the basis of their meanings but also on the basis of their co-occurrence with other words." (Church & Hanks, 2002, p. 22). For the purpose of our study, we rely on Word Association "findAssocs" R package, which uses the sequence of words, their frequency, and distribution to identify their association. Notably, the word "supply" is associated with words such as ensure, chain, global, demand, disruption, challenges, issues, constraints, shortages, and capacity.

Panel A in Table 1 provides descriptive statistics of the main variables used in our baseline regression. The average of *SCRB*, *SCRU,* and SCR PCA are, respectively, 0.913, 1.423, and 0.003. In Panel B, we run a univariate analysis to compare SCR PCA across industries with different vulnerability to supply chain disruptions. We distinguish between top and bottom 10 industries in terms of supply chain vulnerability (as in Ersahin et al., 2022). The most vulnerable industries are (sic 2: 14, Nonmetallic Minerals, Except Fuels; sic 2: 22, Textile Mill Products; sic 2: 25, Furniture & Fixtures; sic 2: 33, Primary Metal Industries; sic 2: 35, Industrial Machinery & Equipment; sic

2: 36, Electronic & Other Electric Equipment; sic 2: 37, Transportation Equipment; sic 2: 50, Wholesale Trade – Durable Goods; sic 2: 52, Building Materials & Gardening Supplies; and sic 2: 75, Auto Repair, Services, & Parking). The least vulnerable industries are (sic2: 21, Tobacco Products; sic2: 27 Printing & Publishing; sic2: 41 Local & Interurban Passenger Transit; sic2: 48 Communications; sic2: 53 General Merchandise Stores; sic2: 54 Food Stores; sic2: 58 Eating & Drinking Places; sic2: 72 Personal Services; sic2: 79 Amusement & Recreation Services; and sic2: 82 Educational Services). Our test for difference in means indicates that firms in industries that are most vulnerable to supply chain disruption display higher SCR than those in industries that are less vulnerable.

In Panel C, we examine the impact of COVID on SCR. The test for difference in means clearly suggests a significant increase in SCR during the COVID period (compared to pre-COVID). We then examine the time-series trends of our main variables by regressing SCR PCA on a linear trend variable, which takes the value of 0 in 2007Q1, 1 in 2007Q2, 3 in 2007Q3, etc. and report the results in Panel D. The coefficient estimate of the trend variable is positive and significant, indicating a sustained increase in SCR over time. Panel E reports the correlation matrix among our main variables. The Pearson correlation coefficients are generally low, suggesting that multicollinearity issues can be safely ignored in our regressions.[113]

Results of the univariate tests lend credence to the validity of our SCR measure. We run additional tests to further evaluate the validity of our SCR proxy. Table 2 summarizes the results. Column 1 examines the impact of SCR PCA on the future volatility of stock returns, controlling for firm fixed effects, year-quarter fixed effects, days of the week fixed effects, as well as

[113] We also conduct a test for multicollinearity using the value of variance inflation factors (VIF). We find that all our variables have a VIF less than 2.

clustering the errors by state. The estimate of SCR PCA loads positively and significantly on our measure of future volatility. On the face of it, this result supports the use of SCR as a measure of risk. However, caution should be exercised since recent studies (e.g., Hassan et al., 2019) used the same textual analysis method to extract other sources of risks: political risk (PRisk), non-political risk (NPRisk), and COVID risk (COVIDRisk). To ascertain the effect of SCR PCA on future return volatility, we run additional tests after including PRisk, NPRisk, and COVIDRisk (columns 2–4). In column 5, we include another textual measure of risk (TRisk), estimated by counting the total number of synonyms of risk and uncertainty in an earnings call divided by the number of words in the call ($TRisk_{it} \frac{\sum_b^{B_{it}} 1[b \in R]}{B_{it}}$). In column 6, we also measure positive and negative sentiments (TSentiments), which are calculated by dividing the sum of positive and negative words in the earnings call by the total number of words in the call ($TSentiment_{it} = \frac{\sum_b^{B_{it}} S(b)}{B_{it}}$). One can see that the coefficient of SCiR PCA loads positively and significantly across all specifications.

In the last column of Table 2, we run another validation test. We regress SCR PCA on PRisk, NPRisk, and COVIDRisk and use the residual of this regression (SCR PCA Residuals) as our proxy for SCR. Importantly, the coefficient of SCR PCA Residuals is positive and significant, confirming that our measure of risk (SCR) is distinct from the other textual proxies of risk.[114]

3.2. Does SCR increase during the COVID-19 pandemic?

To formally investigate the impact of COVID-19 on SCR, we run the following model:

$$SCR_{i,t} = \alpha_0 + \alpha_1 COVID_t + FIRM\ CTRL_{i,t} + \alpha_i + \delta_t + \varphi_d + \varepsilon_{i,t},$$

[114] Controlling for other sources of risk is also important for our validation test because the information content of other sources of risk may overlap with that of SCR, e.g., political risk (such as the Russia–Ukraine war), COVID risk.

where $SCR_{i,t}$ is our textual measure of supply chain risk (SCR PCA). COVID is a dummy variable that takes the value 1 if EC was held after March 20, 2020, when the World Health Organization (WHO) declared COVID-19 a pandemic. $FIRM\ CTRL$ is a set of firm controls. We control for firm size (SIZE) measured as the ratio of total to debt total assets (LEVERAGE); the ratio of capital expenditure to total assets (CAPEX); the book-to-market ratio (BTM); return on assets (ROA); the ratio of cash holdings to assets (CASH); a dummy variable that takes the value 1 if the firm pays dividends and 0 otherwise (DIVIDEND); institutional ownership (INSOWN); a dummy variable that takes the value 1 if the firm reports a negative earnings in the previous quarter (NEGEAR); firm complexity (COMPLEXITY), measured by the number of business segments (Hay et al., 2006), and firm internalization, measured as an indicator variable that takes the value of 1 if a firm has foreign sales and 0 otherwise. We include firm-fixed effects (α_i) to control for time-invariant firm characteristics and the two-digit SIC industry- year-quarter pair fixed effects (δ_t) to control for innovation shocks that are specific to a given industry and year-quarter and unobserved heterogeneity. We also include day-of-the-week fixed effects (φ_d) to account for the possibility that different days may imply more or fewer investors' attention and information content of ECs. While the firm-fixed effects subsume the state-fixed effects, we cluster the standard error at the state level. With these fixed effects, the coefficient on $COVID$ captures the effect of the COVID-19 pandemic on SCR. Results are reported in Table 3.

Results of regressing SCRU (column 1), SCRB (column 2), or SCR PCA (column 3) on COVID show a positive and significant coefficient of COVID. This evidence indicates that COVID resulted in a significant increase in SCR. In column 4, we run our main regression after adding the control variables and the estimated coefficient of SCR PCA remains positive and significant.

To test the robustness of our new evidence, we repeat the results of columns 1–4 after restricting our sample to the period 2018–2022 to have a balanced time period on either side of the COVID-19 pandemic. As reported in columns 5–8, the results are consistent with those obtained from the full sample. Since our evidence remains unchanged regardless of whether we use SCRB, SCRU, or SCR PCA, we focus on SCR PCA in the remainder of this study.

In Table 4, we attempt to control for potentially omitted variables. We sequentially and then concurrently control for the following additional variables: Roll's (1984) illiquidity proxy (*ILL1*), information asymmetry measured by the average effective bid-ask spread for the fiscal year (*AQBAS*), analyst forecast dispersion (*DISP*), accruals (*Accruals*) based on earnings before extraordinary items less cash flow from operations. Our main result remains unchanged, as the coefficient of COVID continues to load positively and significantly at the 1% level, as shown in all specifications in Table 4.[115]

3.3. The cross-sectional variation of the COVID-SCR relationship

To take our new evidence one step further, we focus next on the degree to which different mechanisms might moderate the effect of COVID on SCR. We start by exploring the effect of dispersion of analysts' forecasts (*DISP*) to examine the impact of firm information quality (e.g., Bhattacharya et al., 2013). Results, reported in columns 1 and 2 of Table 5, indicate that the effect of COVID on SCR is more pronounced in firms with high information asymmetry (i.e., analyst forecast dispersion above the sample median). In columns 3 and 4 we investigate a measure of the degree of firm complexity (Cohen & Lou, 2012). Our analysis indicates that firms with increased complexity are exposed to higher SCR during COVID. The last two tests of Table 5 examine the

[115] Unreported results suggest that our evidence of the effect of COVID on SCR does not change when we control for the global financial crisis. The effect of the 2008–2009 crisis on SCR is not significant, plausibly because the shocks are of different natures: one is demand-driven (the financial crisis) and the other is supply-driven (COVID-19).

influence of financial constraints and the extent of industry vulnerability to supply chain disruptions (using Ersahin et al.'s (2022) industry classification of the top (bottom) 10 most (least) vulnerable industries). The results indicate that financially constrained firms and those operating in the most vulnerable industries have higher SCR during COVID.

3.4. SCR real effects

3.4.1. SCR and short-window stock returns around the call

To investigate the stock market response to SCR during the COVID-19 pandemic, we run the following model:

$$CAR[0,t]_{i,q} = \alpha_0 + \alpha_1 CSR\ Talk_{i,q} + \alpha_2 EARN\ SURP_{i,q} + \alpha_3 \log(MVE)_{i,q} + \alpha_4 BTM_{i,q} + \alpha_5 TURNOVER_{i,q} + \alpha_6 INSTOWN_{i,q} + \alpha_7 PRE\ FF\_ALPHA_{i,q} + \varepsilon_{i,q},$$

where $CAR[0,t]_{i,q}$ is equal to the cumulative abnormal (market-adjusted) return from trading day 0 to trading day t relative to the conference call date. We focus on the window [0,1], where day 0 is the day of the earnings call. To reduce the likelihood that SCR captures the information content of other observable firm characteristics on the conference call date, we follow Frankel et al. (2022) and control for: firm earnings surprise (*Earnings Surprise*), calculated as the firm earnings per share in the current quarter less the median earnings per share forecast for the firm made prior to the current-quarter earnings announcement date scaled by the firm's stock price at the end of the quarter and based on the latest forecast prior to the current-quarter earnings announcement date;[116] the (log) of the market value of equity (MVE) for the firm in the current quarter or year calculated as the firm's stock price multiplied by the number of shares outstanding at the end of the quarter or year; the book to market ratio (BTM) calculated as the firm's book value of common equity at

[116] We remove forecasts made more than 90 days prior to the earnings announcement date.

the end of quarter or year divided by MVE; the number of shares traded for the firm in the trading days [−252, −6] relative to the conference call date divided by the firm's shares outstanding at the conference call (*Turnover*); the percentage of shares of the firm held by institutional investors (*Institutional Ownership*); and the Fama–French alpha (*Pre-FF-Alpha*) based on the Fama–French three-factor model and using trading days [−252, −6] relative to the conference call date as the estimation period.[117] We control also for firm-fixed effects (α_i), year-quarter fixed effects (δ_t), and day-of-the-week fixed effects (φ_d). We double cluster the errors by firm and earnings call date. Results are reported in Table 6.

