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Essays on Emerging Issues in Accounting

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by

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ABSTRACT OF THE DISSERTATION

Essays on Emerging Issues in Accounting

by

Wen-Hsin Chang
Doctor of Philosophy in Management
University of California, Los Angeles, 2025
Professor Judson Caskey, Chair

The first essay, titled *Privacy Lost? Consumer Digital Privacy and Earnings Benchmarks*, examines whether earnings benchmarks influence firms' aggressiveness toward consumer digital privacy. I find that firms narrowly beating the prior year's earnings engage in significantly higher third-party online tracking within their domains, even after controlling for conventional accrual-based and real activity-based earnings management (EM) channels. Two mechanisms explain these findings: increased tracking boosts site visits via personalized ads and enhances discretionary spending effectiveness. However, using the Sustainability Accounting Standards Board (SASB) materiality indicator to assess the overall costs of consumer privacy, I find that the main effect weakens when consumer privacy poses a material sustainability risk or when firms assign a board committee to oversee data governance. Overall, this research highlights firms' responses to earnings benchmarks in the increasingly important yet often hidden digital space, affecting almost everyone via the Internet.

The second essay, titled *Do ESG-linked loans increase the credibility of ESG disclosures?*, examines whether ESG-linked loans enhance the credibility of firms' voluntary ESG disclosures. Our predictions are based on a model in which firms may choose to withhold or voluntarily disclose information, subject to potential misreporting costs. Higher misreporting costs lead to more revealing reports and more informative "cheap talk" communications. ESG-linked loans increase misreporting costs by (1) imposing additional monitoring and liability, as misreporting can impact loan terms and potentially defraud creditors; and (2) encouraging caution in voluntary reporting, as syndicated loan contracts typically extend across multiple years. Consistent with our predictions, under a staggered difference-in-differences setting, we find that after issuing ESG-linked loans, firms are more cautious in reporting positive ESG news and more forthcoming with negative ESG news, with some evidence of more specific commitments. However, we do not find incremental effects from the stringency of ESG-linked contractual clauses.

The dissertation of Wen-Hsin Chang is approved.

Carla Hayn

Henry L. Friedman

Mark P. Kim

Judson Caskey, Committee Chair

University of California, Los Angeles

2025

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VITA

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CHAPTER 1

Privacy Lost? Consumer Digital Privacy and Earnings Benchmarks

1.1 Introduction

In the digital era, consumer data holds substantial commercial value, as it enables firms to "read the minds" of consumers and drives advancements in technologies such as business analytics and artificial intelligence (AI). However, as firms increasingly rely on data-driven decision-making, concerns about digital privacy also arise. For example, in 2024, PayPal revised its privacy policies to expand the collection and sharing of consumer data with third-party marketers.[1] As both the benefits and costs increase with the amount of consumer data collected, this study examines whether earnings benchmarks influence firms' aggressiveness toward consumer digital privacy, after controlling for traditional accrual-based and real activity-based earnings management (EM) channels. The research question is highly relevant to accounting as it highlights the evolution of EM channels over time, from traditional accrual-based methods to real activities emerging in the digital space.

While the Business Application Research Center (BARC) finds that data analytics increases revenue by 8 percent and reduces costs by 10 percent, a survey by KPMG reveals that 68 percent of US adults are concerned about how much data businesses collect.[2] Con-

[1] Available at: https://www.wsj.com/personal-finance/paypal-sell-customer-purchase-data-266b0e79

[2] Available at https://bi-survey.com/big-data-benefits, and https://kpmg.com/us/en/articles/2023/bridging-the-trust-chasm.html

cerns about digital privacy prompt firms to continually modify their data strategies to meet evolving needs and comply with regulatory requirements (e.g., Johnson et al., 2023; Lefrere et al., 2022; Abraham et al., 2019). A key development is the "right to be forgotten," established by the European Court of Justice in a 2014 case against Google and later codified in the General Data Protection Regulation (GDPR).[3] The Sustainability Accounting Standards Board (SASB) also identifies consumer privacy as a material sustainability risk that may affect firms' current or future cash flows. In recent years, more firms have emphasized data governance in their SEC filings and have assigned board committees, such as audit committees, to oversee consumer privacy concerns. (e.g., Klein et al., 2022).[4]

This study measures a firm's aggressiveness toward consumer digital privacy based on the intensity of third-party tracking within its domain. To account for variations by industry, website purpose, and year trends, I measure abnormal third-party tracking as the deviation from the industry, year, and site category averages. Third-party trackers are scripts, codes, or pixels embedded on a firm's website that collect and share visitor data with external entities. For example, in September 2024, macys.com had an average of 14 third-party trackers per page load according to Whotracks.me, with the main categories spanning advertising, site analytics, and customer interactions (see Appendix B for examples of third-party trackers).[5] Third-party trackers lead to privacy concerns because site visitors are often "notified but unaware" of the extent of data collection and sharing (Larsson et al., 2021). Additionally, third-party trackers often collect visitors' online activities across multiple websites and share the information within an ecosystem of advertising networks, data brokers, and credit rating

[3]The right to be forgotten primarily imposes an obligation on data processors to promptly erase personal data when it is no longer required for its original purpose.

[4]Firms' data governance practices extend beyond regulatory compliance. For example, The RealReal, Inc.'s 2021 proxy statement mentioned, "there is a cost and risk associated with every piece of data our customers entrust us with, so we take measures to minimize what is collected." Similarly, ServiceNow, Inc.'s 2021 proxy statement mentioned they "consider data use cases which, although legally permitted, may not meet their standards for maintaining customers' trust."

[5]Available at: https://www.ghostery.com/whotracksme/websites/macys.com

agencies, leading to unexpected uses of personal information.[6]

The tests measure trackers relative to the industry-site category-year mean, hereafter "abnormal tracking." Using a difference-in-differences design, I show that US sites exhibit significantly lower abnormal tracking intensity than Canadian sites after the milestone California Consumer Privacy Act (CCPA) took effect in January 2020. The findings validate the abnormal tracking measure as an indicator of firms' aggressiveness toward consumer digital privacy. Abnormal tracking is negatively associated with abnormal accruals and abnormal production. In contrast, it is positively and significantly associated with abnormal cuts in discretionary spending, suggesting that firms intensify online tracking as a complement to remaining discretionary activities, including advertising, research and development (R&D), and selling, general, and administrative (SG&A).

This study focuses on avoiding annual earnings decreases as a crucial benchmark, as maintaining a positive earnings string is often emphasized in the media (e.g., Burgstahler and Dichev, 1997; Myers et al., 2007; Barth et al., 1999). I find that firms narrowly beating the previous year's earnings engage in abnormally high third-party online tracking within their domains, even after controlling for conventional accrual-based and real activity-based earnings management channels. The increase in trackers represents approximately 20 percent of mean tracker usage in the sample.[7] On average, the sample shows an increase in tracking intensity two months before the annual fiscal year-end. Online tracking is expected to sustain earnings growth by monitoring changes in consumer behavior in real-time. These results remain robust when using analysts' consensus annual EPS forecasts as the earnings benchmark.[8] I show two mechanisms underlying the findings: intensified tracking (1)

[6] See Mayer and Mitchell (2012) for a detailed explanation of third-party web tracking. A detailed illustration is also available at: https://www.eff.org/wp/behind-the-one-way-mirror

[7] I interpret the results as firms making decisions with long-term ramifications to meet short-term benchmarks. Approximately 19 percent of the suspect firms in my sample exhibit lower tracking intensity in the following year, similar to Vorst (2016) which shows only 18.3 (9.2) percent of firms subsequently reverse the R&D (SG&A) cuts.

[8] The test using analysts' consensus annual forecasts as a benchmark yields a smaller economic magnitude.

boosts site visits through personalized advertising and expanded advertising networks, and (2) enhances the efficiency of discretionary spending. These mechanisms align with previous research indicating that third-party trackers are frequently utilized for advertising and site analytics purposes (e.g., Karaj et al., 2018).

Moreover, I explore two additional hypotheses that consider (1) the materiality of consumer privacy and (2) board committee privacy oversight. First, the SASB's classification of consumer privacy as a sustainability risk summarizes both the direct (e.g., regulatory and litigation risks) and indirect (e.g., loss of customer trust) costs of abnormal tracking, serving as a useful summary statistic for consumer privacy costs. I find that the relation between abnormal tracking and earnings benchmarks is less pronounced for firms in industries where consumer privacy is a material sustainability risk. Second, to further address the alternative explanation that abnormally high tracking reflects a firm's operating environment rather than incentives to avoid missing earnings benchmarks, I examine cases where a firm publicly designates a board committee to oversee data practices. Failure to adhere to these practices could lead to misleading public statements and potential litigation.[9] I find that the association between abnormal tracking and earnings benchmarks is less pronounced for firms with consumer privacy explicitly delegated to specific board committees, as indicated in their DEF14A proxy statements. If intensified tracking is an optimal response, it becomes difficult to explain why a firm's own privacy oversight and materiality would limit such customer tracking tendencies. Taken together, the two cross-sectional results address why not all firms track their visitors as extensively as possible.

This study contributes to the literature in three ways. First, it adds to the literature on firms' responses to earnings benchmarks. Managers have incentives to sacrifice long-

The primary distinction of analysts' forecasts is that they serve as a moving benchmark, in contrast to the static nature of the previous year's earnings.

[9]For examples of securities class action complaints related to misleading disclosures of firms' consumer online privacy practices, see Complaint, Gordon v. Nielsen Holdings Plc, No. 18-cv-07143 (S.D.N.Y. August 8, 2018), and Complaint, Monsky v. Digital Holdings, Inc., No. 24-cv-01940 (S.D. Tex. May 23, 2024).

term value to avoid missing earnings benchmarks by manipulating accruals or real activities, such as reducing discretionary expenses, overproduction, or temporary sales discounts (e.g., Dechow et al., 1995; Roychowdhury, 2006). Recent studies have examined issues such as employee safety and emissions (Caskey and Ozel, 2017; Liu et al., 2021). In contrast to prior studies, this paper explores an increasingly important yet often overlooked area: the digital space, uncovering a hidden mechanism that firms exploit to meet annual earnings benchmarks at the expense of consumer digital privacy. I also enrich the EM literature by exploring EM strategies in the digital economy. For example, the overproduction earnings management channel may be less relevant for digital platforms, while accrual-based channels may be less applicable to firms with minimal accruals due to direct revenue recognition, prior balance sheet overstatements (e.g., Barton and Simko, 2002), or a higher risk of prosecution.

In addition, the study contributes to the literature on the determinants of firms' data strategies, especially regarding data collection and sharing. Previous marketing research shows that regulations, such as the GDPR, are followed by a short-term drop in third-party online trackers, often those of lower quality, to ensure regulatory compliance (e.g., Peukert et al., 2022; Johnson et al., 2023; Lefrere et al., 2022). I document a financial reporting incentive that prompts aggressive consumer privacy practices- when firms are at risk of missing annual earnings benchmarks. This study also highlights the mitigating effects of board committees' privacy oversight and materiality considerations.

Finally, this study extends the emerging accounting literature on data privacy breaches by viewing firms as potential perpetrators of consumer privacy rather than victims lacking adequate controls. While several accounting studies have focused on cybersecurity (e.g., Ashraf and Sunder, 2023; Ashraf, 2022; Huang and Wang, 2021; Amir et al., 2018), there is relatively less emphasis on consumer digital privacy.[10] It is crucial to study digital privacy

[10]For further reading on recent cybersecurity research from management and accounting perspectives, see Lohrke and Frownfelter-Lohrke (2023) and Haapamäki and Sihvonen (2019). Some studies, such as Klein et al. (2022), have used the term "cyber risk" to encompass the overall risks associated with cybersecurity, cyberattacks, and data privacy. These studies typically use firms' self-reported or governmental records of

and cybersecurity separately, as each has different implications. For example, firms that fall victim to external cyberattacks may receive insurance compensation, and the public may perceive the breach less negatively if firms respond promptly (e.g., Richardson et al., 2019).[11] However, in cases where firms are perpetrators of digital privacy violations, they assume the primary responsibility.

1.2 Background

1.2.1 Public enforcement for consumer digital privacy

Firms' incentives to safeguard consumer digital privacy are driven by heightened privacy-related risk exposures, particularly public and private enforcement. These privacy-related risks are exacerbated by increased data collection and third-party involvement through intensified online tracking. Regulatory risks include fines for privacy noncompliance. For example, the General Data Protection Regulation (GDPR), which took effect in May 2018, is a landmark law aimed at ensuring the privacy of European Union (EU) citizens and applies to many US firms that serve at least one EU user. Penalties for GDPR violations can amount to the higher of 20 million euros or 4 percent of a firm's annual revenue from the prior year (Article 83). The GDPR protects users' data rights and imposes obligations on firms, including the requirement to establish a legal basis for data processing, such as obtaining explicit consent and processing personal data only when necessary.[12] Notably, the GDPR holds companies jointly accountable for third-party violations, making it necessary

data breaches from the Audit Analytics cybersecurity database or Privacy Rights Clearinghouse for their inferences.

[11] In the 2013 high-profile cyberattacks on Target, which led to the CEO stepping down and affected 70 million customers, Target incurred accumulated costs of $252 million by January 2015, of which $90 million was reimbursed by the insurance company, as reported in its 10-K.

[12] This is outlined in Article 6(1), which includes situations of contractual necessity, legal obligation, vital interests, performance of a task carried out in the public interest, or legitimate interests.

for firms to ensure third-party compliance (Article 28(1)).[13]

In recent years, U.S. privacy regulations have seen significant advancements. The California Consumer Privacy Act (CCPA), effective January 1, 2020, marks the first comprehensive state-level data privacy regulation. The CCPA imposes fines of $2,500 for unintentional violations and $7,500 for intentional violations, with each affected consumer counting as a separate violation. The CCPA allows California residents to know what types of personal information companies collect and to opt out of data sales. For example, Sephora was fined $1.2 million under the CCPA for allegedly sharing customer data via third-party trackers for advertising and site analytics purposes while falsely claiming not to sell customers' information. Building on the CCPA, the California Privacy Rights Act (CPRA) took effect on January 1, 2023, expanding the scope and penalties. Virginia and Colorado also enacted state privacy laws following California's lead.

In addition, the US Federal Trade Commission (FTC) enforces privacy regulations under Section 5 of the FTC Act, targeting unfair and deceptive data practices. The FTC mandates corrective actions such as implementing privacy programs, conducting biennial privacy assessments, deleting consumer data, and returning unlawful gains. If a firm violates the FTC consent order, the FTC can seek civil penalties per violation. In June 2024, the FTC fined Avast $16.5 million for falsely claiming its software protected users from online tracking while selling consumer browsing data to more than 100 third parties.

1.2.2 Private enforcement for consumer digital privacy

There has been a surge in various types of consumer privacy lawsuits in the U.S. due to increasing consumer privacy awareness. For example, Google agreed to pay $5 billion in 2023 to settle a consumer privacy class action lawsuit for tracking and collecting personal

[13]The most common GDPR violations are "Insufficient legal basis for data processing" and "Noncompliance with general data processing principles." Available at: https://www.enforcementtracker.com

information in private browsing mode under the Google Chrome browser.[14] Similarly, Meta agreed to pay $90 million for class action settlements in 2022 for tracking Facebook users' online activities through cookies even after they logged out of the platform.[15]

However, litigation concerning consumer privacy has not been limited to tech firms in recent years. Web tracking is broadly costly for various types of firms, and the trend of applying old laws to new technology settings, such as web session replays, has targeted retail firms. For example, according to Bloomberg Law's docket searches, lawsuits for pixel tracking, a type of online tracking, increased by 89 percent from 2022 to 2023.[16] Non-tech firms such as Frontier Airlines, Ray-Ban, and Banana Republic have all been subjected to web-tracking-related class action lawsuits, allegedly violating the Florida Security of Communications Act (FSCA) for tracking website visitors' mouse movements and clicks.[17]

Securities litigation has also emerged regarding firms' approaches to consumer digital privacy, as these practices impact business risk and corporate social responsibility, ultimately influencing investors' valuations. For example, Nielsen Holdings PLC settled a securities class action lawsuit in 2022 for allegedly misrepresenting their readiness for privacy-related regulations, including the GDPR, which would affect their current and future financial performance.[18] Similarly, Direct Digital Holdings, Inc. faced a securities class action lawsuit in 2024 for failing to disclose its inadequate ability to phase out third-party cookies, casting

[14] Available at:
https://www.reuters.com/legal/google-settles-5-billion-consumer-privacy-lawsuit-2023-12-28/

[15] Available at: https://www.reuters.com/technology/metas-facebook-pay-90-million-settle-privacy-lawsuit-over-user-tracking-2022-02-15/

[16] Available at: https://news.bloomberglaw.com/bloomberg-law-analysis/analysis-pixel-privacy-lawsuits-are-up-and-not-just-in-big-tech

[17] See Complaint, Zarnesky v. Frontier Airlines, Inc., No. 6:21-cv-00536 (M.D. Fla. March 24, 2021); Complaint, Goldstein v. Luxottica of Am. Inc., No. 9:21-cv-80546 (S.D. Fla. March 12, 2021); Complaint, Holden v. Banana Republic, LLC, No. 3:21-cv-00268 (M.D. Fla. March 15, 2021).

[18] See Complaint, Gordon v. Nielsen Holdings PLC, No. 18-cv-07143 (S.D.N.Y. August 8, 2018).

doubt on its positive statements regarding financial performance.[19]

1.2.3 Indirect costs of consumer digital privacy

Even if legally permitted, intensive online tracking entails indirect costs that have long-term consequences, such as consumer backlash. Users are often "notified but unaware" of the extent of tracking and data sharing on websites (Larsson et al., 2021). They become aware of this through excessive unsolicited contacts or, worse, when their personal information is transferred among parties to scammers (e.g., Ford, 2019), which results in a significant erosion of customers' trust. Such concerns were apparent when Facebook user engagement dropped by 20 percent within a month after its data privacy scandal.[20] Privacy concerns also manifest in reduced purchase likelihood (Pavlou et al., 2007), reluctance to engage with personalized services (Baruh et al., 2017), and a tendency to switch to competitors offering similar services (Martin et al., 2017; Yu et al., 2022). Specifically, Martin et al. (2017) find that 22 percent of respondents switch to competitors when they sense a firm accessing their personal information.

The increased involvement of third parties on websites has introduced security issues. According to Verizon's 2022 Data Breach Investigations Report, 62 percent of all data breaches occur through third-party vendors. This highlights the risks associated with embedding third-party scripts, which can increase susceptibility to cyberattacks (e.g., Urban et al., 2020). Furthermore, Ikram et al. (2019) find that approximately 40 percent of websites implicitly (blindly) trust third parties. Based on IBM's 2024 Cost of a Data Breach Report, the average cost of a data breach is $4.88 million. Third-party tracking, which directly invites third parties to access a firm's website, exposes firms and site visitors to potentially suspicious or malicious actions.

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[19] See Complaint, Monsky v. Digital Holdings, Inc., No. 24-cv-01940 (S.D. Tex. May 23, 2024).

[20] Available at:
https://www.theguardian.com/technology/2019/jun/20/facebook-usage-collapsed-since-scandal-data-show

1.3 Hypotheses Development

1.3.1 Main hypotheses

Managers aim to avoid reporting annual earnings decreases because such decreases are often publicly scrutinized (e.g., Burgstahler and Dichev, 1997). Firms with consistent earnings growth are typically priced at a premium and may face downward adjustments when this momentum is interrupted (e.g., Myers et al., 2007; Barth et al., 1999; DeAngelo et al., 1996; Lakonishok et al., 1994). Therefore, if managers anticipate not surpassing the previous year's earnings through regular business operations, they may resort to aggressive consumer privacy practices.

Firms face trade-offs when determining their data strategies, including data collection, sharing, and third-party involvement.[21] For example, Karaj et al. (2018) analyze over 1.5 billion page loads and find that firms embed third-party online trackers primarily for advertising and site analytics. Sites offering free editorial content or limited off-site revenue sources (e.g., news sites) tend to embed more trackers to monetize page views. In contrast, sites related to the public sector embed fewer trackers (e.g., Englehardt and Narayanan, 2016). Despite the privacy risks associated with public and private enforcement discussed in the previous section, intensified tracking offers a quick and feasible way to extract additional value from existing visitors. There are two primary mechanisms:

Boosting site visits and re-visits: Empirical and anecdotal evidence suggests that personalized and retargeted advertising can significantly increase site traffic in a short period. Firms often target consumers based on their browsing behavior or cart activity, using persistent ads that follow users across the Internet. In an experiment, Sahni et al. (2019) find that retargeted users exhibit a 14.6 percent increase in return visits within four weeks. Be-

[21] Based on my inquiries with tracker operators, the adoption costs of trackers vary widely, ranging from tens to a few thousands of USD per month. Considering that the sample comprises publicly listed firms in the U.S., these adoption costs are relatively modest.

yond mere site visits, Manchanda et al. (2006) show that retargeting also enhances purchase probability.

Estimating the direct revenue impact of increased tracking is challenging, as it depends on conversion rates, average order value, and firm size. However, anecdotal evidence from third-party tracker operators suggests that clients can achieve a revenue increase of approximately 20 percent within the first 30 days (see associated costs in the previous section).[22] Additionally, Johnson et al. (2020) estimate that the inability to behaviorally target users who opt out results in an average loss of \$8.58 per opt-out consumer in advertising spending. More broadly, prohibiting tracking technologies could reduce advertising effectiveness by approximately 65% (Goldfarb and Tucker, 2011) and lead to a 38.5% decline in online publisher revenue (Johnson, 2013).

Embedding more third-party trackers on websites expands the reach of a firm's advertising networks. Many advertising intermediaries operating third-party trackers emphasize the breadth of their extensive advertising network and their deals with direct publishers. Third-party trackers also allow firms to merge their customer insights with proprietary datasets from the tracker operators. However, advertising network partners often vary in their aggressiveness toward consumer digital privacy and adherence to privacy regulations, further exposing firms to heightened privacy risks.[23]

Effectiveness of discretionary expenses: Apart from reducing discretionary activities under earnings pressure, firms may shift toward more cost-effective methods. In addition to improving advertising effectiveness, increased tracking intensity for analytical purposes, such as analyzing users' web interactions and mouse clicks, can facilitate product development and differential pricing strategies (e.g., Yousfi and Adelakun, 2022; Palmatier et al., 2019). Anecdotal evidence from an online analytics provider shows that web tracking helps

[22] Examples available at: https://www.criteo.com/success-stories/.

[23] Overall, entering and exiting tracking agreements can vary widely based on the nature of the service. Some trackers offer flexible commitments, such as month-to-month agreements, while others require longer commitments in exchange for lower prices.

identify underutilized software and tools, resulting in cost savings of \$805,740 and 2,914 hours saved in internal productivity over three years.[24] These activities affect the overall SG&A and R&D effectiveness. Nonetheless, as discussed in the previous section, the recent trend in privacy litigation shows that new online tracking technologies substantially increase firms' litigation risks.

When traditional EM channels are less feasible, firms may adopt alternative strategies or a mix of techniques to meet earnings benchmarks (e.g., Healy and Wahlen, 1999; Cohen et al., 2008; Zang, 2012). Intensified third-party online tracking offers a new and hidden way to nudge near-term consumer behavior to reach earnings benchmarks, albeit at the expense of long-term consumers' digital privacy. Defining abnormal tracking as the deviation from the average online tracking levels within the same industry, site category, and year, I state the main hypothesis as follows:

H1: Firms engage in abnormally high third-party online tracking within their domains to beat earnings benchmarks, holding traditional accrual-based and real activity-based earnings management channels constant.

1.3.2 Costs considerations

1.3.2.1 The materiality of consumer digital privacy

Abnormally high levels of data collection and sharing expose firms to heightened privacy-related risks. These include regulatory and litigation risks, as well as indirect costs such as consumer backlash. An important consideration is whether these combined risks pose a material threat to the firms. The SASB categorizes firms into 77 industries based on the Sustainable Industry Classification System (SICS) and provides unique sustainability accounting standards for each industry. Among the sustainability-related risks that could

[24]Available at: https://contentsquare.com/blog/total-economic-impact-study-finds-contentsquare-delivered-602-roi-achieving-significant-boost-to-revenue-while-increasing-efficiency-and-customer-happiness/

materially impact a firm's current or future cash flows, the SASB refers to consumer privacy as the "management of risks related to the use of personally identifiable information (PII) and other customer or user data for secondary purposes." This includes managing issues related to data processing (e.g., collection and sharing), consumers' privacy concerns, and the impact of privacy regulations.

Similar to the Securities and Exchange Commission (SEC) and the Public Company Accounting Oversight Board (PCAOB), the SASB adopts the materiality interpretation upheld by the U.S. Supreme Court, defined as "a substantial likelihood that the fact would have been viewed by the reasonable investor as having significantly altered the total mix of information made available." [25] Khan et al. (2016) find that firms with good sustainability ratings on SASB industry-specific material issues outperform those without in terms of sustainability investment returns; however, they do not find the same for firms that obtain good ratings on immaterial issues.[26]

For firms in which consumer privacy constitutes a material sustainability risk to their business models, both the capital market and consumers may react strongly to privacy scandals. This is evident in several securities class action lawsuits alleging that firms misrepresented their readiness for privacy regulations, as such information is expected to significantly affect the firm's future financial prospects.[27] The anticipated remediation costs, long-term reputational damage, and heightened scrutiny drive investors' and consumers' reactions to privacy scandals. On the other hand, if these firms effectively manage consumer privacy, they will foster consumer loyalty and attract privacy-conscious consumers from competitors (e.g., Martin et al., 2017). Based on this argument, I propose the following hypothesis:

[25] TSC Industries v. Northway Inc., 426 U.S. 438, 449 (1976)

[26] To determine materiality, the SASB conducts evidence of materiality tests, including evidence of interest, evidence of financial impacts, and forward impact adjustment (Khan et al., 2016).

[27] See Complaint, Gordon v. Nielsen Holdings Plc, No. 18-cv-07143 (S.D.N.Y. Aug. 8, 2018); Complaint, Monsky v. Digital Holdings, Inc., No. 24-cv-01940 (S.D. Tex. May 23, 2024).

H2a: Firms' use of abnormal tracking to beat earnings benchmarks is mitigated when consumer privacy constitutes a material sustainability risk.

1.3.2.2 Data governance

Data governance broadly refers to exercising authority and control over data management (Abraham et al., 2019). This concept encompasses data strategies, policies, and monitoring practices designed to maximize the value of data while managing data-related risks (Abraham et al., 2019; Borgman et al., 2016). The costs associated with abnormal tracking are greater when a firm publicly designates a board committee to oversee its data practices because, if the firm does otherwise, its public statement could be considered misleading and potentially lead to litigation. Additionally, the board may pose more informed questions regarding the firm's privacy practices and directly restrict the suboptimal use of trackers.

Previous studies show that a board's monitoring role mitigates earnings management (e.g., Klein, 2002) and facilitates the implementation of business ethics codes of conduct (e.g., García-Sánchez et al., 2015). Given that more business decisions now involve cyber components as well as environmental, social, and governance (ESG) considerations, the board's role in overseeing enterprise risks, as endorsed by the SEC and the Committee of Sponsoring Organizations (COSO), extends to managing risks related to the cyber and ESG domains. For example, Uber's 2020 proxy statement noted that they "formally added oversight of data privacy to the charter of the Board's Audit Committee." Similarly, Klein et al. (2022) demonstrate that, following the EU GDPR, U.S. boards tend to increase their focus on cyber risks and add more information technology (IT) experts to the board. Consequently, the board committee responsible for privacy oversight is expected to develop a better understanding of firms' data privacy policies. Based on this argument, I propose the following hypothesis:

H2b: Firms' use of abnormal tracking to beat earnings benchmarks is mitigated when board committees are tasked with privacy oversight.

1.4 Research Design

1.4.1 Sample construction

Online tracking refers to the practice of collecting Internet users' information as they navigate online (Karaj et al., 2018; Mayer and Mitchell, 2012). To assess third-party tracking intensity within a firm's domain, I obtained data from Whotracks.me, which monitors thousands of websites and provides insights into third-party tracker usage.[28] I manually matched all sites in the July 2022 file to their respective owners and the parent companies' NYSE or NASDAQ tickers using Capital IQ.[29] I began with the July 2022 file, as it was the most recent data available at the project's inception.[30] Whotracks.me defines a tracker as a third-party domain that appears on multiple websites and utilizes cookies or fingerprinting methods to transmit user identifiers. I exclude sites that are not owned by publicly listed companies or lack the required data in Compustat.[31]

Next, I use the SICS lookup tool on the SASB website to determine a firm's SICS industry. The SASB categorizes firms into industries according to their business models and sustainability impacts. According to the SASB, there are six industries where customer privacy constitutes a material sustainability risk: E-commerce, Consumer Finance, Internet Media & Services, Software & IT Services, Advertising & Marketing, and Telecommunication Services. After satisfying the requirements for calculating the main variable *Ab_trackers* in

[28]Karaj et al. (2018) provide detailed explanations of how Whotracks.me identifies online trackers, and Lukic et al. (2023) use Whotracks.me data to examine the impact of GDPR on online tracking.

[29]I search for the site, with or without the top-level domain (TLD), to obtain tickers of the site owners in Capital IQ. If the search results are ambiguous, I use the "ipwhois" Python package to identify the domain owner.

[30]To make the panel data collection manageable, for each site with an identified ticker in the July 2022 folder, I retroactively search for tracker usage within the July 2021, 2020, 2019, and 2018 files to construct an annual panel dataset. Thus, the tracker usage in July of each year represents the tracker usage for that fiscal year.

[31]The status of each site's parent company was determined in December 2022.

the next section, as well as the firm-level controls, the final panel dataset spans July 2018 to July 2022 and comprises 2,401 site-year observations, all of which fall within the post-GDPR period.

To identify the board committee's responsibility for consumer privacy oversight, I analyze DEF 14A proxy statements filed in the same year as the tracker data.[32] I read through the paragraphs that include the keyword "privacy" to determine whether a committee is explicitly tasked with overseeing consumer privacy. Instead of simply counting the occurrences of the word "privacy," this approach excludes boilerplate language, ensuring that statements which do not assign accountability for privacy violations are not included (e.g.,"our company has made commitments on issues concerning the public, such as consumer privacy"). Committees responsible for privacy oversight are often audit committees, risk committees, and privacy or technology committees.[33]

1.4.2 Measuring abnormal tracking and suspected earnings management

I measure each site's "abnormal" third-party tracking intensity by the deviation from the mean tracking intensity within the same industry, site category, and year. The industry-category-year grouping is necessary because the normal level of online tracking varies significantly across industries (e.g., manufacturing versus e-commerce), site categories (e.g., news sites versus business sites), and years (e.g., changes in the regulatory environment).

To ensure a sufficient sample size and a meaningful average for each group, at least 15 observations for each group were required.[34] Abnormal tracking ($Ab\_trackers$) is calculated

[32] I search the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) index files for entries with form type equal to DEF 14A.

[33] The information typically appears in the chart of the proxy statement that outlines the responsibilities of each board committee.

[34] Roychowdhury (2006) requires at least 15 observations for each industry-year group when estimating "abnormal" cash flows, cost of goods sold, inventory growth, production costs, and discretionary expenses.

as follows.

$$Average\_trackers_{i,t} = Mean\ trackers(SASB\_industry_i, Site\_category_i, Year_t) \quad (1.1)$$

$$Ab\_trackers_{i,t} = Trackers_{i,t} - Average\_Trackers_{i,t} \quad (1.2)$$

I identify firms suspected of managing earnings to avoid earnings decreases based on Burgstahler and Dichev (1997)'s finding that firms exhibit earnings changes just above zero. Specifically, *Suspect* equals one if changes in earnings, deflated by the beginning-of-the-year total assets, fall within the range [0, 0.0025), the interval used by Burgstahler and Dichev (1997). I also deflate changes in earnings by net sales to generate an alternative *Suspect* variable for the robustness tests.

1.4.3 Model specifications: Baseline regression

To test the main hypotheses on consumer digital privacy and earnings benchmarks, I estimate the following baseline OLS regression model. I employ OLS regression instead of a count model because tracking intensity from Whotracks.me is a continuous variable representing the average number of third-party trackers per page load on the website. Additionally, I include site fixed effects to examine within-site variations, thereby controlling for unobservable site-level factors that are constant over time but may influence tracking intensity.

While site fixed effects in equation (1.3) allow for interpreting the coefficient on *Suspect* compared to the site's average tracking intensity, I directly examine changes in trackers for parsimony in equation (1.4) and control for other higher-order fixed effects.

$$Ab\_trackers_{i,t} = \beta_1 Suspect_{i,t} + \sum EM\_proxies_{i,t} + \sum Controls_{i,t} + Site\_FE + Year\_FE + \epsilon_{i,t} \tag{1.3}$$

$$\Delta Trackers_{i,t} = \beta_1 Suspect_{i,t} + \sum EM\_proxies_{i,t} + \sum Controls_{i,t} + FEs + \epsilon_{i,t} \tag{1.4}$$

where *Suspect* equals 1 for firms that just exceed the previous year's earnings and 0 otherwise. *EM_proxies* include conventional earnings management proxies, constructed such that higher values indicate greater earnings management. To account for firm characteristics that potentially affect both online tracking and the extent of changes in earnings, I control for the natural logarithm of total assets (*Size*), debt divided by beginning total assets (*Lev*), sales divided by beginning total assets (*Turnover*), capital expenditures divided by beginning total assets (*CAPEX*), and whether the site has a foreign top-level domain (*Site_foreign*).[35] A positive β_1 in equation (1.3) would indicate a positive association between meeting or barely beating a target and unusually high third-party tracking, supporting the hypothesis that firms engage in unusually high third-party tracking to avoid earnings decreases. Similarly, a positive β_1 in equation (1.4) suggests a positive association between suspect firms and an increased use of third-party trackers.

1.4.4 Model specifications: Cost considerations

This section examines two cross-sectional variations in the costs of overlooking consumer digital privacy: (1) the materiality of consumer privacy as a sustainability risk and (2) board committee privacy oversight. To explore the mitigating effect of materiality considerations,

[35] It is difficult to list all possible top-level domains as they could vary by country. Thus, I code a site as foreign if its top-level domain is other than .us, .com, or .org.

I estimate the OLS regression below.[36]

$$\begin{aligned} Ab\_trackers_{i,t} = {} & \beta_0 Suspect_{i,t} + \beta_1 Suspect_{i,t} \times SASB\_material_{i,t} \\ & + \sum EM\_proxies_{i,t} + \sum Controls_{i,t} + FEs + \epsilon_{i,t} \end{aligned} \tag{1.5}$$

where *SASB_material* equals one if the SASB deems customer privacy a material sustainability risk for the sector in which the firm operates, and zero otherwise. A negative β_1 supports hypothesis H2a that consumer privacy, when constituted as a material sustainability risk to the firm's cash flow, mitigates the tendency to engage in abnormal tracking to avoid missing earnings benchmarks.

To test the mitigating effect of the board committee's privacy oversight, I estimate the following OLS regression:

$$\begin{aligned} Ab\_trackers_{i,t} = {} & \beta_0 Suspect_{i,t} + \beta_1 Suspect_{i,t} \times Board\_privacy_{i,t} \\ & + \beta_2 Board\_privacy_{i,t} + \sum EM\_proxies_{i,t} + \sum Controls_{i,t} + FEs + \epsilon_{i,t} \end{aligned} \tag{1.6}$$

where *Board_privacy* equals one if a board committee is responsible for overseeing consumer privacy, as indicated in the DEF14A proxy statement, and zero otherwise. A negative β_1 supports the hypothesis (H2b) that board committee privacy oversight mitigates firms' tendency to overlook consumer privacy to sustain earnings growth.