In column 1, we present the results of the impact of SCR on the cumulative abnormal return without controls. In column 2, we augment the regression model with the controls discussed above. In these two columns the dependent variable (CAR [0,1]) is pooled from the first two earnings call transcripts after the WHO declared COVID-19 a pandemic. The coefficient on SCR PCA is negative and statistically significant at the 5% (10%) level in column 1 (2). In columns 3 and 4 we repeat the analysis of columns 1 and 2 of Table 6 after considering the first three quarters of the pandemic. Here again, SCR PCA loads negatively and significantly. Taken together, results reported in Table 6 suggest that SCR bears negatively on conference call short-term returns during the COVID-19 pandemic.

3.4.2. SCR and firm policies

In the next set of tests, we explore the real effects of SCR by exploring the impact of SCR PCA on future profitability, future inventories, future cash conversion cycle, future operating cycle, future research and development, and future sales growth. Of note, for each corporate

[117] We require firms to have at least 60 daily returns to be included in this analysis.

outcome we run two specifications: in the first one (e.g., future profitability, column 1) we present the regression results without time-variant firm characteristics. In the second specification (e.g. future profitability, column 2), we not only augment our model with time-variant firm characteristics, but also use the residuals (SCR PCA residuals) obtained from regressing SCR PCA on all independent variables of column 2. Namely, we run the following model:

$$DEP_{i,t} = \alpha_0 + \alpha_1 SCR\_RES_{i,t} + \alpha_2 FIRMCTRL_{i,t} + \varepsilon_{i,t}, \qquad (6)$$

where $DEP_{i,t}$ is our proxy for corporate outcome (real effect), SCR_RES is measured by residual from regressing the raw level of SCR on FIRMCTRL and COVID. COVID is a dummy variable coded 1 after COVID-19 outbreak (after March 20, 2020) and 0 otherwise, and FIRMCTRL is a set of firm-level control variables. Specifically, we control for the following variables: firm size (Size); cash holdings (*Cash Holdings)*, calculated as the firm cash holdings scaled by net assets; leverage ratio (*Leverage*); book to market (*BTM)*; dividend payment (*Dividend*), and complexity (*Complexity*). As stated above, non-categorical variables are winsorized at the 1% level at each tail of our sample.

The results from the specifications in columns 1 and 2 indicate that the SCR bears a negative and significant effect on firm future profitability.[118] In columns 3 and 4 we report the results of the impact of SCR on future inventories, measured by the ratio of inventories over total assets (e.g., Mills et al., 2013; Craswell et al., 2002; Stice, 1991). All else equal, an increase in inventories may reflect some form of inefficiency in firm operations, which can lead to higher costs and lower profitability. The results reported in columns 3 and 4 suggest that SCR is associated with inefficient supply chain performance, as evidenced by an increase in the level of inventories.[119]

[118] We measure profitability by the ratio of firm operating income before depreciation to total assets.
[119] Caution is merited here since one might argue that in times of uncertainty an increase in inventories may help firms meet demand.

As part of our analysis of SCR's impact on supply chain performance, we examine, in columns 5 and 6, the impact of SCR PCA on the cash conversion cycle (CCC). CCC reflects the “net time interval between actual cash expenditures on a firm's purchase of productive resources and the ultimate recovery of cash receipts from product sales” (Richards & Laughlin, 1980, p. 34), and is a commonly used metric to gauge “the effectiveness of a firm's management and intrinsic need for external financing” (Wang, 2019, p. 472). The CCC of the firm may be improved (i.e., decreased) by streamlining operations (Zeidan & Shapir, 2017) and longer CCC may adversely affect both the investment and financing aspects of the firm’s working capital management (e.g., Richards & Laughlin, 1980).

Considering that high-SCR firms are subject to more supply chain disruptions and exposed to more unpredictable variations in their pattern of future operating cash flow, we expect SPC PCA to be associated with longer CCC. In line with this predication, we document a positive and significant effect of SCR PCA on CCC. This result is confirmed when we use, in lieu of (future) CCC, (future) operating cycle. The operating cycle also reflects the average time elapsed between the disbursement of cash to produce a product and the receipt of cash from the sale (Dechow, 1994) and we measure it as described by Lobo et al. (2012).

The results of columns 1–8 in Table 7 provide consistent evidence that SCR is associated with (inefficient) working capital management evidenced by higher inventories, longer CCC, longer operating cycle, and lower profitabilty. In turn, this will likely lead to a decrease in share value (Zeidan & Shapir, 2017). Columns 9 and 10 demonstrate that SCR PCA deteriorates future R&D investments, suggesting that high-SCR firms are less likely to invest in R&D. In columns 11 and 12 we do not indicate a discernible effect of SCR PCA on future sales growth.

3.4.3. Is there an association between SCR and ESG Talk?

In a final test, we ask whether high-SCR firms may try to oversell their ESG performance. The crux of our logic is that firms may use ESG selective disclosure to promote the societal appearance of conformity, gain legitimacy, and obfuscate their increased exposure to SCR. Meyer and Rowan (1977) introduced the concept of decoupling through which organizations conform their visible structures, but not their core activities, to social norms. Nystrom and Starbuck (1984) suggest that managers construct organizational facades to conceal activities or results they want to hide. Managers may use discretionary narrative disclosures to possibly manage their perceptions (Merkl-Davies & Brennan, 2007). For the purpose of this test, we argue that managers, since they may not be neutral in their presentation of accounting narratives (Sydserff & Weetman, 1999), can use ESG narrative as a voluntary disclosure, to manage the impression of stakeholders and divert their attention from potentially high SCR. Some investors and other stakeholders are susceptible to managerial impression management[120] (Merkl-Davies & Brennan, 2007). This prediction is grounded in the idea that ESG discretionary disclosures are largely voluntary and corporate narratives are primarily unregulated (Merkl-Davies & Brennan, 2007).

To investigate the link between SCR and ESG talk, we follow Attig and Boshanna (2022a) and develop an ESG dictionary by identifying key words in the Sustainability Accounting Standards Board (SASB) codified standards, the 2021 Global Reporting Initiative (GRI) standards, the 2022 International Financial Reporting Standards (IFRS)-climate-related disclosures, and Refinitiv MarketPsych ESG Analytics. We also use "Web of Science" to identify the most cited

[120] A large line of inquiry studies impression management, which refers to the behavioral strategies used to create desired social images or identities (Tetlock & Manstead, 1985) to control or manipulate the reactions of others (Leary & Kowalski, 1990).

CSR-related papers. We namely select the following five studies: “Corporate social responsibility theories: Mapping the territory” (Garriga & Melé, 2004, *Journal of Business Ethics*), “Does doing good always lead to doing better? Consumer reactions to corporate social responsibility” (Sen & Bhattacharya, 2001, *Journal of Marketing Research*), “Implicit and explicit CSR: A conceptual framework for a comparative understanding of corporate social responsibility” (Matten & Moon 2008, *The Academy of Management Review*), “Corporate social responsibility and financial performance: Correlation or misspecification?” (McWilliams & Siegel, 2000, *Strategic Management*), and “What we know and don’t know about corporate social responsibility” (Aguinis & Glavas, 2012, *Journal of Management*). We also consider the wordlist of four existing dictionaries developed by Loughran et al. (2009), Pencle and Mălăescu (2016), and Moss et al. (2018). After manual inspections of the ESG keywords, our disambiguation process resulted in 728 bigrams.

We apply Loughran and McDonald's (2011) equation of term frequency-inverse document frequency after adjusting it for the use of bigrams:

$$\omega_{ij} = \begin{cases} \dfrac{\left(1+\log\left(bf_{i,j}\right)\right)}{(1+\log(\alpha_i))}\log\left(\dfrac{N}{df_i}\right) & if\ tf_{i,j} \geq 1 \\ 0 & otherwsie \end{cases}$$

where N represents the total number of documents in the corpus, df_i the number of documents containing at least one occurrence of the i^{th} bigram, $bf_{i,j}$ the raw count of the i^{th} bigram in the j^{th} document, and α_i the average bigram count in the document. The log transformation attenuates the impact of high frequency words/bigrams and the term $\log\left(\frac{N}{df_i}\right)$ adjusts the impact of a bigram based on its commonality (Loughran & McDonald, 2011).

We then run two tests: in the first we examine the impact of SCR PCA, without time-variant firm characteristics, on our proxy for ESG Talk (i.e. ESG BF, ESG BF-IDF and the principal component of these two proxies ESG PCA). Results, reported in columns 1, 3, and 5 of Table 8, indicate that firms experiencing a surge in SCR tend to engage in more 'ESG overselling', measured using ESG bigrams frequency (*ESG BF*), bigrams frequency inverse document frequency (*ESG BF-IDF*), or the principal components of these two measures (*ESG PCA*). In the second test, we run the following model:

$$DEP_{i,t} = \alpha_0 + \alpha_1 SCR\ RES_{i,t} + \alpha_2 COVID + \alpha_3 SCR_{i,t} \times COVID + \alpha_3 FIRMCTRL_{i,t} + \varepsilon_{i,t},$$

where $DEP_{i,t}$ is our measure of ESG Talk (ESG BF, ESG BF-IDF, and ESG PCA). $SCR\ RES_{i,t}$ is our proxy of SCR measured by the residual from regressing SCR PCA on *COVID, Size, Leverage, CAPEX, Cash Holding, Dividends, Institutional Ownership, Negative Earnings,* and *Complexity*. Results of this test are reported in columns 2 (ESGBF), 4 (ESG BF-IDF), and 6 (ESG PCA) of Table 8. Importantly, two fresh findings stand out in Table 8.

First, in accord with our expectation, all specifications of Table 8 indicate that high-SCR firms appear to engage in overselling their ESG performance. Second, in columns 2, 4, and 6 we augment our regression model with the variable COVID and its interaction variable with SCR PCA residual (SCR RES x COVID) and find that both variables load positively and significantly on our proxies of ESG Talk. The positive effect of COVID on ESG Talk is in line with Attig and Boshanna (2022b), suggesting that the COVID-19 pandemic provided incentives for firms to oversell their ESG performance. The coefficient of interaction variable (COVID x SCR Residual) suggests that the effect of COVID on ESG Talk is more pronounced in high-SCR firms.

4. Conclusion

The COVID-19 pandemic placed significant strain on supply chains and firmly rooted supply chain risk in managers' agendas and government and public thinking. In this context, investors may find it relevant to quantify supply chain risk. Academic research, however, faces the difficult task of developing an empirical proxy that can capture the multifaceted nature of SCR. Building on Loughran and McDonald's (2022, p. 1) view that textual analysis "might uniquely add value in capturing the nuances of multifaceted problem" and relying on the methodology introduced by Hassan et al. (2019), we perform a textual analysis of the transcripts of earnings calls to propose a measure of supply chain risk (SCR).