[36] Since *SASB_material* does not vary within site/firm, it is absorbed by the site/firm fixed effects and, therefore, not separately identified.

1.5 Empirical Results

1.5.1 Descriptive statistics

Panel A of Table 1.1 presents the distribution of site categories within the sample, following the site categorization in Karaj et al. (2018). Of these sites, 42.69 percent belong to the business-related category, 14.41 percent are classified as e-commerce, and 17.87 percent are related to entertainment. News and portal sites have the highest average number of third-party trackers at 18.7, followed by entertainment sites at 8.96, and recreation sites at 8.4. Reference sites have the lowest average number of third-party trackers at 2.91. Trackers related to owned products (e.g., retailers driving traffic to their own online sales) are often prevalent on e-commerce and business sites. In contrast, trackers related to others' products are most commonly used on news and portal sites, which rely heavily on advertising revenue by selling ad space to various advertisers.

Panel B of Table 1.1 shows the distribution of the SICS industries by the SASB at the firm level. Internet Media & Services (33.74 percent), Software & IT Services (29.45 percent), and E-commerce (14.41 percent) emerge as the top three SICS industries. The SICS classification allows for the determination of whether customer privacy is material to the firm. Among the eight SICS industries in the sample, consumer privacy is considered material in four (E-commerce, Internet Media & Services, Software & IT Services, and Telecommunication Services). The media and entertainment industry has the most third-party trackers, averaging 16.98, followed by multi-line and specialty retailers and distributors at 13.02.

Panel C of Table 1.1 presents the distribution of the sample years. In 2018, the first year of the sample, the average number of trackers is the lowest. Panel D of Table 1.1 shows the distribution of board committees responsible for overseeing consumer digital privacy. Among the 61 percent of the sample with a board committee designated for privacy oversight, 76.77 percent are overseen by the audit committee, 13.94 percent by the risk and regulatory committee, 5.95 percent by the privacy committee, 1.06 percent by the technology or security committee, and 2.28 percent by others.

(Insert Table 1.1 about here)

Panel A of Table 1.2 provides summary statistics for site-level variables. I winsorize all continuous variables at the top and bottom one percent. The final sample consists of 2,401 site-year observations across 834 unique firm-years. The average number of trackers is 7.54. By construction, the mean number of abnormal trackers ($Ab\_trackers$) is 0. The median site has a $Site\_foreign$ value of 0, indicating a non-foreign TLD.

Panel B of Table 1.2 provides summary statistics for firm-level variables. Approximately half of the observations come from firms in SICS industries where consumer privacy constitutes a material sustainability risk ($SASB\_privacy$). The median firm size ($Size$), calculated as the logarithm of total assets, is 9.87, indicating that the median firm has total assets of approximately \$19 billion. Moreover, the median firm exhibits a leverage (Lev) of around 66 percent, a sales turnover ratio ($Turnover$) of approximately 66 percent, and capital expenditure ($CAPEX$) of around 3 percent of beginning total assets. Additionally, 61 percent of the firms in the sample have a board committee responsible for overseeing consumer privacy ($Board\_privacy$).

Panel C of Table 1.2 presents the summary statistics for the conventional EM proxies. The median firm exhibits levels of abnormal changes in working capital accruals (Ab_wc_chg) and abnormal operating cash flows (Ab_ocf) similar to the sample mean. However, the median firm shows higher levels of discretionary accruals (Ab_tacc) and overproduction (Ab_prod), but lower levels of discretionary expense (Ab_disexp) compared to the sample mean.

(Insert Table 1.2 about here)

Table 1.3 presents the Pearson correlations between abnormal tracking ($Ab\_trackers$) and the other variables. The correlations reveal that $Ab\_trackers$ is negatively and significantly correlated with abnormal accruals (Ab_tacc), abnormal operating cash flows (Ab_ocf), size (*Size*), capital expenditures (*CAPEX*), foreign domain (*Site_foreign*), and board committee privacy oversight (*Board_privacy*). Conversely, *Ab_trackers* is positively and significantly correlated with abnormal discretionary expense (*Ab_disexp*), leverage (*Lev*), and turnover (*Turnover*). These correlations suggest that, in terms of firm characteristics, smaller firms, firms with lower capital expenditures, leveraged firms, high-turnover firms, and firms without board committee privacy oversight exhibit higher levels of abnormal tracking. Moreover, the correlation matrix provides preliminary evidence that abnormal online tracking may be used as a substitute when conventional EM channels are limited, except for abnormal discretionary expenses EM, which can be complemented by consumer online tracking.

(Insert Table 1.3 about here)

1.5.2 The validity and characteristics of the abnormal tracking measure

Before testing the main predictions, I test the validity and characteristics of the main abnormal tracking measure (*Ab_trackers*). First, I examine whether heightened consumer privacy regulations are associated with less abnormal tracking (*Ab_trackers*). To achieve this, I implement a difference-in-differences design using the California Consumer Privacy Act (CCPA) as an exogenous shock. The CCPA, the first comprehensive consumer privacy state law in the US, came into effect in January 2020. *Treat* equals 1 for U.S. firms (*Site_foreign* equals 0) and 0 for Canadian sites (with TLD ending in .ca). *Post* equals 1 for the years 2020 and 2021, and 0 for the years 2018 and 2019.[37] I then estimate the following OLS regression:

$$Ab\_trackers_{i,t} = \beta_1 Treat_{i,t} + \beta_2 Post_{i,t} + \beta_3 Treat_{i,t} \times Post_{i,t} + \sum Controls_{i,t} + FEs + \epsilon_{i,t} \tag{1.7}$$

[37] I do not include sites with European TLDs because those sites have already been subject to the influential GDPR since 2018, and my sample is post-GDPR.

Columns (1) and (2) of Table 1.4 present the difference-in-differences results for $Ab\_trackers$. The coefficient on $Treat \times Post$ is significantly negative, indicating that after the CCPA came into effect, $Ab\_trackers$ of U.S. sites dropped significantly compared to Canadian sites, both with and without controls. The results support the validity of the main variable, $Ab\_trackers$.[38]

Second, I examine the characteristics of abnormal tracking ($Ab\_trackers$), focusing on its relation with conventional EM methods by estimating the following OLS regression:

$$Ab\_trackers_{i,t} = EM\_proxy_{i,t} + \sum Controls_{i,t} + FEs + \epsilon_{i,t} \tag{1.8}$$

Following Ham et al. (2017), I analyze five commonly used EM proxies: the absolute value of discretionary accruals (Ab_tacc) from the modified Jones (1991) model, modified by Dechow et al. (1995) and Kothari et al. (2005); the abnormal change in working capital accruals (Ab_wc_chg) proposed by Dechow and Dichev (2002) and modified by McNichols (2002); and three real earnings management proxies from Roychowdhury (2006), including abnormal discretionary expenses (Ab_disexp), abnormal cash flows from operations (Ab_ocf), and abnormal production costs (Ab_prod).

Columns (3)-(7) of Table 1.4 present the relation between $Ab\_trackers$ and the five conventional EM proxies. Abnormal tracking ($Ab\_trackers$) is negatively associated with total accruals (Ab_tacc), abnormal working capital accruals (Ab_wc_chg), and overproduction (Ab_prod). The findings are reasonable in the digital-based new economy, where the relevance of production may diminish for firms operating within service-oriented models. Similarly, firms with straightforward revenue recognition processes may have minimal accruals.

Interestingly, abnormal tracking is positively and significantly associated with discretionary expenses (Ab_disexp), implying that intensified tracking complements discretionary expenses. Specifically, when firms exhibit abnormal cuts in discretionary spending, they

[38] The variables $Treat$ and $Post$ are absorbed by the site fixed effects and are therefore not identified.

tend to become more aggressive in their consumer digital privacy practices to enhance the effectiveness of their existing advertising, R&D, and SG&A expenditures.

(Insert Table 1.4 about here)

1.5.3 Consumer digital privacy and earnings benchmarks

Table 1.5 presents the relation between suspect firms and abnormal third-party tracking (H1) by estimating equations (1.3) and (1.4). Columns (1) and (2) of Table 1.5 present the results with abnormal trackers ($Ab\_trackers$) as the dependent variable and include site-level fixed effects to examine within-site variations. The significantly positive coefficient on *Suspect* indicates that suspect firms exhibit significantly higher abnormal tracking intensity within their domains, even after controlling for existing accrual-based and real activity-based EM channels. This finding implies that abnormal online tracking is more than a proxy for conventional EM practices.

Column (3) presents the results using changes in trackers ($\Delta Trackers$) as the dependent variable. The significantly positive coefficient on *Suspect* indicates that suspect firms increase the number of trackers relative to non-suspect firms. Regarding economic significance, column (2) of Table 1.5 shows that suspect firm years are associated with 1.48 more abnormal trackers than non-suspect firm years. In column (3), which directly examines the change in trackers, suspect firm years are associated with a 1.57 increase in trackers. The change in trackers represents approximately 20 percent of the mean tracker usage of 7.54, as reported in the summary statistics.

(Insert Table 1.5 about here)

1.5.4 Cost considerations: Materiality

Table 1.6 presents the results on whether firms' tendency to engage in abnormal tracking to meet earnings benchmarks is mitigated when consumer privacy constitutes a material sustainability risk. Materiality considerations encompass both the direct and indirect costs associated with abnormal tracking. The coefficients on the interaction term between *Suspect* and *SASB_material* in columns (1) and (2) are significantly negative.[39] The results are consistent with the hypothesis that firms in industries where consumer privacy poses a material risk to current and future cash flows are significantly less likely to compromise privacy in order to avoid missing earnings benchmarks. This finding remains statistically significant in column (3), where $\Delta Trackers$ is the dependent variable. The coefficient on *Suspect* $\times$ *SASB_material* in column (2) demonstrates the economic significance of the findings, indicating that suspect firms with customer privacy as a material sustainability risk are associated with approximately 78 percent lower abnormal tracking than other suspect firms.

(Insert Table 1.6 about here)

1.5.5 Cost considerations: Board committee privacy oversight

Table 1.7 presents the results of estimating the mitigating impact of board committee oversight on firms' tendency to overlook consumer privacy to avoid missing benchmarks. The coefficients on the interaction term *Suspect* $\times$ *Board_privacy* in columns (1) and (2) are both significantly negative. The results are consistent with the hypothesis that firms with a board committee responsible for consumer privacy are significantly less likely to compromise digital privacy under earnings pressure. This result is also statistically significant in column (3) when $\Delta Trackers$ is examined as the dependent variable.

The findings in Table 1.7 are economically significant, as indicated by the coefficient on *Suspect* $\times$ *Board_privacy* in column (2), which suggests that suspect firms with board committee privacy oversight are associated with approximately 76 percent lower abnormal tracking than suspect firms without committee oversight. Given that the sample period is post-GDPR, the results build on the findings of Klein et al. (2022) by demonstrating that

[39] The indicator for materiality does not vary over time; thus, *SASB_material* is absorbed by the site/firm fixed effects and is therefore not reported.

U.S. firms not only alter their board compositions in response to GDPR, but also enhance their data governance practices through the oversight of board committees. Moreover, these findings challenge the notion that intensive tracking is the best practice, as firms' own data governance mechanisms reduce such behavior.

(Insert Table 1.7 about here)

1.5.6 Test of mechanisms

I examine whether abnormal tracking enables firms to reach earnings benchmarks via two mechanisms: (1) boosting site popularity ($Popular$) via an expanded advertising network with personalized content, and (2) increasing the effectiveness of discretionary expenses ($Disc\_effective$). Columns (1) and (2) of Table 1.8 present the results of testing whether increased site popularity serves as a mechanism through which suspect firms meet benchmarks through abnormal tracking. The coefficients on the interaction term $Suspect \times Popular$ in both columns are significantly positive. These findings suggest that the associations between $Suspect$ and $Ab\_trackers$, as well as between $Suspect$ and $\Delta Trackers$, are stronger when the suspect firm achieves high site popularity.

Columns (3) and (4) of Table 1.8 present the results of examining whether increased discretionary expense effectiveness serves as a mechanism by which suspect firms meet earnings benchmarks through abnormal tracking. The coefficients on the interaction term $Suspect \times Disc\_effective$ in both columns are positive and significant, supporting the notion that the relation between earnings benchmarks and abnormal tracking is more pronounced when a suspect firm exhibits highly effective discretionary spending. Taken together, the mechanisms in Table 1.8 illustrate the benefits of abnormally aggressive consumer digital privacy practices, which enable firms to extract additional value from existing customers at the expense of their privacy.

(Insert Table 1.8 about here)

1.5.7 Additional tests: Analysts forecasts as an alternative benchmark

This section re-examines the main hypothesis by using consensus analyst annual EPS forecasts as an alternative earnings benchmark. Following Caskey and Ozel (2017), I define $Suspect\_ibes$ as firms that exceed the average analyst forecast by two cents or less. I include annual forecasts issued within 90 days prior to the earnings announcement. Columns (1) and (2) in Table 1.9 indicate that firms narrowly beating analyst forecasts ($Suspect\_ibes$) engage in significantly higher levels of third-party tracking within their domains. This finding holds in column (3), which further controls for conventional EM channels.

Compared to the main finding in Table 1.5, the economic magnitude is about half when analyst forecasts are used as benchmarks rather than the prior year's earnings. One possible reason is that prior-year earnings serve as a static and thus more easily beatable benchmark, reflecting historical data that remains unchanged after reporting. By contrast, analyst forecasts provide a more dynamic benchmark, updating based on new information or changing market conditions. Another possibility is that trackers are stickier than analyst forecasts.[40]

(Insert Table 1.9 about here)

1.5.8 Robustness tests

Table 1.10 presents the results of replicating the main findings using alternative methods to identify suspect firms and abnormal trackers. Columns (1) to (3) replicate the findings using net sales as an alternative deflator for earnings changes to identify suspect firms. This approach generates an alternative group of suspect firms ($Suspect\_sale$) that fall within the interval [0, 0.0025). In column (1), suspect firm-years ($Suspect\_sale$) exhibit significantly

[40]The results are insignificant in untabulated analyses that use the consensus quarterly EPS forecast as the earnings benchmark. This may stem from the use of annual data for trackers, collected each July. For example, analysts have forecasted a calendar year company's Q3 and Q4 earnings after the July collection of tracker data. To the extent that analyst forecasts reflect their estimates of tracking activity, there should be no relation between Q3 and Q4 earnings surprises and the July tracker usage.

higher levels of abnormal tracking (*Ab_trackers*) compared to non-suspect firm-years. The coefficient on the interaction term $SASB\_material \times Suspect\_sale$ in column (2) replicates the finding that the relation between suspect firms and *Ab_trackers* is significantly less pronounced when consumer privacy constitutes a material sustainability risk (*SASB_material*). The coefficient on the interaction term $Board\_privacy \times Suspect\_sale$ in column (3) suggests that suspect firms with a board committee responsible for consumer privacy oversight (*Board_privacy*) are significantly less likely to overlook digital privacy to meet earnings benchmarks.

(Insert Table 1.10 about here)

1.6 Conclusion

This study examines whether earnings benchmarks influence firms' aggressiveness toward consumer digital privacy, holding the conventional accrual-based and real activities-based earnings management channels constant. I find that firms that just beat annual earnings benchmarks exhibit abnormally high levels of third-party tracking within their domains compared to other firms, even after controlling for traditional EM methods. Additionally, online tracking intensifies when traditional earnings management channels are less feasible.

The study validates two mechanisms through which firms at risk of missing benchmarks benefit from abnormal tracking: (1) increasing site visits through expanded advertising networks and personalized ads, and (2) enhancing the effectiveness of discretionary expenses. The main finding is less pronounced for firms in industries where consumer privacy is a material sustainability risk (as per the SASB classification) and for those with a board committee overseeing consumer privacy (based on their proxy statement disclosures).

Overall, this study broadens our understanding of how firms react to earnings benchmarks in an increasingly important yet often hidden digital space, as well as how EM strategies evolve over time, impacting a wide range of stakeholders through the Internet.

1.7 Appendix A: Variable Definitions

Variable	Description
Trackers	The average number of third-party trackers per page load within the website. The third-party tracking data is from Whotracks.me.
Ab_trackers	The abnormal level of third-party tracking, calculated as the deviation from the mean within the SICS industry, site category, and year.
Suspect	Equal to one if changes in earnings deflated by the beginning-of-the-year total assets fall within the range [0,0.0025), the interval used by Burgstahler and Dichev (1997), and zero otherwise.
SASB_material	Equal to one if customer privacy is considered material for the sector in which the firm operates, and zero otherwise (SASB).
Board_privacy	Equal to one if a board committee is explicitly responsible for overseeing consumer privacy (DEF14A), and zero otherwise.
Size	The natural logarithm of the total assets at the beginning of the year.
Lev	Total liabilities divided by the beginning of the year total assets.
Turnover	Net sales divided by the beginning of the year total assets.
CAPEX	Capital expenditures divided by the beginning of the year total assets.
Site_foreign	Equal to one if the top-level domain of the site is not ".us, .com, or .org," and zero otherwise.
Popular	The site's popularity categorized into high, medium, and low each year.
Disc_effective	Sales per SG&A categorized into high, medium, and low each year.
Ab_tacc	The absolute value of discretionary accruals from the modified Jones (1991) model, refined by Dechow et al. (1995) and Kothari et al. (2005).
Ab_wc_chg	Abnormal change in working capital accruals proposed by Dechow and Dichev (2002), as modified by McNichols (2002).
Ab_prod	Abnormal production costs proposed by Roychowdhury (2006).
Ab_disexp	Abnormal discretionary expenses from Roychowdhury (2006) multiplied by negative one to ensure higher values indicate higher EM.
Ab_ocf	Abnormal cash flows from operations from Roychowdhury (2006) multiplied by negative one to ensure higher values indicate higher EM.
Suspect_ibes	Equal to one if firms exceed the mean analyst forecast by two cents or less within 90 days before the earnings announcement; zero otherwise.