We start by validating our measure of SCR and show that it varies intuitively across industries and over time, reaching unprecedented heights during COVID-19. We show that SCR has trended upward over the 2007–2020 sample period. Our multivariate analysis confirms the positive and significant effect of COVID on SCR. Our evidence indicates that SCR is more pronounced in firms with high dispersion in analyst forecasts, high complexity, and more financial constraints, as well as those in industries prone to supply chain disruptions. Equally important, we show that SCR negatively impacts short-term stock market returns, future profitability, and research and development investments. Our results suggest that high-SCR firms are associated with higher inventories and longer cash conversion and operating cycles. These findings are important as they suggest that high-SCR firms are likely to be exposed to increased volatility of their working capital (e.g., Dechow, 1994) and unpredictable variations in their operating cash flow in the future, which might hinder a firm's liquidity position (Richards & Laughlin, 1980) and destroy shareholder value. In a final test, we show that high-SCR firms tend to engage in ESG overselling plausibly to promote the appearance of conformity with stakeholders' expectations of corporate social performance and alleviate the adverse impact of increased SCR. These findings are important as they shed light on the vulnerability of businesses, highlight the need for effective risk management strategies, and emphasize the importance of building resilient supply chains in the face of future crises.

Future research in this area is certainly called for. An empirical examination of the link between SCR and asset pricing is beyond the scope of this study, but it points to a promising direction for future research. Similarly, investigating the linkage between SCR and other corporate outcomes, particularly in a cross-country context, seems warranted.

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Figure 1: The Average of SCR PCA across Years

This figure depicts the average of SCR PCA, our main measure of supply chain risk, over our sample time period.

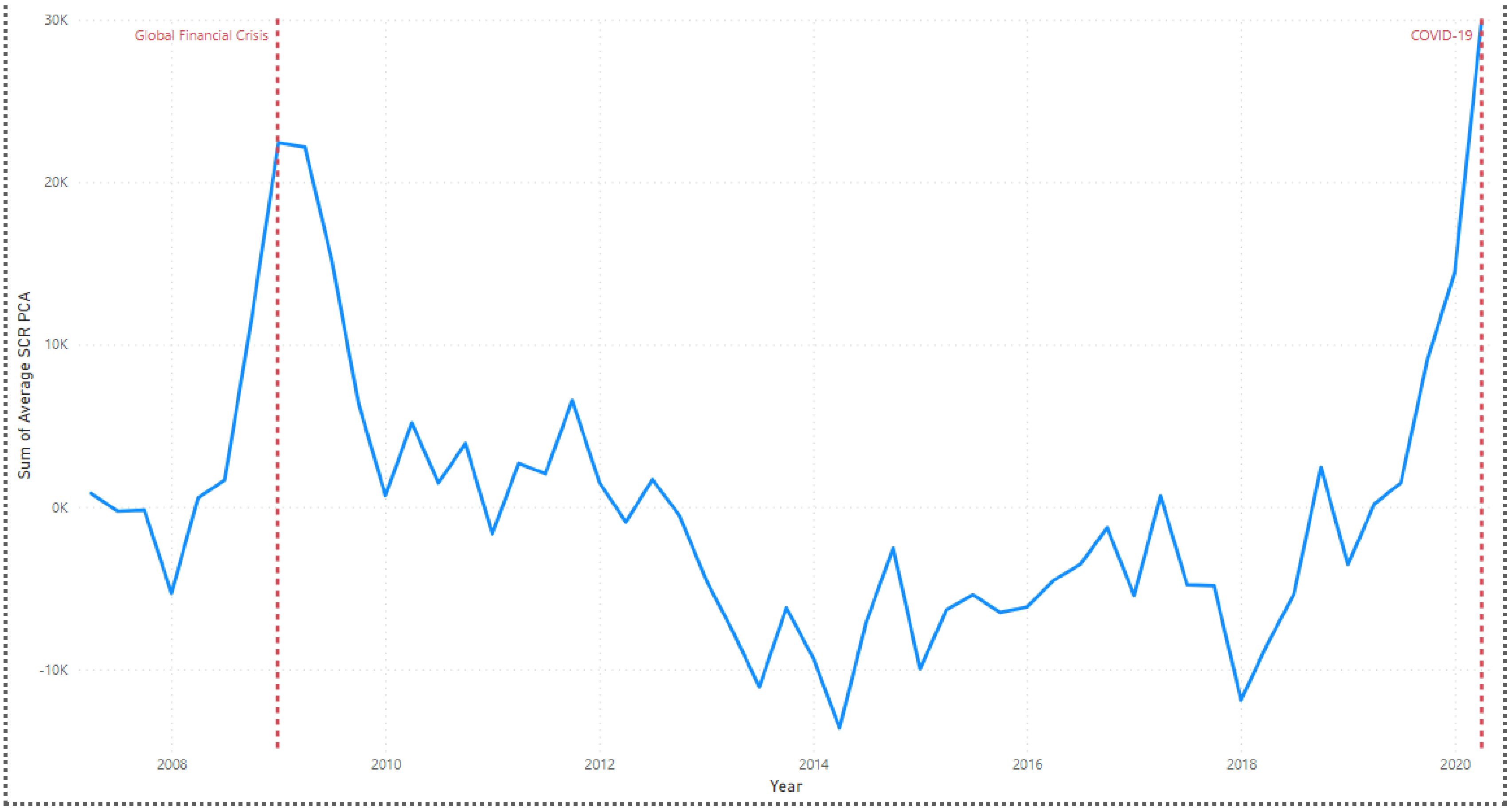

Figure 2: Supply Chain Word Cloud

This figure displays the 300 most frequently used words that occur within ten words before or after the word "supply" in all 2020 earnings conference calls.

Figure 3: Word Association

This figure presents a different representation of the relationship between all words used in earnings calls and the word "supply" for the year 2020 using the method of "word relationship".

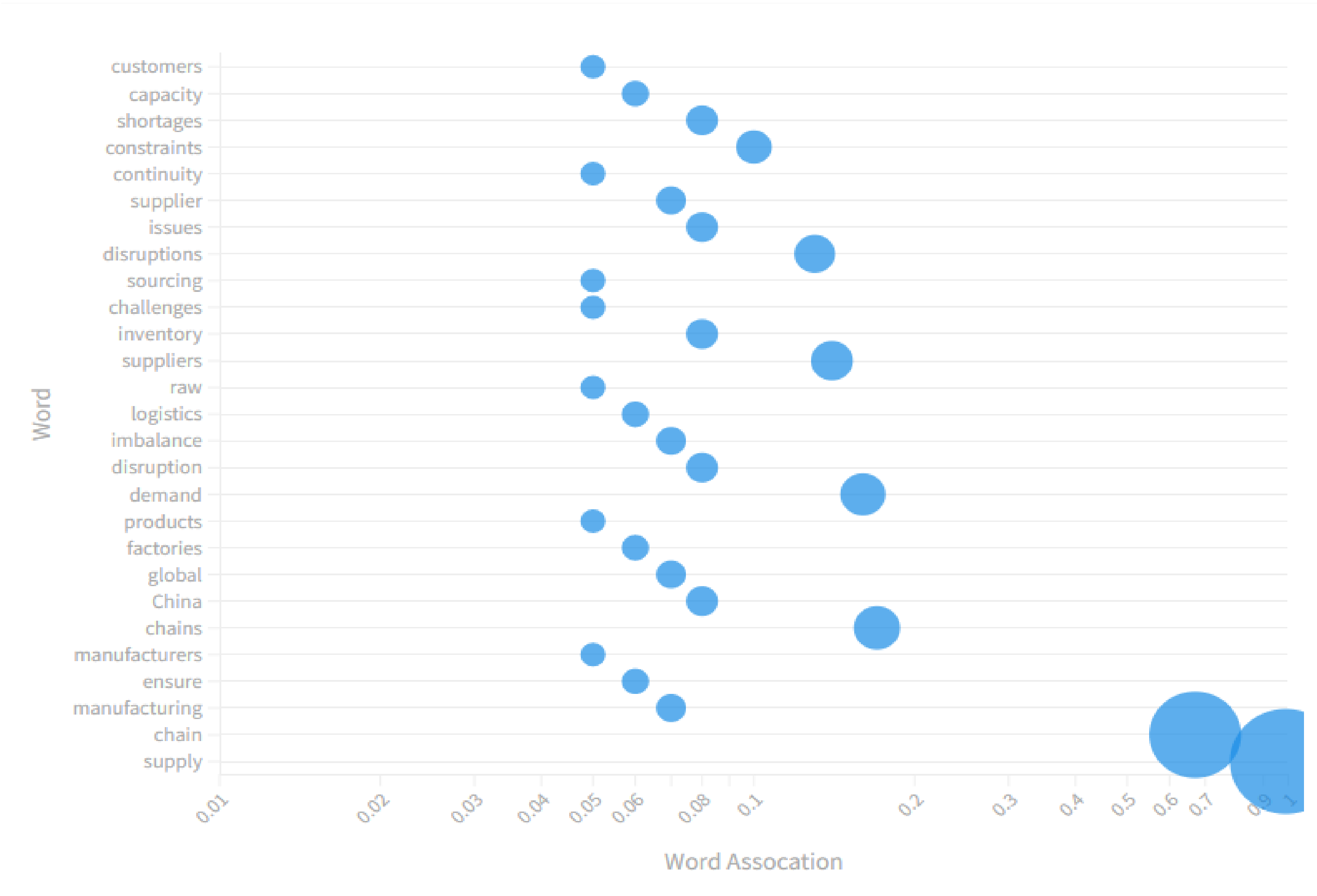

Table 1: Descriptive Statistics for Key Variables

Panel A of this table presents the descriptive statistics of our key regression variables. We measure firm *SCR* using bigrams (*SCRB)*, unigrams *(SCRU)*, and the principal component analysis of *SCRB* and *SCRU (SCR PCA*). In Panel B we report the distribution of our SCR proxies across industries with different vulnerability to supply chain disruptions. Panel C highlights the effect of COVID on SCR exposure. Panel D presents the time trend effect. Panel E reports the correlation matrix among our main variables. All continuous variables are winsorized at the 1% and 99% levels. Appendix A provides detailed definitions for all variables. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

Panel A: Descriptive Statistics

	SCRB	*SCRU*	*SCR PCA*	*Size*	*Leverage*	*CAPEX*	*BTM*	*Cash Holdings*	*Dividend*	*IOWN*	*Negative Earnings*	*Complexity*
N	65577	65577	65577	65577	65577	65577	65577	65577	65577	65577	65577	65577
Mean	0.913	1.423	0.003	7.273	0.258	0.028	0.452	0.481	0.391	0.781	0.287	5.894
SD	0.781	1.595	0.994	1.714	0.221	0.033	0.431	1.163	0.488	0.221	0.452	4.915

SCR-PCA

Panel B: Industry Vulnerability to supply chain disruption

	Most Vulnerable	*Less Vulnerable*	*Difference*	*T-test*
Mean	0.172	-0.138	0.309	20.45***