1.8 Appendix B: Examples of third-party trackers

The following code snippets provide examples of Google Analytics and Google AdSense.

```
***Google Analytics***
<script async src="https://www.googletagmanager.com/gtag/js?
id=G-R7G2******"></script>
<script>
  window.dataLayer = window.dataLayer || [];
  function gtag(){dataLayer.push(arguments);}
  gtag('js', new Date());
  gtag('config', 'G-R7G2******');
</script>


***Google AdSense***
<script async src="https://pagead2.googlesyndication.com/pagead/js
/adsbygoogle.js?
client=ca-pub-4556732768******"
     crossorigin="anonymous"></script>
<!-- ad2 -->
<ins class="adsbygoogle"
     style="display:block"
     data-ad-client="ca-pub-4556732768******"
     data-ad-slot="4570******"
     data-ad-format="auto"
     data-full-width-responsive="true"></ins>
<script>
     (adsbygoogle = window.adsbygoogle || []).push({}); </script>
```

Tables

Table 1.1: Sample Composition

Panel A. Site Category		Freq.	Percent	Trackers
Business		1,025	42.69	7.2
E-Commerce		346	14.41	6.91
Entertainment		429	17.87	8.96
News and Portals		122	5.08	18.70
Recreation		166	6.91	8.40
Reference		313	13.04	2.91
Panel B. SICS industry	**Materiality**	**Freq.**	**Percent**	**Trackers**
E-Commerce	Y	346	14.41	6.91
Hardware	N	73	3.04	6.05
Internet Media & Services	N	810	33.74	5.49
Media & Entertainment	Y	238	9.91	16.98
Multiline and Specialty Retailers & Distributors	N	118	4.91	13.02
Professional & Commercial Services	N	64	2.67	8.00
Software & IT Services	Y	707	29.45	6.32
Telecommunication Services	Y	45	1.87	7.96
Panel C. Year distribution		**Freq.**	**Percent**	**Trackers**
2018		159	6.62	6.34
2019		489	20.37	8.33
2020		564	23.49	7.66
2021		587	24.45	6.84
2022		602	25.07	7.93
Panel D. Board committees for privacy oversight			**Freq.**	**Percent**
Audit Committee			942	76.77
Risk / Regulatory Committee			171	13.94
Privacy Committee			73	5.95
Technology / Security Committee			13	1.06
Others			28	2.28

Table 1.2: Summary Statistics

Panel A. Site-level variables	N	mean	sd	p10	p25	p50	p75	p90
Trackers	2401	7.54	5.61	2.05	3.16	5.95	10.13	15.43
Ab_trackers	2401	0.00	4.14	-4.36	-2.75	-0.77	2.04	5.63
Site_foreign	2401	0.32	0.47	0.00	0.00	0.00	1.00	1.00
Panel B. Firm-level variables								
SASB_material	2401	0.56	0.50	0.00	0.00	1.00	1.00	1.00
Suspect	2401	0.01	0.11	0.00	0.00	0.00	0.00	0.00
Size	2401	9.90	2.12	7.05	8.24	9.87	12.13	12.67
Lev	2401	0.70	0.37	0.31	0.41	0.66	0.88	1.10
Turnover	2401	0.81	0.57	0.34	0.47	0.66	0.86	1.49
CAPEX	2401	0.04	0.04	0.01	0.01	0.03	0.07	0.10
Board_privacy	2021	0.61	0.49	0.00	0.00	1.00	1.00	1.00
Panel C. Conventional EM proxies								
Ab_tacc	2310	0.01	0.12	-0.11	-0.04	0.02	0.07	0.14
Ab_wc_chg	2260	-0.01	0.05	-0.06	-0.03	-0.01	0.01	0.04
Ab_prod	2214	-0.10	0.15	-0.29	-0.18	-0.09	-0.03	0.06
Ab_ocf	2394	0.17	0.16	-0.02	0.06	0.17	0.28	0.37
Ab_disexp	2351	-0.06	0.35	-0.39	-0.33	-0.12	0.10	0.35

Table 1.3: Correlation Matrix

Correlations significant at the 10 percent level are in bold.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Ab_trackers (1)	1.00												
Ab_tacc (2)	**-0.04**	1.00											
Ab_wc_chg (3)	0.01	**0.44**	1.00										
Ab_prod (4)	-0.02	**0.15**	**0.10**	1.00									
Ab_ocf(5)	**-0.07**	0.00	**-0.17**	**-0.37**	1.00								
Ab_disexp (6)	**0.14**	**-0.49**	**-0.16**	**-0.43**	**-0.23**	1.00							
Size (7)	**-0.26**	**0.24**	0.03	**0.16**	**0.24**	**-0.51**	1.00						
Lev (8)	**0.08**	**-0.35**	**-0.20**	**-0.16**	**-0.10**	**0.38**	**-0.33**	1.00					
Turnover (9)	**0.05**	**-0.23**	**-0.14**	**-0.07**	**0.13**	**0.31**	**-0.16**	**0.38**	1.00				
CAPEX (10)	**-0.10**	0.00	**-0.12**	**-0.10**	**0.34**	-0.02	**0.46**	**-0.04**	**0.35**	1.00			
Site_foreign (11)	**-0.19**	-0.03	-0.02	-0.02	**0.13**	**-0.04**	**0.30**	**-0.20**	-0.02	**0.26**	1.00		
Board_privacy (12)	**-0.16**	0.00	**-0.11**	**-0.16**	**0.36**	**-0.13**	**0.47**	**-0.18**	-0.03	**0.35**	**0.35**	1.00	
SASB_material (13)	0.00	**-0.12**	**-0.13**	**0.08**	**-0.12**	**0.08**	**-0.10**	**0.27**	**-0.07**	**-0.11**	**-0.21**	**-0.11**	1.00

Table 1.4: The validity and characteristics of abnormal tracker (*Ab_trackers*)

Table 1.4 reports the results of validity and characteristic tests for abnormal trackers (*Ab_trackers*).Columns (1) and (2) present the results of the difference-in-differences test, using the CCPA as an exogenous shock. Treat equals one for U.S. firms and zero for Canadian sites. Post equals one for the years 2020 and 2021, and zero for the years 2018 and 2019. Columns (3) through (7) examine the relation between *Ab_trackers* and other conventional EM proxies. t-statistics are reported in parenthesis. Appendix A provides variable definitions. Two-tailed significance levels are denoted by: *** 1 percent, ** 5 percent, and * 10 percent.

	Regulatory shock		Relation with traditional EM channels				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Ab_trackers	Ab_trackers	Ab_trackers	Ab_trackers	Ab_trackers	Ab_trackers	Ab_trackers
Treat × Post	-1.663**	-1.528**					
	(-2.23)	(-2.05)					
Ab_tacc			-0.022				
			(-0.04)				
Ab_wc_chg				-1.773			
				(-1.59)			
Ab_prod					-1.593**		
					(-2.08)		
Ab_ocf						0.330	
						(0.60)	
Ab_disexp							1.083***
							(3.22)
Constant	1.412***	5.184	2.724	2.127	-0.060	2.995	1.075
	(3.00)	(1.34)	(1.00)	(0.77)	(-0.02)	(1.20)	(0.43)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,247	1,247	2,286	2,233	2,183	2,384	2,340
R-squared	0.828	0.829	0.805	0.805	0.812	0.808	0.812
Fixed effects	Site&Year	Site&Year	Site&Year	Site&Year	Site&Year	Site&Year	Site&Year

Table 1.5: The relation between consumer digital privacy and earnings benchmarks

Table 1.5 reports the results of examining the relation between consumer digital privacy and earnings benchmarks. Columns (1) and (2) present the results using *Ab_trackers* as the dependent variable, while Column (3) presents the result using $\Delta Trackers$ as the dependent variable. t-statistics are reported in parenthesis. Appendix A provides variable definitions. Cat. denotes website category. Two-tailed significance levels are denoted by: *** 1 percent, ** 5 percent, and * 10 percent.

	(1)	(2)	(3)
VARIABLES	Ab_trackers	Ab_trackers	$\Delta Trackers$
Suspect	1.420***	1.483***	1.570***
	(3.26)	(3.54)	(2.70)
Size	-0.298	0.176	-0.544
	(-1.29)	(0.68)	(-1.13)
Lev	0.117	0.719**	-0.466
	(0.45)	(2.20)	(-0.85)
Turnover	-0.609*	-0.770**	0.222
	(-1.92)	(-1.99)	(0.35)
CAPEX	7.707**	6.100*	-4.256
	(2.47)	(1.92)	(-0.76)
Site_foreign			0.011
			(0.05)
Ab_wc_chg		-0.693	-2.328
		(-0.64)	(-1.41)
Ab_disexp		0.809**	-0.604
		(2.24)	(-1.02)
Ab_prod		-1.995**	-3.674***
		(-2.55)	(-2.74)
Constant	3.008	-2.255	5.226
	(1.22)	(-0.81)	(1.00)
Observations	2,393	2,099	1,659
R-squared	0.810	0.819	0.190
Fixed effects	Site&Year	Site&Year	Firm&Cat.&Year

Table 1.6: Cost considerations: SASB materiality

Table 1.6 presents the mitigating effects of materiality on abnormal tracking in suspect firm-years. Columns (1) and (2) present the results with *Ab_trackers* as the dependent variable, while Column (3) presents the results with $\Delta Trackers$ as the dependent variable. t-statistics are reported in parenthesis. Appendix A provides variable definitions. Cat. denotes website category. Two-tailed significance levels are denoted by: *** 1 percent, ** 5 percent, and * 10 percent.

VARIABLES	(1) Ab_trackers	(2) Ab_trackers	(3) $\Delta Trackers$
Suspect × SASB_material	-2.497***	-2.525***	-3.657***
	(-2.62)	(-2.80)	(-2.89)
Suspect	3.218***	3.238***	4.125***
	(3.99)	(4.30)	(3.90)
SASB_material	-	-	-
Size		0.231	-0.412
		(0.89)	(-0.85)
Lev		0.758**	-0.364
		(2.32)	(-0.67)
Turnover		-0.792**	0.186
		(-2.05)	(0.30)
CAPEX		5.862*	-4.850
		(1.85)	(-0.87)
Site_foreign			0.011
			(0.05)
Ab_wc_chg		-0.704	-2.284
		(-0.65)	(-1.39)
Ab_disexp		0.891**	-0.443
		(2.47)	(-0.74)
Ab_prod		-1.906**	-3.553***
		(-2.44)	(-2.65)
Constant	-0.011	-2.788	3.900
	(-0.25)	(-1.00)	(0.75)
Observations	2,393	2,099	1,659
R-squared	0.809	0.820	0.195
Fixed effects	Site&Year	Site&Year	Firm&Cat.&Year

Table 1.7: Cost considerations: Board committee privacy oversight

Table 1.7 documents the mitigating impacts of board committee privacy oversight on abnormal tracking in suspect firm-years. Columns (1) and (2) present the results with *Ab_trackers* as the dependent variable, while Column (3) presents the results with $\Delta Trackers$ as the dependent variable. t-statistics are reported in parenthesis. Appendix A provides variable definitions. Cat. denotes website category. Two-tailed significance levels are denoted by: *** 1 percent, ** 5 percent, and * 10 percent.

VARIABLES	(1) Ab_trackers	(2) Ab_trackers	(3) $\Delta Trackers$
Suspect × Board_privacy	-2.112**	-2.249**	-4.565***
	(-2.18)	(-2.48)	(-3.61)
Suspect	2.922***	2.955***	4.701***
	(3.63)	(3.95)	(4.51)
Board_privacy	0.511**	0.607**	1.254***
	(2.24)	(2.45)	(2.88)
Size		0.264	-1.221**
		(0.87)	(-2.09)
Lev		1.025**	-1.370**
		(2.55)	(-2.00)
Turnover		-0.640	1.001
		(-1.41)	(1.30)
CAPEX		6.510*	-1.751
		(1.91)	(-0.29)
Site_foreign			0.095
			(0.38)
Ab_wc_chg		-0.117	-2.317
		(-0.09)	(-1.13)
Ab_disexp		1.129**	0.056
		(2.05)	(0.07)
Ab_prod		-1.513*	-3.783**
		(-1.70)	(-2.53)
Constant	-0.451***	-3.869	11.393*
	(-3.02)	(-1.16)	(1.78)
Observations	1,981	1,810	1,440
R-squared	0.809	0.823	0.213
Fixed effects	Site&Year	Site&Year	Firm&Cat.&Year

Table 1.8: Test of mechanisms

Table 1.8 presents the results of two mechanism tests. Columns (1) and (2) examine site popularity as a mechanism by which suspect firms meet benchmarks through abnormal tracking, while Columns (3) and (4) investigate discretionary expense effectiveness as the second mechanism. t-statistics are reported in parenthesis. Appendix A provides variable definitions. Cat. denotes website category. Two-tailed significance levels are denoted by: *** 1 percent, ** 5 percent, and * 10 percent.

	(1)	(2)	(3)	(4)
VARIABLES	Ab_trackers	$\Delta Trackers$	Ab_trackers	$\Delta Trackers$
Suspect × Popular	1.401**	1.893***		
	(2.55)	(2.81)		
Popular	-0.207	0.157		
	(-1.22)	(1.22)		
Suspect × Disc_effective			1.344***	1.584**
			(2.68)	(2.27)
Disc_effective			-0.013	0.047
			(-0.08)	(0.20)
Suspect	-1.616	-2.592	-0.782	-1.096
	(-1.26)	(-1.62)	(-0.83)	(-0.84)
Size	0.186	-0.577	0.232	-0.457
	(0.72)	(-1.20)	(0.90)	(-0.95)
Lev	0.723**	-0.459	0.810**	-0.346
	(2.21)	(-0.84)	(2.46)	(-0.63)
Turnover	-0.773**	0.180	-0.788**	0.155
	(-2.01)	(0.29)	(-1.97)	(0.24)
CAPEX	6.387**	-4.209	5.803*	-4.540
	(2.01)	(-0.76)	(1.80)	(-0.80)
Site_foreign		0.188		0.011
		(0.72)		(0.05)
Ab_wc_chg	-0.772	-2.222	-0.713	-2.325
	(-0.71)	(-1.35)	(-0.66)	(-1.41)
Ab_disexp	0.810**	-0.573	0.859**	-0.490
	(2.25)	(-0.97)	(2.35)	(-0.81)
Ab_prod	-2.037***	-3.689***	-1.924**	-3.682***
	(-2.61)	(-2.75)	(-2.42)	(-2.71)
Constant	-1.964	5.208	-2.811	4.251
	(-0.70)	(1.00)	(-1.00)	(0.81)
Observations	2,099	1,659	2,099	1,659
R-squared	0.820	0.196	0.820	0.193
Fixed effects	Site&Year	Firm&Cat.&Year	Site&Year	Firm&Cat.&Year

Table 1.9: Additional Tests: Analyst forecasts as an alternative benchmark

Table 1.9 presents the results using analysts' forecasts as alternative earnings benchmarks. *Suspect_ibes* equals one for firms that exceed the average analyst forecast by two cents or less, based on forecasts issued within 90 days prior to the earnings announcement, and zero otherwise. t-statistics are reported in parenthesis. Appendix A provides variable definitions. Two-tailed significance levels are denoted by: *** 1 percent, ** 5 percent, and * 10 percent.

	(1)	(2)	(3)
VARIABLES	Ab_trackers	Ab_trackers	Ab_trackers
Suspect_ibes	0.627**	0.693**	0.555**
	(2.32)	(2.52)	(2.01)
Size		-0.049	0.177
		(-0.17)	(0.61)
Lev		0.860**	0.850**
		(2.37)	(2.24)
Turnover		-0.805**	-1.036**
		(-2.14)	(-2.47)
CAPEX		6.926**	7.114**
		(2.07)	(2.04)
Ab_wc_chg			0.450
			(0.40)
Ab_disexp			0.700*
			(1.86)
Ab_prod			-2.092**
			(-2.52)
Constant	-0.159***	0.078	-2.334
	(-3.49)	(0.03)	(-0.73)
Observations	2,039	2,039	1,906
R-squared	0.807	0.809	0.809
Fixed effects	Site&Year	Site&Year	Site&Year

Table 1.10: Robustness tests: Alternative method of identifying suspects

Table 1.10 presents an alternative method of identifying suspects and measuring abnormal tracking. Columns (1) to (3) replicate the findings by using net sales as an alternative deflator for earnings change to identify suspect firms. t-statistics are reported in parenthesis. Appendix A provides variable definitions. Cat. denotes website category. Two-tailed significance levels are denoted by: *** 1 percent, ** 5 percent, and * 10 percent.

VARIABLES	(1) Ab_trackers	(2) Ab_trackers	(3) Ab_trackers
Suspect_sale	0.917**	1.887***	2.510***
	(2.03)	(2.89)	(2.91)
SASB_material × Suspect_sale		-1.754**	
		(-2.00)	
SASB_privacy		-	
Board_privacy × Suspect_sale			-2.254**
			(-2.23)
Board_privacy			0.594**
			(2.39)
Size		0.203	0.232
		(0.78)	(0.76)
Lev		0.774**	1.005**
		(2.36)	(2.49)
Turnover		-0.871**	-0.763*
		(-2.25)	(-1.68)
CAPEX		5.877*	6.606*
		(1.85)	(1.93)
Ab_wc_chg		-0.535	0.179
		(-0.49)	(0.13)
Ab_disexp		0.942***	1.336**
		(2.60)	(2.42)
Ab_prod		-1.895**	-1.533*
		(-2.41)	(-1.72)
Constant	-0.003	-2.437	-3.387
	(-0.08)	(-0.87)	(-1.02)
Observations	2,391	2,099	1,810
R-squared	0.808	0.819	0.822
Fixed effects	Site&Year	Site&Year	Site&Year

CHAPTER 2

Do ESG-linked loans increase the credibility of ESG disclosures?[1]

2.1 Introduction

Environmental, social, and governance (ESG) disclosures have become increasingly common and are demanded by stakeholders (SASB, 2017; Christensen et al., 2021). However, these disclosures can be opaque and include unverifiable or unenforceable claims (e.g., Christensen et al., 2021; Friedman et al., 2021; Pucker, 2021), often reflecting uninformative boilerplate language or boastful "cheap talk" (e.g., Christensen et al., 2021; Bingler et al., 2024), or managers' green-washing incentives (e.g., Delmas and Burbano, 2011). This study employs a theoretical model and empirical tests to examine whether ESG-linked loans serve as mechanisms that induce credible reporting of voluntary ESG disclosures.

ESG-linked loans include margin or fee adjustments that increase or decrease contingent on the firm's agreed-upon ESG-related key performance indicators (KPIs). In 2018, CMS Energy became the first U.S. company to borrow via an ESG-linked loan.[2] According to Refinitiv, in 2021, global ESG-linked loan proceeds increased by more than 300 percent to a record $717 billion. Based on Reuters's global corporate net debt statistics, this amount constitutes approximately 8.8% of the 2021 global debt market. Importantly, the contracts

[1] This is a co-authored work with Judson Caskey (UCLA).

[2] Available at:
https://www.3blmedia.com/news/cms-energy-becomes-first-us-company-enter-sustainability-linked-loan

typically utilize KPIs from the borrower's publicly disclosed ESG reports (see example in Appendix A). By tying ESG disclosures to loan provisions, ESG-linked loans increase the cost of misreporting through both the additional liability for misreporting and the multi-year nature of the contract. Misreporting contract-relevant KPIs in ESG reports can constitute a breach of lending agreements. For example, Occidental Petroleum's ESG-linked contract explicitly requires firms to notify banks of events beyond reasonable control that (a) prevented, hindered, or delayed, or (b) assisted in fulfilling its KPI Metric. Occidental Petroleum is also required to notify banks of changes in methodologies calculating the KPI metrics that will lead to a more than 5% change in reported emissions.[3] Moreover, ESG-linked loans are usually multi-year, general-purpose syndicated loans, with some explicitly specifying escalating ESG targets for each year. This multi-year structure encourages cautious reporting of ESG performance, as firms remain under future scrutiny and still fail to meet future targets if they overstate current achievements (see example in Appendix A).[4]

We develop our predictions using a model based on Kartik (2009), who introduces misreporting costs to Crawford and Sobel's (1982) cheap talk framework. We add a voluntary disclosure choice to the model, and examine the impact of misreporting costs. In the model, firms' disclosure choices reflect a trade-off between the benefits of being perceived as high types and the costs of misreporting. As in Kartik (2009), if lower-type firms disclose, they are more likely to issue exaggerated but fully revealing reports ('separation'), while high types crowd at the top ('pool'), all claiming to be the best type and possibly using more informative cheap talk messages to distinguish themselves. We predict that increases in misreporting costs will weakly decrease whether firms disclose, and strictly increase the information provided by firms that do disclose.

To test our model's predictions on separation and pooling, we create a panel dataset of

[3] Occidental Petroleum's ESG-linked contract

[4] Appendix A shows that the ESG-linked loan contract for American Electric Power Company, Inc. in 2021 has an escalating target for non-emitting generation capacity from 32.8% in 2021 to 45.3% in 2025.

firms' standalone ESG reports and construct four disclosure credibility measures. We measure the degree of separation by the percentage of qualified good news and forthcoming bad news, and we measure the degree of pooling using the percentage of specific commitments and informative cheap talk. We first validate these measures by demonstrating positive and statistically significant correlations within the two separation measures (i.e., qualifying good news and forthcoming bad news) and the two pooling measures (i.e., cheap talk informativeness and specific commitment). Next, we use a staggered difference-in-differences method to examine changes in ESG disclosure credibility around the time ESG-linked loans are initiated.[5]

Our tests provide evidence supporting the predictions that misreporting costs increase the separation of low-type reports. Specifically, firms are more likely to qualify good ESG performance and be forthcoming with bad ESG performance after securing ESG-linked loans. Moreover, we find some, though weaker, evidence that misreporting costs enhance the informativeness of high-type reports. Specifically, firms are more likely to provide detailed information about commitments. Additionally, we find that ESG-related media coverage increases after firms issue ESG-linked loans, consistent with the loans enhancing the perceived credibility of firms' ESG disclosures to external parties.

We provide evidence that contractual reference to KPIs, by itself, increases misreporting costs. In particular, there is no relation between our credibility metrics and the requirement of third-party certification, the magnitude of maximum margin adjustments, or the number of KPIs. These results are consistent with ESG-linked loan contracts increasing misreporting costs, rather than the strictness of contract terms, which are often minor.[6]

We contribute to the theoretical disclosure literature by extending Kartik (2009) to include voluntary disclosure settings and showing how Einhorn and Ziv's (2012) results extend

[5] Our robustness test shows that the results are also robust to stacked difference-in-difference design.

[6] Our examination of ESG-linked contracts shows that the average range of margin adjustment, calculated as the absolute value of the potential rate increase (penalty) plus the rate decrease (incentives), is around 5 basis points (bps).

to a setting with cheap talk. Consistent with our prediction that low-type firms withhold disclosure, Matsumura et al. (2014) find evidence that the market penalizes firms that do not disclose emissions. Our empirical tests support the model's prediction that misreporting costs induce more revealing reports and more informative cheap talk if firms disclose. We expect that our model can also be applied to other disclosure questions where firms face both a disclosure choice, and the potential of 'crowding' at the boundary of plausible reports, which generates cheap talk.

This study also adds to the empirical literature on disclosures, particularly ESG disclosures, by providing evidence that ESG-linked loans serve as a mechanism to mitigate the tendency to overstate ESG performance. In addition, we directly examine changes in the disclosure credibility of a panel dataset of 657 standalone ESG reports by leveraging Generative AI techniques. In the context of firms' financial disclosures, evidence indicates that bad news is inherently more credible than good news (Jennings, 1987; Sansing, 1992), and that firms voluntarily disclose bad news and report accounting mistakes to reduce litigation risk (e.g., Skinner, 1994; Donelson et al., 2012). In the ESG setting, given that firms tend to overstate their ESG performance (Lyon and Montgomery, 2015), we construct ESG disclosure credibility measures that take into account underlying variations in good and bad ESG news.

We also contribute to the ESG financing literature. Prior studies have examined how borrowers' ESG performance affects loan spreads or the inclusion of environmental covenants (e.g., Goss and Roberts, 2011; Choy et al., 2024), and how lenders' ESG ratings relate to their lending decisions (Basu et al., 2022) or borrowers' subsequent ESG performance (e.g., Houston and Shan, 2022). More specifically, emerging studies on ESG-linked loans have examined the determinants of ESG-linked loan issuance (e.g., Kim et al., 2022; Aleszczyk et al., 2022; Du et al., 2023), the announcement period return (Kim et al., 2022), the determinants of contractual terms (e.g., Carrizosa and Ghosh, 2023; Aleszczyk et al., 2022), and the impact on borrowers' sustainability performance or ESG risk (e.g., Kim et al., 2022;

Carrizosa and Ghosh, 2023; Aleszczyk et al., 2022; Du et al., 2023; Dursun-de Neef et al., 2023). In contrast to these studies, we examine whether and how ESG-linked loans affect the credibility of firms' voluntary ESG disclosures. Additionally, we provide theory-based predictions and directly analyze changes in the disclosure of good ESG news, bad ESG news, and ESG cheap talk using a staggered difference-in-differences approach.

The paper proceeds as follows. Section 2.2 develops our theoretical model and empirical predictions. Section 2.3 describes the data research design. Section 2.4 presents empirical results. Section 2.5 concludes.

2.2 Model and predictions

We develop our hypotheses using a variation on Kartik's (2009) uniform distribution example, where we also consider voluntary disclosure. A firm with type t, uniformly distributed over $[0,1]$, sends a (possibly null) message m to a receiver who then takes some action a. With probability p, the firm observes its type *a la* Dye (1985) and Jung and Kwon (1988). The firm and the receiver have the following objective functions where $\tau(m)$ is the type effectively claimed when sending message m, 1_d denotes an indicator function for disclosure, and c_d denotes a disclosure cost *a la* Verrecchia (1983). If the firm does not observe its type, it can send only the null message ($m = \varnothing$).

$$\underbrace{\max_m ba - (a-t)^2 - 1_d \left(k\left(\tau(m) - t\right)^2 + c_d\right)}_{\text{Firm/Sender}}, \quad \underbrace{\max_a -\mathrm{E}\left[(a-t)^2 \,|m\right]}_{\text{Receiver}}, \tag{2.1}$$

The parameter $b \geq 0$ reflects the firm's preference for being viewed as a high type, regardless of the Receiver's preferences. The parameter k indexes the cost of falsely asserting a type. The receiver's action is $a = \mathrm{E}[t|m]$.

The type can be viewed as 'good', which in our context means low emissions, high community engagement, and so on. Because the true and asserted types $t, \tau(m) \in [0,1]$, they can be viewed as reflecting percentiles. Similarly, the action $a = \mathrm{E}[t|m] \in (0,1)$ can be viewed as the receiver's inference about the firm's percentile. An assertion $\tau(m) = 1$ can be viewed as a claim such as "our firm leads the industry" and an action $a = 1$ can be viewed as "we believe that the firm is the best in the industry." The bias parameter b indirectly indexes the range of possible types. For example, if t were uniformly distributed over $[0, T]$, we obtain the same objective functions as (2.1) except that c_d is scaled by T^2, b is scaled by T, and k is not affected by scale.

We focus on a low-separate/high-pool (LSHP) equilibrium as in Kartik (2009), which has the following form:

Definition 1 (Kartik, 2009)**.** *If an* LSHP equilibrium *exists, there are types* $0 \leq \hat{t} \leq \underline{t} \leq 1$ *such that:*

(a) Types $t < \hat{t}$ *do not disclose.*

(b) Types $t \in [\hat{t}, \underline{t})$ *issue a fully revealing message* $\rho(t) \geq t$ *where* $\rho(t)$ *solves the differential equation* $\rho'(t) = \frac{b}{2k(\rho(t)-t)}$ *with the boundary condition* $\rho(\hat{t}) = \hat{t}$.

(c) Types $t \geq \underline{t}$ *claim to by type* 1 *and issue a partially revealing message equivalent to* $t \in [t_n, t_{n+1})$ *where* $t_0 = \underline{t}$, $t_N = 1$, *and* $t_n = 1 - \left(\frac{1-\underline{t}}{N} + bn\right)(N-n)$.

If some types issue fully revealing reports, then the lowest disclosing type $\hat{t}$ issues a truthful report so that the disclosure threshold with misreporting is the same as with truthful reporting. Einhorn and Ziv (2012) find a similar result in the context of unbounded, normally distributed payoffs. Following Mailath (1987), their fully-revealing reporting function satisfies their version of the differential equation in Definition 1(b).

2.2.1 Equilibrium

We conjecture an equilibrium where informed types above some $\hat{t}$ disclose, and neither firms with $t < \hat{t}$ nor uninformed firms disclose. If the equilibrium is such that some types issue fully revealing signals, the lowest disclosing type reports truthfully. Accordingly, the lowest disclosing type faces the following indifference condition:

$$\underbrace{b\mathrm{E}\left[t|m=\varnothing\right]-\left(\mathrm{E}\left[t|m=\varnothing\right]-\hat{t}\right)^2}_{\text{Payoff to withhold}}=\underbrace{b\hat{t}-c_d}_{\text{Payoff to disclose}}, \tag{2.2}$$

where $\mathrm{E}\left[t|m=\varnothing\right]$ denotes the expected value of t given nondisclosure:

$$\mathrm{E}\left[t\right]\frac{\overbrace{1-p}^{\mathrm{P(Uninformed)}}}{\underbrace{1-p+p\mathrm{P}\left(t<\hat{t}\right)}_{\mathrm{P}(m=\varnothing)}}+\mathrm{E}\left[t|t<\hat{t}\right]\frac{\overbrace{p\mathrm{P}\left(t<\hat{t}\right)}^{\mathrm{P}(\text{Informed},t<\hat{t})}}{1-p+p\mathrm{P}\left(t<\hat{t}\right)}=\frac{1}{2}\frac{1-p\left(1-\hat{t}^2\right)}{1-p\left(1-\hat{t}\right)}. \tag{2.3}$$

The indifference condition (2.2) is solved by:

$$\mathrm{E}\left[\hat{t}-t|m=\varnothing\right]=\sqrt{\left(\tfrac{b}{2}\right)^2+c_d}-\tfrac{b}{2}\quad\Rightarrow\quad\hat{t}=\frac{\sqrt{1-p+p^2\hat{x}^2}-(1-p)}{p}+\hat{x}, \tag{2.4}$$

where $\hat{x}=\sqrt{\left(\frac{b}{2}\right)^2+c_d}-\frac{b}{2}$. A solution with $\hat{t}\geq 0$ requires that $\hat{x}\geq -\frac{1}{2}$, which always holds because $\hat{x}\geq 0$. A solution with $\hat{t}\leq 1$ requires that $\hat{x}\leq\frac{1}{2}$ or, equivalently $c_d\leq\frac{1+2b}{4}$. If $c_d>\frac{1+2b}{4}$, then no types report if that entails revealing their type t. The threshold $\hat{t}$ decreases in p from $\frac{1}{2}+\hat{x}$ at $p=0$ to $2\hat{x}$ at $p=1$. It increases in $\hat{x}$ from $\frac{\sqrt{1-p}-(1-p)}{p}$ at $\hat{x}=0$, to $\mathrm{E}[t]=\frac{1}{2}$ at $\hat{x}=\frac{1}{4}\frac{p}{2-p}$, to 1 at $\hat{x}=\frac{1}{2}$. The term $\hat{x}$ increases (decreases) with c_d (b) so that $\hat{t}$ increases (decreases) with c_d (b).

Given the threshold $\hat{t}$ defined by (2.4), firms in the 'low separate' portion of the LSHP equilibrium have fully revealing reports given in Definition 1(b), which have the form:

$$\rho(t) = t + \tfrac{b}{2k}\left(1 + \omega\left(-\mathrm{e}^{-\left(1+2k\left(t-\hat{t}\right)/b\right)}\right)\right), \tag{2.5}$$

where $\omega(\cdot)$ denotes the Lambert-W function.

For the 'high pool' portion of the LSHP equilibrium, first define the type $\bar{t} = 1 - \tfrac{b}{2k}\left(1 - \mathrm{e}^{-2k\left(1-\hat{t}\right)/b}\right)$ by $\rho(\bar{t}) = 1$, where $\hat{t} \leq \bar{t} \leq 1$. In a LSHP equilibrium, there is a type $\underline{t} \leq \bar{t}$ such that types $t \in [\hat{t}, \underline{t})$ issue the exaggerated, but fully revealing report $\rho(t)$, and types $t \geq \underline{t}$ claim to by type 1 and issue a message that conveys a partition as in Crawford and Sobel's (1982) uniform example. The partitions are of the form given in Definition 1(c), and are such that type $t = t_n$ is indifferent between reporting the $[t_{n-1}, t_n)$ or $[t_n, t_{n+1})$ partitions, and satisfy the boundary conditions $t_N = 1$ and $t_0 = \underline{t}$.

The threshold $\underline{t}$ is determined by the indifference condition:

$$\underbrace{b\mathrm{E}\left[t|t \in (\underline{t}, t_1)\right] - \left(\mathrm{E}\left[t|t \in (\underline{t}, t_1)\right] - \underline{t}\right)^2 - \left(k\left(1-\underline{t}\right)^2 + c_d\right)}_{\text{Payoff to claim 1 and message } t\in(\underline{t},t_1)}$$

$$= \underbrace{b\underline{t} - \left(k\left(\rho\left(\underline{t}\right) - \underline{t}\right)^2 + c_d\right)}_{\text{Payoff to reveal } t=\underline{t}}, \tag{2.6}$$

which is equivalent to solving $f\left(\underline{t}, \hat{t}\right) = 0$ where:

$$f\left(\underline{t}, \hat{t}\right) = \mathrm{E}\left[t - \underline{t}|t \in (\underline{t}, t_1)\right]\left(b - \mathrm{E}\left[t - \underline{t}|t \in (\underline{t}, t_1)\right]\right) - k\left(1 - \rho\left(\underline{t}\right)\right)\left(1 + \rho\left(\underline{t}\right) - 2\underline{t}\right), \tag{2.7}$$

where $\hat{t}$ affects $\rho(\underline{t})$. The function $f(\underline{t}, \hat{t}) > 0$ if and only if the payoff to pooling exceeds the payoff to separation.

We can now present the equilibrium.

Proposition 1. *Firms' disclosure behavior depends on the disclosure cost c_d and misreporting cost k as follows:*

(a) *If the disclosure cost* $c_d > \frac{1+2b}{4}$, *there is no equilibrium where firms disclose.*

(b) *If* $c_d < \frac{1+2b}{4}$ *and the misreporting penalty* k *exceeds the threshold* $\hat{k}$ *that sets* $f\left(\hat{t}, \hat{t}\right) \leq 0$, *then there is a unique LSHP equilibrium where the disclosure threshold* $\hat{t}$ *is given by* (2.4), *the lowest pooling type* $\underline{t}$ *is given by the unique solution to* $f(\underline{t}, \hat{t}) = 0$, *and the number of partitions is* $N(\underline{t}) = \left\lceil \frac{1}{2}\left(\sqrt{1 + 4\frac{1-t}{b}} - 1\right) \right\rceil$.[7]

(c) *If* $c_d < \frac{1+2b}{4}$ *and the misreporting penalty* $k < \hat{k}$, *then there is an equilibrium where types* $\hat{t}_c > \hat{t}$ *claim to be type and* 1 *and issue cheap talk reports, and types* $t < \hat{t}_c$ *disclose nothing.*

Fully revealing disclosure depends on high misreporting costs, note that the separating region ($\hat{t} < t < \underline{t}$) reflects signal jamming. Even though firms exaggerate and incur costs for doing so, they gain no benefit because the receiver can perfectly infer their types. A high misreporting cost reduces the amount of exaggeration, and results in an overall reduction in the cost of disclosure.