Panel C: COVID Effects 2018–2020

	COVID	*Pre-COVID*	*Difference*	*T-test*
Mean	0.11	-0.005	0.114	7.2***

Panel D: Time Trend

VARIABLES	*Time Trend*	*FFE*	*Year-Q-FF*	*Days of the Week FE*	*Errors Clustered by State*	*Observations*	*R-squared*
SCR-PCA	0.001***	YES	NO	YES	YES	64,099	0.379

Table 1 (continued):

***Panel E:* Correlation Coefficients of Our Key Variables**											
	(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***	***(7)***	***(8)***	***(9)***	***(10)***	***(11)***
(1) SCRB	1.000										
(2) SCRU	0.052	1.000									
(3) PCA_SCR	0.719	0.725	1.000								
(4) Size	0.030	0.031	0.044	1.000							
(5) Leverage	0.016	0.005	0.016	0.290	1.000						
(6) CAPEX	0.009	-0.003	0.004	0.044	0.029	1.000					
(7) BTM	0.004	0.099	0.072	-0.008	-0.173	0.027	1.000				
(8) Cash Holdings	-0.063	-0.105	-0.119	-0.314	-0.169	-0.138	-0.154	1.000			
(9) Dividend	0.067	0.071	0.096	0.434	0.086	0.004	-0.046	-0.217	1.000		
(10) Institutional Ownership	-0.002	0.023	0.016	0.263	0.029	-0.029	-0.045	-0.085	0.035	1.000	
(11) Negative Earnings	-0.038	-0.051	-0.063	-0.306	0.037	-0.025	0.096	0.285	-0.295	-0.167	1.000
(12) Complexity	0.006	-0.016	-0.006	0.257	0.017	-0.037	0.069	-0.179	0.220	0.057	-0.158

Table 2: Corporate Supply Chain Risk and Firm Volatility

In this table, we examine the impacts of SCR on firms' quarterly lead-realized volatility (our dependent variable across all models). We measure firm realized volatility using a firm's standard deviation of stock holding returns of firm i in quarter t. The political risk (*PRisk*), non-political risk (*NPRisk*), risk (*TRisk)*, and sentiment (*TSentiment*) measures are from Hassan et al. (2019).

VARIABLES	***Lead-Realized Volatility***						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
SCR PCA	0.013***	0.013***	0.012***	0.012***	0.011***	0.011***	
	(4.401)	(4.181)	(3.925)	(3.892)	(3.507)	(3.488)	
PRisk		0.000***	0.000**	0.000**	0.000	-0.000	
		(3.606)	(2.351)	(2.360)	(0.980)	(-1.036)	
NPRisk			0.000***	0.000***	0.000***	0.000	
			(5.534)	(5.377)	(2.791)	(1.631)	
Covid_Risk				0.122	0.111	0.086	
				(0.932)	(0.890)	(0.706)	
TRisk					0.446	0.873**	
					(1.114)	(2.182)	
TSentiment						-0.307***	
						(-20.184)	
SCR PCA Residual							0.012***
							(3.708)
Firm FE	YES	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES	YES
Observations	63,860	63,860	63,860	63,860	63,860	63,860	63,860
R-squared	0.738	0.738	0.738	0.738	0.738	0.738	0.738

Table 3: Corporate Supply Chain Risk and COVID-19

Using a full sample in columns 1–4 and a small sample in columns 5–8, Table 3 shows the results of a multiple regression analysis examining the impact of COVID-19 on firm SCR. Several proxy measures are used to measure firm CSR: SCRU with unigrams (columns 1 and 5), SCRB with bigrams (columns 2 and 6), and PCA_SCR with the principal component analysis (columns 3, 4, 7, and 8). *Covid* is an indicator variable that takes the value of 1 for date equal to and after March 20, 2020, and zero otherwise. We control for *Size*, the natural logarithm of total assets in year t, *Leverage*, the ratio of total debt to total assets, *CAPEX*, capital expenditures scaled by net assets, *BTM*, a firm's book value of common equity at the end of the year divided by MVE, *Cash Holdings*, calculated as the firm cash holding scaled by net assets, *Dividend*, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, *Institutional Ownership*, the percentage of shares of the firm held by institutional investors, *Negative Earnings*, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, *Complexity*, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

	Full Sample				*Small Sample*			
VARIABLES	***SCRU***	***SCRB***	***SCR-PCA***	***SCR-PCA***	***SCRU***	***SCRB***	***SCR-PCA***	***SCR-PCA***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
COVID	0.361*	0.356**	0.474***	0.480***	0.301	0.301***	0.396***	0.403***
	(2.013)	(2.331)	(3.239)	(3.140)	(1.401)	(2.746)	(3.008)	(3.147)
Size				-0.009				-0.068**
				(-0.833)				(-2.438)
Leverage				0.073**				0.147***
				(2.090)				(3.072)
CAPEX				0.367**				0.935***
				(2.436)				(3.238)
BTM				0.085***				0.002
				(9.484)				(0.085)
Cash Holdings				-0.028***				-0.039***
				(-6.354)				(-11.934)
Dividend				-0.001				-0.071***
				(-0.054)				(-3.011)
Institutional Ownership				-0.015				0.306***
				(-0.503)				(4.117)
Negative Earnings				0.041***				0.037**
				(5.825)				(2.708)
Complexity				-0.010***				-0.001
				(-5.276)				(-0.304)

Firm Internationalization				-0.041***				0.001
				(-3.710)				(0.051)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES	YES	YES
Observations	63,860	63,860	63,860	63,860	16,533	16,533	16,533	16,533
R-squared	0.500	0.330	0.422	0.423	0.580	0.420	0.513	0.515

Table 4: Corporate Supply Chain Risk and COVID-19: Omitted important variables

In this table we examine the effects of COVID on SCR (*SCR-PCA*) with additional control variables. Our results remained unchanged after controlling for the following variables: illiquidity (*ILL1*) in column 2, information asymmetry (*AQBAS*) in column 3, analyst dispersion (*ADISP*) in column 4, accruals (*Accruals*) in column 5, and add all the above in column 6. *Covid* is an indicator variable that takes the value of 1 for dates equal to and after March 20, 2020, and 0 otherwise. We also control for *Size*, the natural logarithm of total assets in year t, *Leverage*, the ratio of total debt to total assets, *CAPEX*, capital expenditures scaled by net assets, *BTM*, a firm's book value of common equity at the end of the year divided by MVE, *Cash Holdings*, calculated as the firm cash holding scaled by net assets, *Dividend*, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, *Institutional Ownership*, the percentage of shares of the firm held by institutional investors, *Negative Earnings*, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, *Complexity*, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES			***SCR-PCA***			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
COVID	0.480***	0.480***	0.480***	0.481***	0.478***	0.479***
	(3.140)	(3.145)	(3.148)	(3.126)	(3.101)	(3.098)
ILL1		-0.017*				-0.017
		(-1.801)				(-1.484)
AQBAS			-1.460			-0.215
			(-1.232)			(-0.133)
ADISP				0.075***		0.076***
				(6.187)		(6.314)
Accruals					-0.000***	-0.000***
					(-3.735)	(-3.733)
Size	-0.009	-0.010	-0.011	-0.013	-0.012	-0.018
	(-0.833)	(-0.926)	(-0.965)	(-1.228)	(-1.110)	(-1.563)
Leverage	0.073**	0.074**	0.075**	0.073**	0.074**	0.076**
	(2.090)	(2.192)	(2.153)	(2.104)	(2.136)	(2.209)
CAPEX	0.367**	0.364**	0.362**	0.387**	0.311**	0.328**
	(2.436)	(2.396)	(2.396)	(2.569)	(2.124)	(2.237)
BTM	0.085***	0.085***	0.086***	0.085***	0.085***	0.086***
	(9.484)	(9.381)	(9.513)	(9.472)	(9.444)	(9.406)
Cash Holdings	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***
	(-6.354)	(-6.320)	(-6.349)	(-6.463)	(-6.443)	(-6.513)
Dividend	-0.001	-0.001	-0.002	-0.000	-0.002	-0.001
	(-0.054)	(-0.060)	(-0.070)	(-0.006)	(-0.073)	(-0.033)
Institutional Ownership	-0.015	-0.017	-0.021	-0.010	-0.011	-0.009

	(-0.503)	(-0.586)	(-0.668)	(-0.338)	(-0.365)	(-0.277)
Negative Earnings	0.041***	0.041***	0.041***	0.040***	0.038***	0.037***
	(5.825)	(5.858)	(5.863)	(5.747)	(5.051)	(5.018)
Complexity	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(-5.276)	(-5.263)	(-5.280)	(-5.273)	(-5.272)	(-5.247)
Firm Internationalization	-0.041***	-0.041***	-0.041***	-0.040***	-0.040***	-0.039***
	(-3.710)	(-3.755)	(-3.710)	(-3.594)	(-3.627)	(-3.556)
Firm FE	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES
Observations	63,860	63,860	63,860	63,860	63,860	63,860
R-squared	0.423	0.423	0.423	0.424	0.424	0.424

Table 5: The Effects of Firm Characteristics

In this table we examine the role of firm characteristics in altering the impact of COVID (*Covid*) on SCR-PCA (*SCR-PCA*). We examine the role of analyst forecast dispersion (*ADISP*, columns 1–2), firm complexity (*Complexity*, columns 3–4), financial constraint (Kaplan-Zingales-Index, in columns 5–6), and the top and bottom 10 industries in terms of Ersahin et al.'s (2022) measure of overall supply chain risk (*Industry-SCRisk*, columns 7–8). *Covid* is an indicator variable that takes the value of 1 for date equal to and after March 20, 2020, and 0 otherwise. We control for *Size*, the natural logarithm of total assets in year t, *Leverage*, the ratio of total debt to total assets, *CAPEX*, capital expenditures scaled by net assets, *BTM*, a firm's book value of common equity at the end of the year divided by MVE, *Cash Holdings*, calculated as the firm cash holding scaled by net assets, *Dividend*, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, *Institutional Ownership*, the percentage of shares of the firm held by institutional investors, *Negative Earnings*, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, *Complexity*, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

	ADISP		**Complexity**		**Kaplan-Zingales Index**		**Industry-SRisk**	
	Below	**Above**	**Below**	**Above**	**Below**	**Above**	**Bottom**	**Top**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Covid	0.280	0.771***	0.120	1.225***	0.134	0.662***	-0.895**	1.523***
	(1.154)	(5.208)	(1.324)	(8.109)	(1.420)	(4.001)	(-2.485)	(5.585)
Size	-0.043***	0.013	-0.009	-0.018	-0.037**	-0.005	-0.035	-0.041
	(-2.724)	(0.770)	(-0.432)	(-0.592)	(-2.184)	(-0.357)	(-0.885)	(-1.451)
Leverage	0.081	0.031	0.071	0.176***	0.120***	0.087**	-0.069	0.212***
	(1.585)	(0.940)	(1.522)	(3.717)	(2.751)	(2.308)	(-0.631)	(3.060)
CAPEX	0.304	0.382**	0.160	0.516*	0.987***	0.161	-0.721**	1.028***
	(1.593)	(2.442)	(0.883)	(1.963)	(4.870)	(0.882)	(-2.656)	(3.839)
BTM	0.153***	0.052***	0.123***	0.069***	0.136***	0.065***	0.006	0.091***
	(6.414)	(3.763)	(7.487)	(2.806)	(5.357)	(5.824)	(0.166)	(3.781)
Cash Holdings	-0.010**	-0.038***	-0.028***	0.004	-0.026***	-0.009**	0.021	-0.011
	(-2.321)	(-6.464)	(-5.264)	(0.169)	(-11.108)	(-2.054)	(0.490)	(-0.170)
Dividend	-0.017	-0.003	0.037	-0.018	0.006	0.001	0.024	0.034
	(-0.837)	(-0.119)	(0.860)	(-1.353)	(0.191)	(0.024)	(0.643)	(0.721)
Institutional Ownership	0.011	-0.043	-0.050*	0.063	0.084	-0.082***	0.024	0.033
	(0.214)	(-1.613)	(-1.770)	(1.015)	(1.171)	(-3.865)	(0.212)	(0.470)
*Negative Earnings**	0.043***	0.036**	0.025	0.045***	0.030***	0.040***	0.049**	0.067***
	(7.020)	(2.417)	(1.455)	(5.894)	(2.956)	(6.167)	(2.694)	(3.245)

Complexity	-0.013***	-0.004**	0.020**	-0.018***	-0.012*	-0.006***	0.001	-0.009
	(-3.705)	(-2.087)	(2.295)	(-5.445)	(-1.965)	(-3.323)	(0.101)	(-1.625)
Firm Internationalization	-0.062***	-0.009	-0.049***	-0.020	-0.073***	-0.014	-0.105*	-0.060***
	(-3.510)	(-0.655)	(-3.553)	(-0.858)	(-3.355)	(-0.952)	(-1.952)	(-2.947)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES	YES	YES
Observations	32,347	30,517	34,631	28,570	19,180	43,979	5,843	16,440
R-squared	0.457	0.468	0.481	0.427	0.472	0.451	0.433	0.386

Table 6: Supply Chain Risk and Short-Window Stock Returns around the Call

Using the risk-adjusted return model (RAR), Table 6 presents the regression results of the effects of firm SCR (*SCR-PCA*) on the cumulative abnormal returns (CAR) during the [0, 1] trading window surrounding the earnings conference call filing date. We set our estimation window to be [-252, -6] before March 20, 2020, when the WHO declared COVID-19 a pandemic. In columns 1–2, we constrained our sample to the period March 20 to September 30, 2020, the two quarters after COVID hits, whereas in columns 3–4, we constrained our sample to the period March 20 to December 30, 2020, the three quarters after COVID hits. We control for the following variables: earnings surprise (*Earnings Surprise*), the difference between actual earnings and consensus analysts' forecast divided by the actual earnings, *Log (MVE)*, the firm in the current quarter calculated as the firm's stock price multiplied by the number of shares outstanding at the end of the quarter, *BTM*, the firm's book value of common equity at the end of quarter divided by MVE, *Turnover*, the number of shares traded for the firm in the trading days [−252, −6] relative to the conference call date divided by the firm's shares outstanding at the conference call date, *Pre_FFAlpha*, the Fama–French alpha based on a regression of their three-factor model using trading days [−252, −6] relative to the conference call date [at least 60 observations of daily returns must be available to be included in the sample], *Institutional Ownership*, the percentage of shares of the firm held by institutional investors. Standard errors are double clustered by firm and earnings call date. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

Variables	***Quarters 2-3***		***Quarters 2-4***	
	CAR [0, 1]		***CAR [0, 1]***	
	(1)	***(2)***	***(3)***	***(4)***
PCA_SCR	-0.003**	-0.003*	-0.004***	-0.002**
	(-2.220)	(-1.923)	(-3.095)	(-2.297)
Earnings Surprise		0.502***		0.507***
		(8.803)		(8.071)
Log (MVE)		0.161***		0.111***
		(11.083)		(28.903)
BTM		-0.037**		-0.051***
		(-2.055)		(-6.958)
Turnover		-0.014***		-0.007***
		(-10.607)		(-6.284)
Pre_FFAlpha		-12.749***		-13.426***
		(-13.215)		(-22.026)
Institutional Ownership		-0.245***		-0.199***
		(-4.110)		(-5.669)
Firm FE	YES	YES	YES	YES

SICxYear-Quarter FE	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES
Double Clustered Errors	YES	YES	YES	YES
Observations	2,419	2,419	3,508	3,508
R-squared	0.523	0.599	0.428	0.497

Table 7: Supply Chain Risk and Corporate Polices:

In this table, we examine the effects of SCR (*SCR-PCA*) on lead profitability (*Lead-Profitability*), lead inventories (*Lead-Inventories*), lead cash conversion cycle (*Lead-CCC*), lead operating cycle (*Lead-Operating Cycle*), lead research and development (*Lead-RD*), lead sales growth (*Lead-Sales-Growth*), and lead research and development (*Lead-RD*). Leads are expressed as one year-quarter ahead of the variable calculated over the period following the release of the earnings announcement. We measure firm profitability (*Profitability*) as a firm's operating income before depreciation divided by total assets. Inventories (*Inventories*) are measured as inventory scaled by total assets. We proxy for cash conversion cycle (*CCC*) as: days sales of inventory (DSI) + days sales outstanding (DSO) – days payable outstanding (DPO). Operating cycle (*Operating Cycle*) is measured (see Lobo et al., 2012) as follows: 360/(Sales-i.t/Accounts Receivable-i.t) + 360/(COGS-i.t/inventories-i.t). We measure R&D (*R&D*) by the ratio of research and development expenses to total assets. Sales growth (*Sales Growth*) measured by the ratio of difference between this year-quarter's and last year-quarter's sales to last year-quarter's sales. *SCR-PCA* is the principal component analysis of the two measures *(SCRB* and *SCRU*). *SCR-PCA Residual* obtained by orthogonalizing *SCR* on *PRisk*, *NPRisk*, *COVIDRisk*, and *TRisk.* We control for COVID (*Covid*) as an indicator variable that takes the value of 1 for a date equal to or after March 20, 2020, and 0 otherwise, *Size*, the natural logarithm of total assets in year t, *Leverage*, the ratio of total debt to total assets, *BTM*, a firm's book value of common equity at the end of the year divided by MVE, *Cash Holdings*, calculated as the firm cash holding scaled by net assets, *Dividend*, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, *Institutional Ownership*, the percentage of the firm's shares held by institutional investors, *Complexity*, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES	***Lead-Profitability***		***Lead-Inventories***		***Lead-CCC***		***Lead-Operating Cycle***		***Lead-RD***		***Lead-Sales-Growth***	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
SCR_PCA	-0.025**		0.093***		5.029***		4.186***		-0.015***		-0.106**	
	(-2.158)		(4.290)		(6.508)		(6.019)		(-3.692)		(-2.028)	
SCR_PCA Residual		-0.024**		0.089***		4.579***		3.820***		-0.014***		0.039
		(-2.112)		(4.092)		(5.685)		(4.869)		(-3.565)		(0.716)
Size		0.266***		-1.562***		37.792***		40.813***		-0.645***		-2.759***
		(4.057)		(-14.516)		(8.130)		(10.872)		(-13.996)		(-14.291)
Cash Holdings		-0.305***		-0.591***		-18.851***		-25.801***		-0.047***		1.037***
		(-12.402)		(-17.496)		(-8.464)		(-6.153)		(-3.841)		(4.223)
Covid		0.151		0.130		-19.970		49.015		-0.019		1.191
		(0.526)		(0.299)		(-1.569)		(1.011)		(-0.185)		(0.428)
Leverage		-0.890***		-1.227**		-1.614		25.026***		-0.208***		4.672***
		(-5.151)		(-2.236)		(-0.175)		(3.020)		(-2.961)		(3.898)
BTM		-1.746***		-0.154		33.842***		41.631***		0.004		-3.002***
		(-28.290)		(-1.595)		(13.254)		(13.592)		(0.435)		(-15.796)
Dividend		0.209***		-0.197***		-8.493*		-11.820*		-0.011		-0.476
		(3.153)		(-3.348)		(-1.813)		(-1.961)		(-1.020)		(-0.818)
Institutional Ownership		0.326***		-0.015		29.563***		54.730***		-0.215***		2.457***
		(3.599)		(-0.122)		(3.066)		(5.246)		(-9.029)		(5.969)

Complexity		-0.002		0.018		-1.765***		-2.933***		0.010***		0.131***
		(-0.349)		(1.624)		(-6.015)		(-6.274)		(6.515)		(8.334)
Firm Internationalization		0.476***		-0.111		-16.481***		-18.041***		-0.048***		-0.260**
		(8.126)		(-1.649)		(-3.784)		(-3.829)		(-3.730)		(-2.382)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	63,860	63,860	63,860	63,860	63,860	63,860	50,252	50,252	63,860	63,860	63,860	63,860
R-squared	0.742	0.753	0.950	0.952	0.811	0.813	0.840	0.842	0.888	0.895	0.217	0.220

Table 8: Supply Chain Risk and ESG Talk

This table reports regression results examining the effects of SCR, SCR residual (*SCR-PCA-Residual*), and the interaction of SCR residual and COVID (*SCR-PCA-ResidualxCovid*) on CSR talk. First, we regress COVID (*Covid*), size (*Size*), capital expenditures (*CAPEX*), Book to market (*BTM*), cash holdings (*Cash Holdings)*, dividend *(dividend)*, Institutional Ownership *(Institutional Ownership)*, Negative Earnings *(Negative Earnings)*, *and* Complexity *(Complexity)* on SCR (SCR-PCA). Then, we obtain the residual as a measure of SCR residual (*SCR-PCA-Residual*). Firm ESG talk is measured using several proxies: *ESG-BF* (columns 1–2) is measured by using bigram frequency scaled by the number of bigrams in the earnings call while *CSR-BF-IDF* (columns 3–4) is measured using bigram frequency inverse document frequency. *CSR-PCA* (columns 5–6) is the principal component analysis of the two measures *(ESG-BF* and *ESG-BF-IDF*). *Covid* is an indicator variable that takes the value of 1 for dates equal to and after March 20, 2020, and 0 otherwise. We control for *Size*, the natural logarithm of total assets in year t, *Leverage*, the ratio of total debt to total assets, *CAPEX*, capital expenditures scaled by net assets, *BTM*, a firm's book value of common equity at the end of the year divided by MVE, *Cash Holdings*, calculated as the firm cash holding scaled by net assets, *Dividend*, an indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise, *Institutional Ownership*, the percentage of shares of the firm held by institutional investors, *Negative Earnings*, an indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise, *Complexity*, the number of business segments. All continuous variables are winsorized at the 1% and 99% levels. Significance level: *** p < 0.01, ** p < 0.05, * p < 0.1.