2.2.2 Empirical predictions

We derive our empirical predictions from the comparative statics in the model. Our objects of interest are (i) the probability of disclosure, and (ii) the posterior variance given disclosure. We use the posterior variance as a representation of the information available to stakeholders.[8]

Corollary 1.1. *The proportion of firms disclosing is increasing in the probability of being informed. Specifically, both* $\hat{t}_c$ *and* $\hat{t}$ *are decreasing in* p. *The proportion of firms disclosing is weakly decreasing in the misreporting cost. Specifically,* $\hat{t}_c$ *increases in* k *and* $\hat{t}$ *does not vary*

[7] The expression $\lceil z \rceil$ denotes the smallest integer greater than or equal to z.

[8] In this paper, we focus on testing (ii) because most firms already have standalone ESG reports ready to be approved for ESG-linked loans.

with k. When some firms partially separate, the proportion of firms issuing fully revealing reports is increasing in the misreporting cost (i.e., $\underline{t}$ is increasing in k).

Figure 2.1 illustrates the effect of the misreporting cost k. When misreporting costs are small, firms issue only cheap talk reports. As k increases, it eventually becomes possible for some firms to issue fully revealing reports, although they continue to exaggerate their type. As in Kartik (2009), there is 'bunching' at the top with a pool of firms claiming to the be the highest type 1. The likelihood of disclosing increases with the probability p of being informed, as in Dye (1985) and Jung and Kwon (1988). As p increases, the curves in Figure 2.1 shift downward.

(Insert Figure 2.1 about here)

Note that once the misreporting cost k exceeds $\hat{k}$, further increases in k have no impact on the number of firms disclosing – it only affects what firms disclose. In other words, increasing the credibility of ESG disclosures via audits and enforcement does not entice additional firms to disclose. It would require some sort of mandate, such as a nondisclosure penalty, to increase the number of firms that provide ESG information.

Based on our model, we hypothesize that firms with ESG-linked loans (hereafter 'ESG-linked firms') are more likely to issue revealing reports (i.e., partially separate). We empirically capture the degree of revealing by examining firms' likelihood to qualify good ESG news and be more forthcoming with bad ESG news. Specifically, the terms of ESG-linked loans increase the cost of misreporting by making it a contract violation in addition to a reporting violation. Additionally, the multi-year nature of syndicated ESG-linked contracts increases the cost of misreporting and induces more cautious reporting about the future, as firms' ESG disclosures are examined over consecutive years, not just once. However, our hypothesis is not without tension. If banks issue ESG-linked loans mainly for window dressing purposes or banks have low incentives to enforce the credibility of borrowers' ESG disclosures, we will not find any significant results. This leads to our first hypothesis:

Hypothesis 1. *ESG-linked loans increase the credibility of firm's voluntary ESG disclosures. Specifically:*

(a) Firms are more likely to qualify good ESG news after the inception of ESG-linked loans.

(b) Firms are more forthcoming with bad ESG news after the inception of ESG-linked loans.

(c) Firms provide more specific commitments after the inception of ESG-linked loans.

(d) Firms provide more informative cheap talk after the inception of ESG-linked loans.

Since the firm's ESG disclosures may subject to higher misreporting costs for the KPIs specifically referenced in their loan agreements, we conjecture that the strictness of contractual clauses will have an incremental impact. Nonetheless, if the contractual clauses are too minor to make an impact, we will not find any significant results. We then form our second hypothesis below:

Hypothesis 2. *The contractual clauses of ESG-linked loans have incremental impact on firm's credibility of ESG disclosures. Specifically,*

(a) The relation between ESG-linked loans and ESG disclosure credibility is more pronounced for ESG-linked contracts involving third-party verification.

(b) The relation between ESG-linked loans and ESG disclosure credibility is more pronounced for ESG-linked contracts with higher range of margin adjustments.

(c) The relation between ESG-linked loans and ESG disclosure credibility is more pronounced for ESG-linked contracts with more KPIs.

It is clear from Figure 2.1 that our model predicts that higher misreporting costs increase the credibility of disclosures. Specifically, the range of types covered by each cheap talk message becomes narrower as k increases, and more firms issue fully revealing reports.

The following corollary formally states this in terms of the expected posterior variance, conditional on disclosure $\mathrm{E}[\mathrm{var}(t|m); m \neq \varnothing]$.

Corollary 1.2. *The expected posterior uncertainty conditional on a report,* $\mathrm{E}\left[\mathrm{var}\left(t|m\right); m \neq \varnothing\right]$*, is decreasing in the misreporting cost* k*.*

Our empirical tests use ESG-related media coverage as a proxy for the perceived credibility of ESG disclosures. We conjecture that the media seeks to relay credible information, suggesting that a company with more credible ESG disclosures will receive more ESG-related media coverage. This leads to our third hypothesis below:

Hypothesis 3. *The inception of ESG-linked loans leads to an increase in ESG-related media coverage.*

We conclude this section with the effect of an exogenous change in the disclosure threshold.

Corollary 1.3. *The fully revealing report* $\rho(t)$ *is decreasing in the disclosure threshold* $\hat{t}$*, and the thresholds for the cheap talk reports (*$\underline{t}$ *and* $t_n, n \in \{1, \ldots, N\}$*) are increasing in the disclosure threshold* $\hat{t}$ *or* $\hat{t}_c$*.*

Corollary 1.3 is relevant for predicting the impact of an ESG reporting mandate. A mandate is equivalent to reducing the disclosure threshold $\hat{t}$ to zero. We predict that, absent an accompanying increase in misreporting penalties, a mandate will increase the exaggeration in fully revealing reports ($\rho(t) - t$), increase the amount of cheap talk (lower $\underline{t}$), and reduce the informativeness of cheap talk reports (lower cheap talk partition boundaries t_n). In other words, a reporting mandate will hamper the communications of firms that already disclose ESG news, unless the mandate is accompanied by an increase in misreporting penalties.

2.3 Data and test design

2.3.1 Data

We use keyword searches to identify ESG-linked credit agreements in Electronic Data Gathering, Analysis, and Retrieval (EDGAR) from 2018 to 2021.[9] The sample period starts in 2018, when CMS Energy became the first US company to enter into an ESG-linked loan contract. This procedure yields 105 unique firms, for which we hand-collect the contractual clauses, including KPIs, maximum margin adjustments, and any third-party certification requirements. We then retain firms that have standalone ESG reports and non-missing values in Compustat and Refinitiv's Asset4 ESG score for the year they entered into ESG-linked loan contracts, resulting in 95 unique ESG-linked firms. Next, we use propensity scores to match each ESG-linked firm to the nearest non-ESG-linked firm within the same 2-digit SIC code, based on their ESG score (*ESG_score*), firm size (*Size*), leverage (*Lev*), and profitability (*ROA*) at the beginning of 2018.[10] If the matched firm does not have a standalone ESG report, we search for the next nearest neighbor recursively until we obtain 95 matched control firms for each of the 95 ESG-linked firms.[11] The final sample includes a total of 190 unique firms.

To facilitate our statistical inferences, we construct a panel dataset of ESG reports for each of the 190 unique firms during the fiscal years 2018-2021. The ESG reports are downloaded from either ResponsibilityReports.com or the firms' websites.[12] The final panel

[9] We search Forms 8-K, 10-Q, and 10-K filings for the following keywords: Sustainability Adjustment, Sustainability Agent, Sustainability Structuring Agent, Sustainability Coordinator, Sustainability Metric, Sustainability Pricing, and Sustainability Rating. We then manually identify the ESG-linked loan contracts.

[10] To prevent our ESG-linked firm sample size from shrinking, if a firm's ESG score for the year is missing, we use the most recent available score.

[11] 92.63% of matched firms are the nearest neighbor to the ESG-linked firm, and the remaining matches are the second-nearest neighbor.

[12] Since ResponsibilityReports.com does not provide the actual release dates of ESG reports, we rely on its automatically generated labels. We assume that the ESG report labeled Ticker_year by Responsi-

dataset consists of 657 reports, totaling 39,021 pages of non-missing ESG disclosures. Our sample construction allows us to make inferences based on a staggered difference-in-difference setting with pure controls as benchmarks.[13]

2.3.2 Measures of ESG disclosures- Separation

We use Generative AI techniques to classify the credibility of the ESG disclosures in our panel dataset. Following Eloundou et al. (2023) and Eisfeldt et al. (2023), we construct rubric languages and prompts for API calls to GPT. We make 8 predictions for each page— $Qualify\_good$, $Report\_good$, $Anticipate\_bad$, $Report\_bad$, $Cheaptalk$, $Cheap\_inform$, $Commit$, and $Specific$, resulting in a total of 312,168 predictions. For each prediction, we record a brief reasoning and the certainty level—high, medium, or low. We only identify predictions with high certainty for parsimony. Details of the prompts and rubrics are in Appendix D.[14]

This study hypothesizes that ESG-linked firms report more cautiously due to higher misreporting costs and the multi-year nature of syndicated loans. Therefore, we develop two measures of firms revealing adverse ESG news ("separation"). The first measure, *Qualify_good*, identifies firms that qualify good ESG performance by attributing it to non-self-initiated factors that mechanically boost ESG performance or by cautioning readers about a one-time or temporary boost. For example, the International Energy Agency (IEA) reports that COVID-19 led to a reduction in global CO_2 emissions of approximately 2 billion tons.[15]

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bilityReports.com, when downloaded, is published in year+1, and thus the disclosure decision is made in year+1. This rationale is based on an article from the Harvard Law School Forum on Corporate Governance, which shows June of the following year as the most popular month for issuing ESG reports. Available at: https://corpgov.law.harvard.edu/2021/11/02/the-state-of-u-s-sustainability-reporting/.

[13] As mentioned in Clarke and Tapia-Schythe (2021) (documentation of Stata eventdd package), pure controls in a staggered difference-in-difference setting are assigned a value of 0 for all leads and lags relative to the treatment, thereby serving as the counterfactual for the estimation.

[14] We use the API of OpenAI GPT-4o model via Microsoft Azure for the analysis.

[15] We provide additional examples of adverse ESG news in Appendix E.

However, the *Qualify_good* measure faces a common challenge in accounting research: distinguishing between underlying fundamentals (i.e., actual ESG performance) and disclosure credibility (i.e., whether firms credibly disclose such performance). To mitigate this concern, we use a percentage measure, *Qualify_good_prc*, which scales the number of *Qualify_good* by 1 plus the number of reported good news (*Report_good*) for each firm-year, as described below:

$$Qualify\_good\_prc = \frac{\#Qualify\_good}{1 + \#Report\_good}. \tag{2.8}$$

The second measure of separation, *Anticipate_Bad*, identifies firms that explicitly anticipate having poor ESG-related performance in the future with some certainty, and this anticipation is not attributed to external factors. For example, JetBlue's 2021 ESG report indicates that "we are expecting some increase in emissions per ASM..." and Cabot Corp's 2019 ESG report mentioned that "we anticipate increased waste generation from the air pollution controls being installed." We then use the percentage measure *Anticipate_bad_prc*, which scales the number of *Anticipate_Bad* by 1 plus the number of reported bad news (*Report_bad*) for each firm-year, as described below:

$$Anticipate\_bad\_prc = \frac{\#Anticipate\_bad}{1 + \#Report\_bad}. \tag{2.9}$$

2.3.3 Measures of ESG disclosures- Pooling

Our model predicts that firms with high ESG performance will issue more informative reports while pooling at the top. We use two measures to assess the informativeness of such reports. The first measure is based on Bingler et al. (2024), which defines cheap talk as non-specific commitment. As such, the informativeness of pooling in our paper is calculated as the number of specific commitments over the 1 plus the number of commitment-type disclosures as shown below.

$$Commit\_specific\_prc = \frac{\#Commit \cap Specific}{1 + \#Commit}. \tag{2.10}$$

The second measure, *Cheap_inform* gauges the extent to which the report provides comparative context with industry peers, making the cheap talk more evaluable (see Appendix E for examples). Specifically, we calculate *Cheap_inform_prc* as the number of *Cheap_inform* over the 1 plus the number of cheaptalk-type disclosures as shown below.

$$Cheap\_inform\_prc = \frac{Cheap\_inform}{1 + \#Cheaptalk}. \tag{2.11}$$

2.3.4 Regression model

We test our main predictions regarding the relation between ESG-linked loans and ESG disclosure credibility (Hypothesis 1) using a staggered difference-in-difference design. We examine the degree of revealing disclosures (i.e., separation) using the following regressions.[16]

$$Qualify\_Good\_prc = \beta_0 + \beta_1 ESG\_Linked + \boldsymbol{\beta}'\text{Controls} + e, \tag{2.12}$$

$$Anticipate\_Bad\_prc = \beta_0 + \beta_1 ESG\_Linked + \boldsymbol{\beta}'\text{Controls} + e, \tag{2.13}$$

Where *Qualify_Good_prc* indicates the percentage of good news qualified by the firm— either attributing good ESG performance to external factors or cautioning readers about temporarily high ESG performance. *Anticipate_Bad_prc* indicates how forthcoming the firm is in disclosing future bad news. The variable of interest is the difference-in-difference estimator, *ESG_Linked*, which equals 1 for ESG disclosures made after the inception of ESG-linked loans. A positive coefficient on *ESG_linked* (β_1) implies that ESG-linked loans increase the credibility of the firm's ESG disclosures. *Controls* include variables related to firm characteristics, such as *Size*, *Leverage*, *Profitability*, and fixed effects.

[16]Since the dependent variable is bounded between 0 and 1, we estimate the effect using a fractional logit model. To avoid the incidental variable problem that may bias the results, we also include an estimation using an ordinary least squares (OLS) regression as a robustness check.

Next, we examine the informativeness of pooling using the following regressions.

$$Commit\_specific\_prc = \beta_0 + \beta_1 ESG\_linked + \boldsymbol{\beta}'\text{Controls} + e, \tag{2.14}$$

$$Cheap\_inform\_prc = \beta_0 + \beta_1 ESG\_linked + \boldsymbol{\beta}'\text{Controls} + e, \tag{2.15}$$

Where *Commit_specific_prc* indicates the percentage of specific commitments over all disclosed commitments. *Cheap_inform_prc* denotes the portion of "cheap talk" that provides comparative context with peers, making the claim more evaluable.

To examine the incremental impact of contractual clauses on a firm's ESG disclosure (Hypothesis 2), we conduct the following regressions.[17]

$$Qualify\_good\_prc = \beta_0 + \beta_1 ESG\_linkedxContract\_clauses + \boldsymbol{\beta}'\text{Controls} + e, \tag{2.16}$$

$$Anticipate\_bad\_prc = \beta_0 + \beta_1 ESG\_linkedxContract\_clauses + \boldsymbol{\beta}'\text{Controls} + e, \tag{2.17}$$

$$Commit\_specific\_prc = \beta_0 + \beta_1 ESG\_linkedxContract\_clauses + \boldsymbol{\beta}'\text{Controls} + e, \tag{2.18}$$

$$Cheap\_inform\_prc = \beta_0 + \beta_1 ESG\_linkedxContract\_clauses + \boldsymbol{\beta}'\text{Controls} + e, \tag{2.19}$$

Where *Contract_clauses* include whether the ESG-linked contract stipulates third-party KPI verification (*External_verify*) (e.g., KPI metrics auditor, external reviewer, green building certificates), the magnitude of margin adjustment (*Swing*), and the number of KPIs (*KPI_num*). Significant coefficients on the interaction term (β_1) will support the notion that ESG-linked contractual clauses affect the credibility of a firm's ESG disclosures.

Finally, we examine whether the adoption of ESG-linked loans induce subsequent changes

[17] The single term *Contract_clauses* is subsumed because it holds the same value as *ESG_linked* x *Contract_clauses*. The main reason is that the contractual clauses only apply after the firm has obtained an ESG-linked loan.

in ESG-related media coverage (Hypothesis 3). We estimate the following OLS regression:

$$ESG\_news = \beta_0 + \beta_1 ESG\_linked + \boldsymbol{\beta}'\text{Controls} + e, \tag{2.20}$$

ESG_News is the number of ESG-related news from Factiva that include "ESG" or "Sustainability" in the headline. We use Factiva Free-Text Search and index codes to match firms to related news articles and export the corresponding news counts. We measure the news count semiannually from January 2018 to December 2021.[18] A positive coefficient on *ESG_Linked* (β_1) is consistent with the hypothesis that ESG-linked loans improve the credibility of firms' ESG disclosures and attract greater media coverage.

2.4 Empirical results

2.4.1 Covariate Balance and Pre-treatment Trends

Since this paper employs a staggered difference-in-differences approach with a propensity score-matched (PSM) control group, we need two preliminary tests before proceeding with the main analysis: (1) verify that the PSM matching achieves covariate balance, and (2) perform a diagnostic test for the parallel trends assumption. Since the parallel trend is inherently unobservable, this assumption posits that if the pre-treatment differences between the treated and control groups are not parallel, they are unlikely to be parallel post-treatment (Armstrong et al., 2022).

Table 2.1, Panel A presents the estimates of the first stage logistic regression results for propensity score matching. ESG-linked firms are positively and significantly associated with *ESG_Score* and *Size*, and they are also positively related to *Profitability.* The pseudo-R-squared for our first-stage regression is 0.293, and the area under the Receiver Operator

[18] In each semiannual period, we obtain the news count output in two batches, one searches for all ESG-linked firms' index codes, and the other searches for all PSM-matched control firms' index codes.