VARIABLES	***ESG-BF***		***ESG-BF-IDF***		***ESG-PCA***	
	(1)	(2)	(3)	(4)	(5)	(6)
SCR-PCA	0.155***		0.018***		1.353***	
	(4.829)		(4.029)		(4.448)	
SCR-PCA-Residual		0.135***		0.016***		1.179***
		(3.690)		(3.082)		(3.398)
Covid		6.912***		0.430***		47.209***
		(13.595)		(4.310)		(8.501)
SCR-PCA-ResidualxCovid		0.258**		0.033**		2.359**
		(2.361)		(2.700)		(2.533)
Size		1.803***		0.241***		16.902***
		(14.096)		(17.293)		(15.689)
Leverage		-0.737		-0.098		-6.829
		(-1.678)		(-1.622)		(-1.643)
CAPEX		-2.419		-0.315		-22.559
		(-1.625)		(-1.591)		(-1.622)
BTM		-0.519***		-0.075***		-5.026***
		(-3.192)		(-3.177)		(-3.175)
Cash Holdings		-0.008		-0.010		-0.378
		(-0.215)		(-1.668)		(-0.992)
Dividend		0.012		-0.014		-0.408

		(0.053)		(-0.441)		(-0.188)
Institutional Ownership		0.042		0.025		1.060
		(0.063)		(0.277)		(0.168)
Negative Earnings		0.112*		0.008		0.781
		(1.695)		(0.923)		(1.281)
Complexity		-0.042		-0.005		-0.384
		(-1.376)		(-1.276)		(-1.358)
Firm Internationalization		-0.081		-0.013		-0.873
		(-0.522)		(-0.522)		(-0.541)
Firm FE	YES	YES	YES	YES	YES	YES
SICxYear-Quarter FE	YES	YES	YES	YES	YES	YES
Days of the Week FE	YES	YES	YES	YES	YES	YES
Errors Clustered by State	YES	YES	YES	YES	YES	YES
Observations	63,860	63,860	63,860	63,860	63,860	63,860
R-squared	0.401	0.403	0.398	0.400	0.387	0.388

Appendix A: Variable definitions

Variable definitions

Variables	Definition	Source
Dependent Variables		
CAR [0, 1]	The cumulative market-adjusted return for the firm in the [0,1] trading window surrounding the current-quarter conference call date.	CRSP
ESG-BF	Counting the number of ESG bigrams and scaled by the total number of bigrams in the earnings call.	Corporate earnings conference calls from Capital IQ
ESG-BF-IDF	CSR bigram frequency inverse document frequency.	Corporate earnings conference calls from Capital IQ
ESG-PCA	The principal component analysis of the two measures (ESG-BF and ESG-DF-IDF).	Corporate earnings conference calls from Capital IQ
Lead-CCC	One year-quarter ahead cash conversion cycle calculated over the period following the release of the earnings call. Cash Conversion Cycle (CCC) measured as days sales of inventory (DSI) + days sales outstanding (DSO) – days payable outstanding (DPO).	CRSP
Lead-Inventories	One year-quarter ahead inventories calculated over the period following the release of the earnings call. Inventories measured as the ratio of inventories on total assets	As above
Lead-Operating Cycle	One year-quarter ahead operating cycle calculated over the period following the release of the earnings call. Operating Cycle measured (see Lobo et al., 2012) as following: 360/(Sales-i.t/Accounts Receivable-i.t) + 360/(COGS-i.t/inventories-i.t)	As above
Lead-Profitability	One year-quarter ahead firm profitability calculated over the period following the release of the earnings call. Profitability measured as the operating income before depreciation divided by total assets**.**	As above
Lead-RD	One year-quarter ahead research and development calculated over the period following the release of the earnings call, where RD is measured as the research and development expenses scaled by total assets.	As above
Lead-Realized Volatility	One year-quarter ahead realized volatility calculated over the period following the release of the earnings call. Realized Volatility calculated as the firm's standard deviation of stock holding returns of firm i in quarter t.	As above
Lead-Sales-Growth	One year-quarter ahead sales growth calculated over the period following the release of the earnings call, where Sales-Growth is the ratio of difference between this year-quarter's and last year-quarter's sales to last year-quarter's sales.	As above
Main Independent Variables		
Covid	An indicator variable that takes the value of 1 for date equal to and after March 20, 2020, and 0 otherwise.	Authors' calculation

SCRB	Firm-level supply chain risk measure constructed from earnings conference calls using unigrams	Corporate earnings conference calls from Capital IQ
SCRU	Firm-level supply chain risk measure constructed from earnings conference calls using bigrams	Corporate earnings conference calls from Capital IQ
SCR-PCA	The principal component analysis of the two measures (*SCRB* and *SCRU*	Corporate earnings conference calls from Capital IQ
SCR PCA Residual	We regress SCR PCA on PRisk, NPRisk, and COVIDRisk and use the residual of this regression (SCR PCA Residuals) as our proxy for SCR.	Corporate earnings conference calls from Capital IQ
Control Variables		
Accruals	Defined as earnings before extraordinary items less cash flow from operations.	Compustat
ADISP	Dispersion of analyst forecasts defined as the coefficient of variation of one-year-ahead analyst forecasts of earnings per share.	Authors' calculations
ANAN	Analyst coverage, measured by number of equity analysts following a firm; equals the logarithm of 1 plus the number of one-year-ahead earnings forecasts.	I/B/E/S
AQBAS	Average effective bid-ask spread over the fiscal year.	Compustat
BTM	The firm's book value of common equity at the end of quarter divided by MVE.	CRSP
CAPEX	Capital expenditures scaled by total assets.	As above
Cash holdings	Ratio of cash holding to net assets.	As above
Complexity	The number of business segments.	Compustat
COVID_Risk	COVID risk measure from Hassan et al. (2022)	
Dividend	An indicator variable that equals 1 if a firm pays cash dividends on common equity and 0 otherwise.	As above
Earnings Surprise	The difference between actual earnings and consensus analysts' forecast divided by the actual earnings.	Authors' calculations and I/B/E/S
FirmInternationalization	An indicator variable that takes the value of 1 if a firm has foreign sales, and 0 otherwise.	Compustat
ILL	Roll's (1984) illiquidity proxy measured as the average effective bid-ask spread over the fiscal year.	Authors' calculations
Industry Vulnerability	Ersahin et al.'s (2022) top and bottom 10 industries in terms of supply chain vulnerability.	
Institutional Ownership	The percentage of shares of the firm held by institutional investors.	Thomson 13-F data
Leverage	Measured by the ratio of total debt to total assets.	CRSP
Log (MVE)	Market value of equity for the firm in the current quarter calculated as the firm's stock price multiplied by the number of shares outstanding at the end of the quarter.	As above
Negative Earnings	An indicator variable equal to 1 if the firm has negative earnings in that quarter and 0 otherwise.	As above
NPRisk	Non-political risk measure from Hassan et al. (2019).	
Pre-FF-Alpha	It is the Fama–French alpha based on a regression of their three-factor model using trading days [−252, −6] relative to the conference call date. At least 60 observations of daily returns must be available to be included in the sample.	CRSP + Corporate earnings conference calls from Capital IQ + Fama and French Three-Factor Model.
PRisk	Political risk measure from Hassan et al. (2019).	
ROA	A firm's total net income scaled by total assets.	CRSP

Kaplan-Zingales Index	Kaplan and Zingales' (1997) index (as implemented by Lamont et al. (2001)).	Authors' calculations
SCR PCA	Obtained by orthogonalizing SCR on PRisk, NPRisk, COVIDRisk, and TRisk.	
Size	Natural logarithm of total assets in year-quarter t.	As above
Time Trend	The time-series trends of our main variables by regressing SCR PCA on a linear trend variable, which takes the value of 0 in 2007Q1, 1 in 2007Q2, 3 in 2007Q3, etc.	As above
TRisk	Total number of synonyms for risk and uncertainty divided by the total number of words in an earnings call.	
TSentiment	The sum of positive and negative words, scaled by the total number of words in an earnings call.	
Turnover	The number of shares traded for the firm in the trading days [−252, −6] relative to the conference call date divided by the firm's shares outstanding at the conference call date.	CRSP + Corporate earnings conference calls from Capital IQ.

Appendix B: Supply Chain Keywords: Bigrams & Unigrams

In this appendix we report 114 of our 474 supply chain bigrams (Panel A) and 22 unigrams (Panel B).

Panel A: a sample of our 474 Supply Chain Keywords-Bigrams

abc analysis	chains international	products services	management integration	product category	shipping lines
abc classification	channel inventory	products shipping	management international	product delivery	shipping new
able supply	cleaner production	proof delivery	management supply	product group	shipping now
acquisition cost	closed loop	proximity supplier	managing supply	product groupings	shipping product
acquisition costs	coming soon	pull system	manufactured part	product groups	shipping products
across supply	coming sooner	purchase price	manufactured parts	product lifecycle	shipping rates
active Inventory	companies supply	purchase prices	manufacturing logistics	product recovery	start shipping
adoption supply	component part	purchasing lead	manufacturing resource	product shipping	started shipping
advanced shipping	component parts	purchasing price	manufacturing supply	product supply	still shipping
affect supplier	finished goods	push system	material requirements	production economics	stock rotation
affects supplier	first batch	quarantine stock	materials management	production lead	stock site
aggregate inventory	first in	radio frequency	matrix bar	production leading	stock turn
allocated stock	first inventory	random sample	maximum order	production research	stock turned
along supply	first out	rapid acquisition	maximum stock	products category	stock turning
alongside ship	first pick	raw material	minimum order	round time	stock turnover
already shipping	first picked	ready packaging	minimum stock	rounding order	stock turns
anticipation stock	forward supply	rebuild order	model supply	safety stock	stock types
application blockchain	free board	reduce inventory	much inventory	safety stocking	stock valuation
article numbering	free carrier	strategic stock	network design	safety stocks	stock valuations

Panel B: 22 Supply Chain Keywords-Unigrams

availability	category	incoterms	outsourcing	traceability
backflushing	component	fob	rotatable	transaction
backhaul	consolidation	inventory	slotting	
backorder	consumable	logistics	warehouse	
benchmarking	fifo	offshoring	stocktaking	

Appendix C. Transcript excerpts with highest SCRB in 2020

Firm name	Call date	SCRB	Section	Speaker	Title	Text surrounding SCR bigram
NeoPhotonics Corporation	Thursday, February 27, 2020, 9:30 PM GMT	14.2	Presentation	Elizabeth Eby	Senior VP of Finance & CFO	As Tim mentioned, we are constantly assessing the impact of the coronavirus on our operations. We have included approximately $10 million of impact to Q1 revenue in our outlook, reflecting reduced production in the quarter and added **supply chain risks**.
			Presentation	Timothy Storrs Jenks	Chairman, CEO & President	Our China suppliers are recovering steadily, but remain below capacity. At this point, we believe very few suppliers are at **risk** of not being able to meet our current **demand forecasts**. Our manufacturing outside of China, again, is more than half of our manufacturing footprint and is not directly impacted.
			Q&A	Timothy Storrs Jenks	Chairman, CEO & President	Let's all keep in mind that from a demand point of view, our business is really driven by deployment of bandwidth and it's neither consumer demand nor perishable demand. So we don't really anticipate major changes in demand as a result of this. Business is continuing to go, carriers are continuing to deploy, those normal drivers are actually all in place. And so I think we need to be cautious and careful given the **risk**, but I think we have to keep it in perspective because throughout our **supply chain,** below us and above us through to the carriers, business is continuing to flow.
			Q&A	Timothy Storrs Jenks	Chairman, CEO & President	I think demand is strong and steady. Production is increasing for the part of our production that is in China and has some impact. We have **supply chain risks**, we don't have supply chain problems, and I think we're managing those closely, hence Beth's prepared remarks commenting on the fact that working with and talking directly to our suppliers, we're feeling pretty comfortable as we've provided in our outlook.
			Q&A	Fahad Najam	Cowen and Company LLC, Research Division	If I could ask you on any linearity you're seeing in the last few weeks as this coronavirus starts to blow up. Are you seeing your non-Chinese customers kind of ramp demand just to kind of hedge their own **supply chain risk**? And if that's the case, what would be the true demand run rate going forward? How do you see that?
			Q&A	Elizabeth Eby	Senior VP of Finance & CFO	As Tim mentioned, we are constantly assessing the impact of the coronavirus on our operations. We have included approximately $10 million of impact to Q1 revenue in our outlook, reflecting reduced production in the quarter and added **supply chain risks**. We have assessed our supply chain, and based on what we know now, this revenue outlook is supported by our inventory and what can be produced by our suppliers. While we anticipate that the supply chain impact may extend beyond Q1, our suppliers are steadily increasing production and we expect to be able to ship unfulfilled Q1 demand in subsequent periods.

Mercury Systems	Tuesday, April 28, 2020, 9:00 PM GMT	11.3	Presentation	Mark Aslett	President, CEO & Director	Looking ahead, we're aware of the **risks** that we face, especially around the **supply chain**, our manufacturing facilities, and hiring. We believe Mercury has the strength and liquidity to endure a range of possible downside scenarios.
			Presentation	Mark Aslett	President, CEO & Director	We've been closely monitoring our supply chain, which is predominantly US-based. During Q3, we made some forward inventory buys and preordered raw materials to mitigate **risk** in both the short as well as the midterm. Thus far, however, the pandemic's impact on our **supply chain** suppliers has been relatively low.
			Presentation	Mark Aslett	President, CEO & Director	The key supply chain issues that we're facing are twofold. The first is that suppliers may be financially vulnerable. This applies more so to those suppliers that are heavily exposed to the commercial aerospace sector. As you know, commercial aerospace has been significantly more impacted by COVID than defense. The other major **supply chain risk** is the potential for COVID-related manufacturing disruptions, that is temporary site shutdowns that could affect the supply of US source components to Mercury.
			Presentation	Michael D. Ruppert	Executive VP, CFO & Treasurer	As Mark said, we acted quickly to protect the health, safety, and livelihoods of our employees. We worked to reduce and mitigate both **supply chain** and manufacturing **risk**, and we continue to fulfill our commitments to our customers.
			Q&A	Mark Aslett	President, CEO & Director	I believe that's correct, Ken. So I think if you—as you kind of go back to what I said in the prepared remarks, there's really, I think, 3 **risks** that we see. The first is a potential impact to our **supply chain**. We began focusing on our supply chain actually in January. The initial focus was on Asia. It very quickly then morphed into other international, particularly Europe and then the US. We've got 80% of our spend with round about 81 suppliers. We're all over it. So we know exactly what's happening with those suppliers who have been impacted, who are back online, the parts that we need for the next several quarters. We're tracking it daily. So we've done a tremendous amount, literally beginning in January to, I think, buy down risk to our financial plan.
			Q&A	Michael Frank Ciarmoli	SunTrust Robinson Humphrey, Inc., Research Division	Nice quarter. Glad to hear everybody is safe and healthy. Mark, maybe just to stay on that initial line of questioning where Ken was asking, talking about **building inventory** to absorb some delays. Where are you seeing specifically the most **risk** in the supply chain? I mean what types of products or inventory have you built up? And are you comfortable that some additional supply chain strain might not materialize with—do you think you have enough buffer on hand?
			Q&A	Michael D. Ruppert	Executive VP, CFO & Treasurer	I would say that we're doing everything we can to mitigate **risk**. But at this point, the **supply chain** and our suppliers are continuing to deliver. We're keeping an eye on all the critical suppliers. We're having our ops team and purchasing team are talking to our critical

						suppliers every single day to track the key deliveries. So we haven't seen anything yet, but we are doing everything we can to mitigate it and make those advanced purchases.
			Q&A	Mark Aslett	President, CEO & Director	Yes. So if you think of the industry trends that we talked about, delayering is one, and that is continuing to happen and we see it. What I think is probably going to be the more dominant theme around the macro level trends is that flight to quality suppliers as a result of just the impact that COVID has had. I think it's **exposed** some vulnerabilities from a supply **chain perspective** around dealing with small businesses that aren't necessarily as well capitalized or able to deal with the risks and the challenges that COVID has presented.
			Q&A	Mark Aslett	President, CEO & Director	The other thing that obviously this has **exposed** is just the domestic **supply chain** and the need to bring back some of that capability to the US. And as you know, we have invested in our own trusted domestic manufacturing facilities for quite some time. And I think that's going to play out as well. So I think we're well positioned, just given everything that we had previously been doing with the strategy that is even more important with what has just happened.
EVI Industries, Inc.	Monday, May 11, 2020, 12:00 AM GMT	11	Presentation	Henry M. Nahmad	Chairman, CEO & President	We source commercial laundry equipment from 12 domestic and international OEMs and sell over 25 brand names with a wide **variety** of price points, features, and capabilities to meet the needs of varying commercial laundry end-user customers. Given our position in the industry **value chain**, specifically the fact that we own the end customer relationship, we have visibility to and are pursuing revenues and profits from complementary products and services our customers purchase for their laundry operations from other businesses, most of which represent long-term growth opportunities for our company and have been accelerated as a result of the COVID-19 pandemic.
			Presentation	Henry M. Nahmad	Chairman, CEO & President	The combination of geographic and end-user customer diversity and a broad product range mitigates the **risk** that a disruption to any one geography, any one end-user customer, and any one **product category** can materially impact the entire company, despite the short-term turbulence caused by the COVID-19.
						Finally, it is important to appreciate that our company operates in a historically resilient industry and that our growth strategy and operating model are focused on long-term growth and **risk** mitigation. We provide commercial laundry **products and services** to industrial, on-premise, vended, and route laundry customers. Our customers operate across a wide range of industries. And given the nature of their operations, our customers need the products and services we provide in order to effectively and profitably deliver clean linens, uniforms, blankets, textiles...

NeoPhotonics Corporation	Thursday, April 30, 2020, 8:30 PM GMT	10.5	Presentation	Timothy Storrs Jenks.	Chairman, CEO & President	Our China suppliers have largely recovered, but there remains potential for new **supply chain risks** to emerge. As manufacturers around the world comply with local public health guidelines, we have teams in place to address these issues, and we're confident in our ability to support our Q2 outlook.
			Presentation			While we believe there is immediate demand to increase network bandwidth capacity to handle the increased traffic, we continue to see **supply chain risks**. We have included approximately $10 million of impacts to Q2 revenue in our outlook due to concerns about supplier shutdowns as they comply with their local public health orders. We expect the **supply chain risks** to continue into the second half of the year.
			Q&A	Richard Cutts Shannon	Craig-Hallum Capital Group LLC, Research Division	Okay. And let's take that into the second quarter with your sales guide here. At the midpoint, it's a modest growth here. Was this because you had such a strong first quarter? Are you building in, again, some of these **risks** here from the **supply chain** and others? Are there **inventory build** in the first quarter that you're worried about? If you could help us unpack kind of that trend in the second quarter that's a little bit lower than normal, especially in what looks like a favorable environment for you.
			Q&A	Richard Cutts Shannon	Craig-Hallum Capital Group LLC, Research Division	So, Tim, would you say the **supply chain risk** there are very specific and you're watching it closely? Or is this more of a generic cover-all statement for...
			Q&A	Timothy Storrs Jenks	Chairman, CEO & President	Yes. The -- a couple of things there. Going back a few years, we certainly saw in 2016 a strong year but recall that that was also followed by a very soft 2017. And we did express in our last 2 quarterly calls that we had some customers in China and in the West who were increasing their procurement and perhaps risk mitigating their go-forward plans. So I think for these reasons of potential customer inventory as well as the **supply chain risks**, I think we need to be a little cautious about how it might prove out.

Appendix D: Synonyms of risk

The following table lists all synonyms for "risk," "risky," "uncertain," and "uncertainty" that have been used to construct supply chain risk. The synonyms were identified using the Oxford Dictionary following Hassan et al. (2019).

Synonyms of risk words				
ambivalence	erratic	insecurity	risked	unforeseeable
ambivalent	exposed	instability	riskier	unknown
apprehension	faltering	irregular	riskiest	unpredictability
bet	fear	jeopardize	riskiness	unpredictable
chance	fickleness	jeopardy	risking	unreliability
chancy	fitful	likelihood	risks	unreliable
changeability	fluctuant	menace	risky	unresolved
changeable	fluctuating	misgiving	skepticism	unsafe
danger	gamble	niggle	speculative	unsettled
dangerous	gnarly	oscillating	sticky	unstable
debatable	hairy	parlous	suspicion	unsure
defenseless	halting	pending	tentative	unsureness
dicey	hazard	peril	tentativeness	untrustworthy
diffidence	hazardous	perilous	threat	vacillating
diffident	hazy	possibility	torn	vacillation
dilemma	hesitancy	precarious	treacherous	vague
disquiet	hesitant	precariousness	tricky	vagueness
dodgy	hesitating	probability	uncertain	variability
doubt	iffy	prospect	uncertainties	variable
doubtful	imperil	qualm	uncertainty	varying
doubtfulness	incalculable	quandary	unclear	wager
dubious	incertitude	queries	unconfident	wariness
endanger	indecision	query	undecided	wavering

equivocating	indecisive	reservation	undependable
equivocation	insecure	risk	undetermined

Appendix E: Examples of SCR construction

In Panel A of this Appendix, we use three examples to illustrate how we construct $SCRB_{it} = \frac{\sum_{b}^{B_{it}}(1[b \in S\backslash N] \times 1[|b-r| < k] \times \frac{f_{b,S}}{B_S})}{B_{it}}$. For the convenience of understanding the examples, we assume that we have one bigram "supply chain" and one unigram "risk". In Panel B, we show the number of bigrams in each example (i.e. each text).