Characteristic (ROC) curve is 0.888.[19] In Panel B, we conduct a two-sample t-test for post-matching covariate balance. The results show that the difference between the ESG-linked group and the control group becomes insignificant in all aspects, including *Size*, *ESG_Score*, *Leverage*, and *Profitability*.

(Insert Table 2.1 about here)

Figure 2.2 presents the diagnostic parallel trends, along with the p-values of the joint test for pre-treatment significance. Visually, all four disclosure credibility measures exhibit parallel pre-treatment trends between the treated and control groups, compared to the omitted benchmark period. This is further supported by the joint test results for the pre-treatment periods, which show p-values of 0.43, 0.17, 0.41, and 0.16, respectively.

(Insert Figure 2.2 about here)

2.4.2 Summary statistics

Table 2.2 presents the composition of our final sample. Panel A shows the distribution of industries based on 2-digit SIC codes.The final sample consists of 39,021 pages of ESG disclosures from a panel dataset of 657 ESG reports, representing 190 unique tickers. The distribution of unique tickers indicates that 'Holding and Other Investment Offices,' 'Electric, Gas, and Sanitary Services,' and 'Industrial and Commercial Machinery and Computer Equipment' have the highest number of firms with ESG-linked loans. Panel B presents the cross-sectional characteristics of the 95 unique ESG-linked loan contracts. Approximately 46% of ESG-linked firms involve some third-party verification requirements. In particular, 35% of ESG-linked contracts stipulate KPI metrics auditor, KPI assurance provider, or external reviewer, and 12% involve other third-party certificates. Panel B also shows common ESG-linked KPI categories. About 85% of ESG-linked firms have ESG-linked provisions

[19] According to Hosmer Jr et al. (2013), areas between 0.7 and 0.8 are "acceptable discrimination", and areas between 0.8 and 0.9 represent "excellent discrimination".

concerning environmental subjects, and 20% concerning social issues.[20]

(Insert Table 2.2 about here)

Table 2.3 presents the descriptive statistics of the main variables in our final dataset. We winsorize all variables at the 1st and 99th percentiles. For our two measures of separation, the mean of the qualified good percentage ($Qualify\_good\_prc$) is 0.03, indicating that, on average, firms qualify 3 percent of their good ESG news. This may include instances where the surrounding text attributes this performance to non-self-initiated factors that mechanically boost ESG performance, or where the firm cautions readers about a one-time or temporary boost in its past good ESG performance. The relatively low qualification is expected, as prior studies generally find that firms have incentives to boost voluntary ESG disclosures (e.g., Christensen et al., 2021; Bingler et al., 2024; Delmas and Burbano, 2011). The mean for the forthcoming bad news percentage ($Anticipate\_bad\_prc$) is about 13 percent. This includes anticipating poor ESG-related performance in the future with some certainty.

Our first measure of pooling, specific commitment percentage ($Commit\_specific\_prc$), has a mean of 0.85. This indicates that, on the one hand, firms in our sample provide specific information—such as clear details on past or future events, verifiable goals and how they are tracked, and detailed plans of action for 85 percent of their ESG commitment disclosures. On the other hand, our second measure of pooling, the percentage of cheap talk informativeness ($Cheap\_inform\_prc$), has a lower mean of 0.01. This indicates that, on average, firms provide comparative context with industry peers, making the cheap talk more evaluable, for around 1 percent of their ESG disclosures. In terms of ESG-linked clauses, the 90th percentile of firm-years in our panel data has a maximum margin adjustment ($Swing$) of 8 bps (maximum penalty plus maximum reduction), 2 KPIs in the contracts, and is required to seek external ESG verification. The median firm has about \$13 billion in total assets ($Size$), a profitability ($Profitability$) of 0.03, and a leverage ratio ($Leverage$) of 0.61.

[20]The ESG-linked KPI category classification is based on the sustainability-linked loan principle published in March 2022. The numbers do not add up to 100% since a firm may have multiple KPIs that span different categories.

(Insert Table 2.3 about here)

Table 2.4 shows pairwise Pearson correlations. To examine the validity of our four ESG disclosure credibility measures, we first show that our two separation measures, $Qualify\_good\_prc$ and $Anticipate\_bad\_prc$, are positively and significantly correlated. Similarly, our two pooling measures, $Cheap\_inform\_prc$ and $Commit\_specific\_prc$, are also positively and significantly correlated. Additionally, firm-years after initiating ESG-linked loans (ESG_linked) are positively correlated with all four ESG disclosure credibility measures. These positive correlations are expected and align with our main hypotheses.

(Insert Table 2.4 about here)

2.4.3 The Relation Between ESG-Linked Loans and the Credibility of ESG Disclosures

Table 2.5 reports the effect of ESG-linked loans on firms' qualification of good ESG performance under a staggered difference-in-difference setting. Column (1) shows the Poisson regression where the dependent variable is the number of qualifications of good news ($Qualify\_good$). After entering ESG-linked loan contracts, firms exhibit more instances of qualifying good ESG news. However, an important assumption when comparing the number of qualified good news is to ensure that firms have a homogeneous amount of ESG-related good news to begin with. To address this concern, we scaled $Qualify\_good$ by the number of good news to calculate the percentage of good news qualification ($Qualify\_good\_prc$). Column (2) shows, under a fractional logistic regression, that firms increase the percentage of qualification of good news after entering ESG-linked loans.[21] To mitigate concerns about the incidental parameter problem associated with logistic regression when combined with firm fixed effects, Columns (3) and (4) present the results of running the same regression using

[21] We acknowledge the potential concern of incidental parameter bias in logistic regression with panel fixed effects, as discussed in Papke and Wooldridge (1996), particularly in panels with a limited number of time periods.

OLS, with and without controls.[22] The results are consistent with those of the fractional logistic regression.

(Insert Table 2.5 about here)

Table 2.6 reports the effects of ESG-linked loans on firms being forthcoming with bad ESG news. Column (1) presents the results from the Poisson regression where the dependent variable is the number of anticipations of bad ESG news (*Anticipate_bad*). The results in Column (1) show that after entering ESG-linked loan contracts, firms have more instances of forthcoming bad ESG news. Similar to the qualification of good ESG news, we scaled *Anticipate_bad* by the number of bad news instances to account for the fact that firms have heterogeneous amounts of bad ESG news to begin with. Columns (2) and (3) of the OLS regression show that firms increase the percentage of forthcoming bad news (*Anticipate_bad_prc*) after entering ESG-linked loans.

(Insert Table 2.6 about here)

Collectively, Table 2.5 and Table 2.6 are consistent with the hypothesis that ESG-linked loans induce revealing disclosures of ESG performance due to higher misreporting costs and the likelihood of being uncovered during the multi-year contract period. The economic significance in Table 2.5 is small, at around 1.5 percent, due to the inherently low occurrence of voluntary good news disclosures. Nonetheless, the results in Table 2.6 indicate that ESG-linked loans increase the percentage of forthcoming bad news by 8.3 percent.

Table 2.7 provides the regression results that estimate the effect of ESG-linked loans on our first measure of pooling, which examines the proportion of specific commitments. Column (1) shows the results from the Poisson regression where the dependent variable is the number of specific commitments ($Commit\_specific$). The results in Column (1) indicate that firms have more instances of specific commitments after entering ESG-linked loan contracts. In Column (2), we scaled $Commit\_specific$ by the total number of commitments to

[22] The number of observations is slightly smaller because the $reghdfe$ Stata command dropped singleton observations.

standardize the measure and estimated the relationship using a fractional logit regression. The results in Column (2) show that after the inception of ESG-linked loans, firms significantly increase the specificity of ESG commitments. Column (3) and (4) presents similar results using an OLS regression, with and without controls.

(Insert Table 2.7 about here)

Table 2.8 provides the regression results that estimate the effect of ESG-linked loans on our second measure of pooling, which examines the informativeness of cheap talk ($Cheap\_inform$). Column (1) shows the results from the Poisson regression where the dependent variable is the number of instances of informative cheap talk ($Cheap\_inform$). In Column (2), we scale $Cheaptalk\_inform$ by the total number of cheap talk to obtain a standardized measure $Cheaptalk\_inform\_prc$ and estimate the relation using a fractional logit regression. Neither of the results are statistically significant. Column (3) and (4) present similar results using an OLS regression. Overall, Table 2.8 provides no evidence for or against the hypothesis.

(Insert Table 2.8 about here)

The results in Table 2.7 and Table 2.8 show that while there is some evidence of more informative pooling after entering ESG-linked contracts, the results depend on how we define cheap talk and cheap talk informativeness. Overall, the findings in Table 2.5 through Table 2.8 support our hypothesis that ESG-linked loans increase misreporting costs, thereby eliciting credible ESG disclosures. This credibility manifests in various forms, including qualifying good news, revealing bad news, and providing more specific commitments.

2.4.4 The relation between ESG-linked contractual clauses and ESG disclosures

Table 2.9 presents the incremental effect of third-party verification ($External\_verify$) in ESG-linked loan contracts on ESG disclosure credibility. Columns (1) through (4) show a statistically insignificant association for the interaction term between ESG_linked and $External\_verify$ across all disclosure credibility measures. These results imply that the increase in ESG disclosure credibility following ESG-linked loans is primarily driven by the misreporting costs between the firm and the bank, rather than the effect of external third-party verification.

(Insert Table 2.9 about here)

Table 2.10 presents the incremental effects of ESG-linked margin adjustments (*Swing*) on ESG disclosures. Columns (1) through (4) show no statistically significant relationship for the interaction term between the staggered difference-in-difference indicator *ESG_linked* and the maximum margin adjustment, defined by the sum of the maximum margin increase and margin decrease (*Swing*). This is consistent with the fact that the margin adjustments in ESG-linked loan contracts are often small, with the average interest rate adjustment range being around 5 basis points (bps).

(Insert Table 2.10 about here)

Table 2.11 shows the incremental effects of the number of KPIs (KPI_num) on ESG disclosures. Similar to Table 2.9 and Table 2.10, Columns (1) through (4) in Table 11 mostly show a statistically insignificant relationship for the interaction term between the ESG-linked indicator *ESG_linked* and the number of KPIs in the contracts. In summary, Tables 2.9 through 2.11 suggest that while referencing ESG KPIs in loan contracts may influence firms' disclosure behaviors, this is not further associated with the characteristics of contractual clauses, such as the magnitudes of the margin adjustments.

(Insert Table 2.11 about here)

2.4.5 ESG linked loan and ESG news coverage

Table 2.12 presents the results of estimating the effect of entering into ESG-linked loans on subsequent ESG-related news (ESG_news) coverage from January 2018 to December 2021. Columns (1) and (2) present the OLS regression estimates of the impact of ESG-linked loans on subsequent ESG-related media coverage. On average, ESG-linked firms are associated with a subsequent increase of approximately 1.56 (3) ESG-related news articles semiannually

(annually). The results support the argument that the media either responds to firms that release more credible ESG signals to avoid erroneous reporting, or that firms engage in innovative ESG financing instruments to attract media attention. Column (3) shows the diagnostic test result on the parallel trends, using the year preceding the treatment as the benchmark period. The results indicate no significant difference in the pre-treatment period and a significant difference after the treatment.

(Insert Table 2.12 about here)

2.4.6 Alternative estimator: Stacked difference-in-difference

Recent papers have raised concerns about the staggered difference-in-differences design due to heterogeneous treatment effects occurring at different times across groups (e.g., Cengiz et al., 2019; Baker et al., 2022; Barrios, 2022). While our PSM sample alleviates these concerns, we also employ a stacked regression to re-estimate the effect of ESG-linked loans on the credibility of ESG disclosures. The stacked regression uses "clean" controls (i.e., firms that are never treated within the sample period) to create separate datasets for each cohort of treated firms, which are then stacked to form an event-specific dataset. Table 2.13 demonstrates that our primary results remain robust under this approach: firms are more likely to qualify favorable ESG news, be transparent with unfavorable ESG news, and provide more specific commitments following the initiation of ESG-linked loans.

(Insert Table 2.13 about here)

2.5 Conclusion

With ESG disclosures becoming increasingly prevalent, concerns about their credibility also arise. We develop and test an analytical model with trade-offs between the benefits of being perceived as a high type versus the costs of misreporting. We predict that ESG-linked loans increase the cost of misreporting ESG information because the loans typically reference firms' public ESG disclosures, and the syndicated contracts often span multiple years. To test our predictions, we construct four measures of disclosure credibility and utilize Generative AI techniques to examine a panel dataset of ESG reports with a total of 39,021 pages. We find that after entering ESG-linked loan contracts, firms are more likely to qualify good ESG performance or be forthcoming with bad ESG performance. Additionally, we find weak evidence that firms with ESG-linked firms are more likely to provide informative context when making cheaptalk-type disclosures. However, the contractual clauses in the ESG-linked contracts, such as the magnitudes of the ESG-linked margin adjustments or the number of KPIs, have no incremental effect on ESG disclosures. It therefore appears that firms' disclosure behavior depends on whether the loan contract is linked to ESG KPIs, rather than the extent to which the contract uses them.

We acknowledge certain research limitations. First, our sample consists of early adopters of U.S. ESG-linked loans. As these loans become more widespread, banks' ESG-linked loan granting and monitoring policies may evolve. Additionally, a portion of the sample period overlaps with the COVID-19 years, which may introduce a concurrent shock affecting firms' ESG disclosures. Lastly, two of our measures of disclosure credibility capture relatively few observations, reducing the economic significance of our findings. We encourage future research to develop improved measures for identifying good news or informative cheap talk that may better capture relevant instances.

Appendix A – Examples ESG-linked loan terms

The following are excerpts from American Electric Power Company, Inc.'s credit agreement dated March 31, 2021 with Wells Fargo Bank as the administrative agent.[23] The contract includes two ESG-related key performance indicators (KPIs): Non-Emitting Generation Capacity and the Days Away Restricted or Transferred (DART) Rate. According to the following excerpts, for each KPI, the corresponding margin adjustment is between -2.5 bps (incentive) to 2.5 bps (penalty).

- From section **2. Defined terms** in Schedule I-3:

  "Annual KPI Report" means the Annual EEI ESG/Sustainability Report For Investors in respect of the Non-Emitting Generation Capacity Percentage and the DART Rate publicly reported by the Borrower and published on an Internet or an intranet website to which each Lender, the Administrative Agent and the Sustainability Structuring Agent have been provided access.

  "Applicable DART Rate Fee Adjustment" means, with respect to any calendar year, (a) an increase of 0.50 basis points if the DART Rate for such calendar year is greater than the DART Rate Threshold for such calendar year, (b) no reduction or increase if the DART Rate for such calendar year is less than or equal to the DART Rate Threshold for such calendar year and greater than or equal to the DART Rate Target for such calendar year, and (c) a reduction of 0.50 basis points, if the DART Rate for such calendar year is less than the DART Rate Target for such calendar year.

  "Applicable DART Rate Margin Adjustment" means, with respect to any calendar year, (a) an increase of 2.50 basis points if the DART Rate for such calendar year is greater than the DART Rate Threshold for such calendar year, (b) no reduction or increase if the DART Rate for such calendar year is less than or equal to the DART Rate Threshold for such calendar year and greater than or equal to the DART Rate Target for such calendar year, and (c) a reduction of 2.50 basis points, if the DART

[23] Available from SEC EDGAR.

Rate for such calendar year is less than the DART Rate Target for such calendar year.

"Applicable Non-Emitting Generation Capacity Fee Adjustment" means, with respect to any calendar year, (a) a reduction of 0.50 basis points if the Non-Emitting Generation Capacity Percentage for such calendar year is greater than the Non-Emitting Generation Capacity Target for such calendar year, (b) no reduction or increase if the Non-Emitting Generation Capacity Percentage for such calendar year is less than or equal to the Non-Emitting Generation Capacity Target for such calendar year and greater than or equal to the Non-Emitting Generation Capacity Threshold for such calendar year, and (c) an increase of 0.50 basis points, if the Non-Emitting Generation Capacity Percentage for such calendar year is less than the Non-Emitting Generation Capacity Threshold for such calendar year.

"Applicable Non-Emitting Generation Capacity Margin Adjustment" means, with respect to any calendar year, (a) a reduction of 2.50 basis points if the Non-Emitting Generation Capacity Percentage for such calendar year is greater than the Non-Emitting Generation Capacity Target for such calendar year, (b) no reduction or increase if the Non-Emitting Generation Capacity Percentage for such calendar year is less than or equal to the Non-Emitting Generation Capacity Target for such calendar year and greater than or equal to the Non-Emitting Generation Capacity Threshold for such calendar year, and (c) an increase of 2.50 basis points, if the Non-Emitting Generation Capacity Percentage for such calendar year is less than the Non-Emitting Generation Capacity Threshold for such calendar year.

"Pricing Certificate" means a certificate signed by a financial officer of the Borrower substantially in the form of Exhibit E to the Agreement setting forth (with computations in reasonable detail in respect thereof) the KPI Metrics for the immediately preceding calendar year which shall be based on and consistent with the KPI Metrics reported in the Annual KPI Report for such year, together with the resulting KPI Adjustment to apply from the KPI Pricing Adjustment Date of the then current calendar year.