Panel A: Examples of SCR construction									
Text	**Bigram found in text**	**$[b \in S\backslash N]$ * the bigram belong to SC library**	**$[\|b-r\| < k]$ Where K =10**	**$\|B-r\|$**	**$f_{b,S}$**	**B_S**	**B_{it}**	**$SCRB_{it}$**	**SCRB for text 1**
Text 1									
Before applying pre-processing techniques									
As Tim mentioned, we are constantly assessing the impact of the coronavirus on our operations. We have included approximately $10 million of impact to Q1 revenue in our outlook, reflecting reduced production in the quarter and added supply chain risks. We have assessed our strategy, and based on what we know now, this revenue outlook is supported by our inventory and what can be produced by our suppliers.									
After applying pre-processing techniques									
tim mentioned constantly assessing impact coronavirus operations included approximately million impact revenue outlook reflecting reduced production quarter added supply chain risks assessed strategy based know now revenue outlook is supported inventory can produced suppliers	Supply chain	Yes	Yes	10	1	1	33	$=\frac{10*(\frac{1}{1})}{33}*10^3$	303
Text 2									
Before applying pre-processing techniques									
As Tim mentioned, we are constantly assessing the impact of the coronavirus on our operations. We have included approximately $10 million of impact to Q1 revenue in our outlook, reflecting reduced production in the quarter and added supply. We have assessed our supply chain and based on the risk and what we know now, this revenue outlook is supported by our inventory and what can be produced by our suppliers.									
After applying pre-processing techniques									
tim mentioned constantly assessing impact coronavirus operations included approximately million impact revenue outlook reflecting reduced production quarter added supply assessed supply chain based risk know now revenue outlook is supported inventory can produced suppliers.	Supply chain	Yes	Yes	9	1	1	34	$=\frac{9*(\frac{1}{1})}{34} * 10^3$	265
Text 3									

Before applying pre-processing techniques									
As Tim mentioned, we are constantly assessing the impact of the coronavirus on our operations. We have included approximately $10 million of impact to Q1 revenue in our outlook, reflecting reduced production in the quarter and added supply chain risk. We have assessed our supply, and based on what we know now, this revenue outlook is supported by our inventory and what can be produced by our suppliers. While we anticipate that the supply chain risk impact may extend beyond Q1, our suppliers are steadily increasing production and we expect to be able to ship unfulfilled Q1 demand in subsequent periods.									
After applying pre-processing techniques									
tim mentioned constantly assessing impact coronavirus operations included approximately million impact revenue outlook reflecting reduced production quarter added supply chain risk assessed supply based know now revenue outlook supported inventory can produced suppliers anticipate supply chain risk impact may extend beyond suppliers steadily increasing production expect able ship unfulfilled demand subsequent periods	Supply chain	Yes	Yes	10	2	2	53	$\frac{10*\left(\frac{2}{2}\right)+10*\left(\frac{2}{2}\right)}{53}*10^3$	377

*Red= Stop-words, Green = Numbers, Blue = remove tokens with fewer than three letters. Remove comma and period.

Appendix E (continued)

Panel B: Number of bigrams in each example

Text 1		Text 2		Text 3	
Bigrams	**Frequency**	**Bigrams**	**Frequency**	**Bigrams**	**Frequency**
revenue outlook	2	revenue outlook	2	chain risk	2
added supply	1	added supply	1	revenue outlook	2
approximately million	1	approximately million	1	supply chain	2
assessed strategy	1	assessed supply	1	able ship	1
assessing impact	1	assessing impact	1	added supply	1
based know	1	based risk	1	anticipate supply	1
can produced	1	can produced	1	approximately million	1
chain risks	1	chain based	1	assessed supply	1
constantly assessing	1	constantly assessing	1	assessing impact	1
Coronavirus operations	1	coronavirus operations	1	based know	1
impact coronavirus	1	impact coronavirus	1	beyond suppliers	1
impact revenue	1	impact revenue	1	can produced	1
included approximately	1	included approximately	1	constantly assessing	1
inventory can	1	inventory can	1	coronavirus operations	1
know now	1	know now	1	demand subsequent	1
mentioned constantly	1	mentioned constantly	1	expect able	1
million impact	1	million impact	1	extend beyond	1
now revenue	1	now revenue	1	impact coronavirus	1
operations included	1	operations included	1	impact may	1
outlook reflecting	1	outlook reflecting	1	impact revenue	1
outlook supported	1	outlook supported	1	included approximately	1
produced suppliers	1	produced suppliers	1	increasing production	1
production quarter	1	production quarter	1	inventory can	1
quarter added	1	quarter added	1	know now	1
reduced production	1	reduced production	1	may extend	1

reflecting reduced	1	reflecting reduced	1	mentioned constantly	1
risks assessed	1	risk know	1	million impact	1
strategy based	1	supply assessed	1	now revenue	1
supply chain	1	supply chain	1	operations included	1
supported inventory	1	supported inventory	1	outlook reflecting	1
tim mentioned	1	tim mentioned	1	outlook supported	1
				produced suppliers	1
				production expect	1
				production quarter	1
				quarter added	1
				reduced production	1
				reflecting reduced	1
				risk assessed	1
				risk impact	1
				ship unfulfilled	1
				steadily increasing	1
				subsequent periods	1
				suppliers anticipate	1
				suppliers steadily	1
				supply based	1
				supported inventory	1
				tim mentioned	1
				unfulfilled demand	1
Total	**33**		**34**		**53**

Chapter 5: conclusion

In light of the growing awareness and social pressure for gender equality in the workplace, firms and their leaders are expected to play a significant role in addressing gender-based frictions. However, it remains uncertain whether firms will genuinely embrace corporate virtue and take substantive actions to close the gender gap at various levels of their corporate landscape, or if they may resort to impression management tactics to merely showcase their gender diversity performance without meaningful changes. To shed light on this conjecture, we add to the related literature by providing one of the first pieces of evidence on "gender diversity washing" during the MeToo movement (Chapter 2). Our evidence indicates that firms tend to engage in efforts to present a positive image of their gender diversity initiatives, particularly those with less female-friendly cultures and with more secondary activist stakeholders. The study also reveals that high levels of gender diversity talk are not always accompanied by substantive female-friendly initiatives, indicating a disconnect between talk and walk of gender diversity.

In Chapter 3, we extend our investigation of the extent to which firms walk the talk of their corporate virtues and show that firms oversell their ESG performance during the COVID-19 pandemic. This effect is particularly present in small and financially unconstrained firms. However, this CSR overselling does not translate into value relevance for investors, suggesting that "cheap talk is not cheap." The findings of Chapter 3 also reveal that ESG talk is associated with the use of positive or negative words, indicating the strategic nature of ESG communication.

In Chapter 4, we introduce a novel measure of supply chain risk (SCR) faced by US firms using natural language processing and show that exposure to SCR increased significantly during the COVID-19 pandemic. The study identifies factors that exacerbate the effect of COVID-19 on

SCR, such as less profitable operations, increased complexity, and financial constraints. The findings also highlight the negative impact of SCR on short-term returns, profitability, and cash conversion cycles, as well as the association between high-SCR firms and ESG overselling.

The research questions addressed in this dissertation are important as they reflect a growing recognition of the interconnectedness between various dimensions of sustainable development and the achievement of the United Nations Sustainable Development Goals (UN SDGs). As stated in the outset, gender diversity has been identified as a catalyst for improved decision-making and social progress and relates to SDG 5 (Gender Equality) and SDG 8 (Decent Work and Economic Growth). ESG principles connect to SDG 13 (Climate Action) and SDG 16 (Peace, Justice, and Strong Institutions) and supply chain risk management links to SDG 12 (Responsible Consumption and Production) and SDG 17 (Partnerships for the Goals). Importantly, in the realm of corporate governance and sustainability, gender diversity, ESG and supply chain risk have emerged as focal points.

Taken together, the findings of this thesis contribute to our understanding of firms' behavior during times of social and economic crises and shed light on the extent to which firms engage in impression management or take substantive actions in response to societal pressures. The results stress the need for more genuine and meaningful corporate efforts towards gender equality and supply chain resilience. The findings of this thesis have implications for policymakers, practitioners, and scholars interested in ESG/CSR, gender diversity, and supply chain risk management. Further research in these areas can provide valuable insights for effective corporate strategies and policies to promote sustainable and responsible business practice.

The findings of this thesis highlight the need for further policy initiatives aimed at enhancing ESG reporting and disclosure by firms, as well as fostering greater engagement for truly meaningful corporate responsibility that goes beyond mere lip service. In order to achieve more substantial progress, it is essential to prioritize concrete actions that promote transparency and accountability across all dimensions of ESG performance.

Of particular relevance to the focus of this thesis is the urgency of addressing gender and other diversity gaps in the corporate world requires more than just lip service. Concrete and substantive corporate initiatives are necessary to bring about meaningful change. To this end, it is essential to prioritize the implementation of actionable plans and programs that focus on promoting diversity, equity, and inclusion in all aspects of corporate operations and , in particular, in leadership positions. This is important because women continue to face significant barriers to equal representation and opportunities in the workplace, specifically in leadership positions. Chilazi, Bohnet and Hauser (2021) suggest that it is common for organizations to have gender parity or close to it in entry-level roles. To be sure, while gender gap is slowly closing at the entry-level positions of organizations, women are still underrepresented in the senior leadership of corporate America (Mckinsey & Co. 2022).[121] LinkedIn (2021) reports that 46% of entry-level roles globally are held by women, whereas only 25% of C-suite roles are held by women. LinkedIn (2021) suggests also that, globally, men were 33% more likely to receive an internal leadership promotion than women, lending credence to Mckinsey & Co.'s (2022) conclusion that women are less likely to be promoted to senior positions.[122] This in turn will exacerbate inequalities between men and women in the workplace and compound the effects of gender gaps in the corporate landscape. For

[121] Mckinsey, in partnership with LeanIn.Org, collected information from 333 participating organizations employing more than 12 million people, surveyed more than 40,000 employees.
[122] "For every 100 men who are promoted from entry-level roles to manager positions, only 87 women are promoted, and only 82 women of color are promoted" (Mckinsey & Co. 2022)

instance, the World Economic Forum (2020) finds that the global gender pay gap stands at 50%.[123] Further, in 2021, women earned 82 cents for every dollar earned by men (Statista 2021).

Against this backdrop, and according to the International Labour Organization (2020), women appear to dominate the occupations of personal care workers (88% female compared to 12% male), cleaning, teaching, clerical support, and food preparation (at least 60% female) and hospitality (54% female), reinforcing the idea that women are still facing a 'glass ceiling' challenge.[124] These industries have been disproportionately affected by the pandemic and associated lockdowns and other economic shocks. Unsurprisingly, the over-representation of women in these industries results in significant job losses, income reduction, and increased job insecurity for many women, suggesting that collective efforts (of various stakeholders) are needed to challenge and change the societal norms and biases that reinforce gender inequality.

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[123] "over 40% of the wage gap (the ratio of the wage of a woman to that of a man in a similar position) and over 50% of the income gap (the ratio of the total wage and non-wage income of women to that of men) are still to be bridged" World Economic Forum (2020, page 5).

[124] International Labour Organization (2020) suggests that men continue to dominate senior management positions, 72% of which are filled by men.

5.1. References

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