• From Exhibit A to Pricing Schedule – Sustainability Table

KPI Metrics		Annual Sustainability Targets and Thresholds					
		2021	2022	2023	2024	2025	
Non-Emitting Generation Capacity		32.8%	36.3%	38.3%	41.6%	45.3%	Non-Emitting Generation Capacity Target
		27.8%	31.3%	33.3%	36.6%	40.3%	Non-Emitting Generation Capacity Threshold
DART Rate	Baseline DART Rate	0.337	0.337	0.337	0.337	0.337	DART Rate Target
	0.374	0.412	0.412	0.412	0.412	0.412	DART Rate Threshold

Appendix B – Proofs

Proof of Proposition 1 For an equilibrium where low types separate, Part (a) follows from the discussion after expression (2.4). The later part of this proof shows that this condition is also necessary for equilibria with only cheap talk.

$$f\left(\underline{t},\hat{t}\right)=\frac{1}{4N^2}\left(\underline{t}_N-\underline{t}\right)\left(\underline{t}-\underline{t}_{N+1}\right)-k\left(1-\rho\left(\underline{t}\right)\right)\left(1+\rho\left(\underline{t}\right)-2\underline{t}\right), \tag{B1}$$

where $\underline{t}_N=1-bN\left(N-1\right)$ and the first term is weakly positive if and only if $\underline{t}\in\left(\underline{t}_{N+1},\underline{t}_N\right)$ or, equivalently, $N=\left\lceil\frac{1}{2}\left(\sqrt{1+4\frac{1-\underline{t}}{b}}-1\right)\right\rceil=N\left(\underline{t}\right)$. If $b\geq\frac{1}{2}$, then $N=1$ for all $\underline{t}$. The second term is strictly negative for $\underline{t}<\bar{t}$. Differentiating with respect to $\underline{t}$ gives $\frac{\partial f}{\partial\underline{t}}=\frac{1-\underline{t}}{2N^2}+\frac{b}{2}+2k\left(1-\rho\left(\underline{t}\right)\right)>0$. The function f is continuous at the partition switching points with:

$$\lim_{\underline{t}\nearrow\underline{t}_N}f\left(\underline{t},\hat{t};N\right)=\lim_{\underline{t}\searrow\underline{t}_N}f\left(\underline{t},\hat{t};N-1\right)=-k\left(1-\rho\left(\underline{t}_N\right)\right)\left(1+\rho\left(\underline{t}_N\right)-2\underline{t}_N\right). \tag{B2}$$

The differential equation in Definition 1(b) follows from optimizing $b\tilde{t}-\left(\tilde{t}-t\right)^2-\left(k\left(\rho\left(\tilde{t}\right)-t\right)^2+c_d\right)$ with respect to the asserted type $\tilde{t}$, and setting $\tilde{t}=t$ to reflect full revelation (Mailath, 1987; Kartik, 2009). The boundaries in Definition 1(c) follow from the condition for type t_n be indifferent between signalling (t_{n-1},t_n) versus (t_n,t_{n+1}). It is always the case that $0\leq f\left(\bar{t},\hat{t}\right)=\frac{1}{4N^2}\left(\underline{t}_N-\bar{t}\right)\left(\bar{t}-\underline{t}_{N+1}\right)$ because $N=N(\bar{t})$. If $f\left(\hat{t},\hat{t}\right)\leq 0$, then a unique solves $f(\underline{t},\hat{t})=0$. The condition $f\left(\hat{t},\hat{t}\right)=\frac{1}{4N^2}\left(\underline{t}_N-\hat{t}\right)\left(\hat{t}-\underline{t}_{N+1}\right)-k\left(1-\hat{t}\right)^2\leq 0$ holds if and only if $k>\hat{k}=\frac{1}{4N^2}\frac{\underline{t}_N-\hat{t}}{1-\hat{t}}\frac{\hat{t}-\underline{t}_{N+1}}{1-\hat{t}}\geq 0$ where $N=N\left(\hat{t}\right)$. This completes Part (b).

If no types separate, then the disclosure threshold coincides with the cheap talk threshold $\underline{t}$. In this case, denote the lowest disclosing type $\hat{t}_c$, where the c subscript denotes 'cheap talk' to distinguish it from the threshold $\hat{t}$ given by (2.4). A threshold type $\hat{t}_c$ prefers to disclose if:

$$\underbrace{b\mathrm{E}\left[t|t\in(\hat{t}_c,t_1)\right]-\left(\mathrm{E}\left[t|t\in(\hat{t}_c,t_1)\right]-\hat{t}_c\right)^2-\left(k\left(1-\hat{t}_c\right)^2+c_d\right)}_{\text{Payoff to claim 1 and message } t\in(\hat{t}_c,t_1)}$$
$$\geq \underbrace{b\mathrm{E}\left[t|m=\varnothing\right]-\mathrm{E}\left[t-\hat{t}_c|m=\varnothing\right]^2}_{\text{Payoff to withhold}}, \quad \text{(B3)}$$

After some rearranging, this can be shown to be equivalent to:

$$\underbrace{\mathrm{E}\left[\hat{t}_c-t|m=\varnothing\right]-\underbrace{\left(\sqrt{\left(\frac{b}{2}\right)^2+c_d-f_c\left(\hat{t}_c\right)}-\frac{b}{2}\right)}_{\hat{x}_c\left(\hat{t}_c\right)}}_{g\left(\hat{t}_c\right)}\geq 0, \quad \text{(B4)}$$

where $f_c(\hat{t}_c)=f\left(\hat{t}_c,\hat{t}_c\right)$. Note that $f_c(\hat{t}_c)\leq\left(\frac{b}{2}\right)^2$, which implies that $g\left(t\right)$ is always real. If $g\left(\hat{t}_c\right)>0$ for some type $\hat{t}_c$, then all types $t>\hat{t}_c$ prefer disclosure.[24] Condition (B4) has the same form as (2.4), except that the term under the square root subtracts $f_c\left(\hat{t}_c\right)$. If there is no partial separation, $f\left(\hat{t},\hat{t}\right)>0$ implies that type $\hat{t}$ strictly prefers to disclose when all disclosures are cheap talk ($g\left(\hat{t}\right)>0$).

Differentiating g gives:

$$g'\left(\hat{t}_c\right)=\frac{1}{2}\left(\frac{1-p}{\left(1-p\left(1-\hat{t}\right)\right)^2}+\frac{\hat{x}_c\left(\hat{t}_c\right)+\frac{b}{2}+f_c'\left(\hat{t}_c\right)}{\hat{x}_c\left(\hat{t}_c\right)+\frac{b}{2}}\right)>0, \quad \text{(B5)}$$

where the inequality follows because $\hat{x}_c\left(\hat{t}_c\right)+\frac{b}{2}$ and $\hat{x}_c\left(\hat{t}_c\right)+\frac{b}{2}+f_c'\left(\hat{t}_c\right)$ are both positive. Specifically, $\hat{x}_c\left(\hat{t}_c\right)+\frac{b}{2}>0$ so that $f_c'\left(\hat{t}_c\right)\geq 0$ implies that $\hat{x}_c\left(\hat{t}_c\right)+\frac{b}{2}+f_c'\left(\hat{t}_c\right)>0$. If

[24]The gross payoff $b\mathrm{E}\left[t|t\in\left(\hat{t}_{n-1},t_n\right)\right]-\left(\mathrm{E}\left[t|t\in\left(\hat{t}_{n-1},t_n\right)\right]-t\right)^2$ is weakly greater, with equality at the partition points, and the misreporting cost $k\left(1-t\right)^2$ strictly decreases in t.

$f_c'\left(\hat{t}_c\right) < 0$, then $\hat{x}_c\left(\hat{t}_c\right) + \frac{b}{2} + f_c'\left(\hat{t}_c\right) > 0$ if and only if:

$$\begin{aligned} c_d &> f_c\left(\hat{t}_c\right) + \left(f_c'\left(\hat{t}_c\right)\right)^2 - \left(\tfrac{b}{2}\right)^2 \\ &= -2k\left(1-\hat{t}_c\right)\left(\tfrac{1+4k}{2}\left(1-\hat{t}_c\right) - 2f_c'\left(\hat{t}_c\right)\right) - \tfrac{N^2-1}{N^2}\left(\tfrac{1-\hat{t}_c}{2N} - \tfrac{Nb}{2}\right)^2, \end{aligned} \tag{B6}$$

which always holds when $f_c'\left(\hat{t}_c\right) < 0$. The prior analysis establishes that $f_c\left(\hat{t}_c\right)$ is continuous at the partition switching points. Having established that g is increasing in $\hat{t}_c$ and that $g(\hat{t}) > 0$, a necessary and sufficient condition for disclosure is that $g\left(\hat{t}_c = 0\right) \leq 0$, which always holds.[25] If $\hat{t} > 1$, which holds if and only if $c_d > \frac{1+2b}{4}$, then there will be disclosure with cheap talk only if $g\left(\hat{t}_c = 1\right) > 0$, but that also holds if and only if $c_d < \frac{1+2b}{4}$, so there is no disclosure when $c_d > \frac{1+2b}{4}$. This proves Part (a) for equilibria with only cheap talk. $\square$

Proof of Corollary 1.1 The proof follows from direct computations:

$$\begin{gathered} \frac{\mathrm{d}\hat{t}_c}{\mathrm{d}p} = -\frac{\overbrace{\partial g/\partial p}^{>0}}{\underbrace{\partial g/\partial \hat{t}_c}_{>0}} < 0, \quad \frac{\mathrm{d}\hat{t}}{\mathrm{d}p} = -\frac{\overbrace{\partial \mathrm{E}\left[\hat{t}-t|m=\varnothing\right]/\partial p}^{>0}}{\underbrace{\partial \mathrm{E}\left[\hat{t}-t|m=\varnothing\right]/\partial \hat{t}}_{>0}} < 0, \\ \frac{\mathrm{d}\underline{t}}{\mathrm{d}p} = \underbrace{-\frac{\overbrace{b\omega\left(-\mathrm{e}^{-\left(1+2k\left(\underline{t}-\hat{t}\right)/b\right)}\right)}^{\frac{\partial f}{\partial \rho}\frac{\partial \rho}{\partial \hat{t}}<0}}{\underbrace{\partial f/\partial \underline{t}}_{>0}}}_{\frac{\mathrm{d}\underline{t}}{\mathrm{d}\hat{t}}>0} \underbrace{\frac{\mathrm{d}\hat{t}}{\mathrm{d}p}}_{<0} < 0 \end{gathered} \tag{B7}$$

and:

$$\frac{\mathrm{d}\hat{t}_c}{\mathrm{d}k} = -\frac{\overbrace{\partial g/k}^{<0}}{\underbrace{\partial g/\partial \hat{t}_c}_{>0}} > 0, \quad \frac{\mathrm{d}\hat{t}}{\mathrm{d}k} = 0, \quad \frac{\mathrm{d}\underline{t}}{\mathrm{d}k} = -\frac{\overbrace{\frac{\partial f}{\partial \rho}}^{>0}\overbrace{\frac{\partial \rho}{\partial k}}^{<0} + \overbrace{\frac{\partial f}{\partial k}}^{<0}}{\underbrace{\partial f/\partial \underline{t}}_{>0}} > 0. \tag{B8}$$

[25] If $b < 1$, the inequality $g(0) \leq 0$ is immediate. If $b > 1$, then $N = 1$ and the inequality $g(0) \leq 0$ can be written as $c_d + k \geq 0$.

$\square$

Proof of Corollary 1.2 The posterior variance is positive for only cheap talk reports. Given the cheap talk threshold $\tilde{t} \in \{\hat{t}_c, \underline{t}\}$, the expected posterior variance given a cheap talk report is:

$$\sum_{n=1}^{N} \underbrace{\tfrac{1}{12}\left(t_n - t_{n-1}\right)^2}_{\mathrm{var}(t|t\in(t_{n-1},t_n))} \underbrace{\tfrac{t_n - t_{n-1}}{1-\tilde{t}}}_{\mathrm{P}\left(t\in(t_{n-1},t_n)|t>\tilde{t}\right)} = \tfrac{1}{3}\left(\left(\tfrac{b}{2}\right)^2\left(N^2-1\right) + \left(\tfrac{1-\underline{t}}{2N}\right)^2\right). \tag{B9}$$

The expected posterior variance given disclosure is then:

$$\mathrm{E}\left[\mathrm{var}\left(t|m\right); m \neq \varnothing\right] = \begin{cases} \frac{1-\underline{t}}{1-\hat{t}}\frac{1}{3}\left(\left(\frac{b}{2}\right)^2\left(N^2-1\right) + \left(\frac{1-\underline{t}}{2N}\right)^2\right) & \text{if } k > \hat{k}, \\ \frac{1}{3}\left(\left(\frac{b}{2}\right)^2\left(N^2-1\right) + \left(\frac{1-\hat{t}_c}{2N}\right)^2\right) & \text{if } k < \hat{k}. \end{cases} \tag{B10}$$

Furthermore, the expected variance is continuous at the switching points in the number of partitions:

$$\begin{aligned} \lim_{\underline{t}\nearrow\underline{t}_N} \mathrm{E}\left[\mathrm{var}(t|m)|m\neq\varnothing; N\right] &= \lim_{\underline{t}\searrow\underline{t}_N} \mathrm{E}\left[\mathrm{var}(t|m)|m\neq\varnothing; N-1\right] \\ &= \begin{cases} \frac{b^3}{6\left(1-\hat{t}\right)}N^2\left(N-1\right)^2 & \text{if } k > \hat{k}, \\ \frac{b^2}{6}N\left(N-1\right) & \text{if } k < \hat{k}. \end{cases} \end{aligned} \tag{B11}$$

This gives:

$$\frac{\mathrm{d}\,\mathrm{E}\left[\mathrm{var}\left(t|m\right); m\neq\varnothing\right]}{\mathrm{d}k} = \begin{cases} \underbrace{-\frac{1}{3\left(1-\hat{t}\right)}\left(\left(\frac{b}{2}\right)^2\left(N^2-1\right) + \left(\frac{1-\underline{t}}{2N}\right)^2\right)}_{\partial\mathrm{E}[\mathrm{var}(t|m);m\neq\varnothing]/\partial\underline{t}<0} \underbrace{\frac{\mathrm{d}\underline{t}}{\mathrm{d}k}}_{>0} < 0 & \text{if } k > \hat{k}, \\ \underbrace{-\frac{2}{3}\frac{1-\hat{t}_c}{2N}}_{\mathrm{d}\,\mathrm{E}[\mathrm{var}(t|m)|m\neq\varnothing]/\mathrm{d}\hat{t}_c<0} \underbrace{\frac{\mathrm{d}\hat{t}_c}{\mathrm{d}k}}_{>0} < 0 & \text{if } k < \hat{k}. \end{cases} \tag{B12}$$

$\square$

Proof of Corollary 1.3 Direct computations give $\frac{\partial \rho(t)}{\partial \hat{t}} = \frac{\omega\left(\mathrm{e}^{-\left(1+2k(1-\hat{t})/b\right)}\right)}{1+\omega\left(\mathrm{e}^{-\left(1+2k(1-\hat{t})/b\right)}\right)} < 0$. The proof of Corollary 1.1 shows that $\underline{t}$ is increasing in $\hat{t}$ which implies that t_n is increasing in $\hat{t}$ per Definition 1(c). $\square$

Appendix C – Variable definitions

Variable	Definition
Main Independent Variables	
ESG_linked	The staggered difference-in-difference indicator equals 1 for ESG reports issued after a firm's first initiation of ESG-linked loans. We rely on automatically generated labels (Ticker_year) from ResponsibilityReports.com. Loan agreements are obtained from EDGAR.
Main Dependent Variables	
Qualify_good_prc	The percentage of good news qualified by the firm—either attributed to good ESG performance due to external factors or cautioning readers about temporarily high ESG performance. It is calculated as the number of *Qualify_good* scaled by (1 + the number of *Report_good*) for each firm-year.
Anticipate_bad_prc	The percentage of forthcoming bad ESG news—such as conveying pessimistic future ESG performance. It is calculated as the number of *Anticipate_bad* scaled by (1 + the number of *Report_bad*) for each firm-year.
Cheaptalk	The total number of unverifiable ESG-related claims that are boastful for each firm-year. The prompts and rubrics are provided in Appendix D.
Cheap_inform_prc	The percentage of comparative context around cheap talks. It is calculated as the number of *Cheap_inform* scaled by (1 + the number of *Cheaptalk*) for each firm-year.
Commit_specific_prc	The percentage of specific information when disclosing commitment. It is calculated as the number of *Commit_specific* scaled by (1 + the number of *Commit*) for each firm-year.
ESG_news	The number of ESG or sustainability-related news articles from Factiva that include "ESG" or "Sustainability" in the headline. We use Factiva Free-Text Search and index codes to match companies to related news articles and determine the corresponding news count.
Contractual clauses of ESG-linked loans	
External_verify	An indicator variable equal to 1 if the ESG-linked loan contract for the firm requires third-party KPI verification (e.g., KPI metrics auditor, external reviewer, green building certificates).
KPI_num	The total number of key performance indicators (KPIs) in the ESG-linked loan agreement for the firm.

Variable	Definition
Swing	The maximum margin adjustments in the ESG-linked loan agreement. For instance, if the firm faces a 2.5 bps decrease (incentives) for achieving ESG KPIs and a 2.5 bps increase (penalties) for falling short of ESG KPIs, then *Swing* is calculated as 2.5 + 2.5 = 5 bps. An example of margin adjustment is provided in the Appendix A.
ESG_score	Asset4 ESG score from Refinitiv workspace
Size	Natural logarithm of the firm's total assets
Leverage	Total liabilities divided by the firm's total assets
Profitability	Net income divided by the firm's total assets

Appendix D – AI Prompts and Rubrics

We gauge our disclosure credibility proxies using the prompt structure based on Eloundou et al. (2023) and Eisfeldt et al. (2023) for API calls on GPT classification for each page of the ESG reports. We generate 8 predictions for each page, and for each prediction, we record the brief reasons for such predictions and the certainty of the prediction. We deploy the GPT-4o model (May 13, 2024 version) using Microsoft Azure OpenAI, setting the model's temperature to 0. The prompts and rubrics used in the API calls are shown below.

message_text = [”role”:”system”,”content”: ”Consider the most powerful OpenAI large language model (LLM). This model can complete many tasks that can be formulated as having text input and text output where the context for the input can be captured in 2000 words. The model also cannot draw up-to-date facts (those from < 1 year ago) unless they are captured in the input. Assume you are a worker with an average level of expertise in your role trying to complete the given task. You have access to the LLM as well as any other existing software or computer hardware tools mentioned in the task. You also have access to any commonly available technical tools accessible via a laptop (e.g. a microphone, speakers, etc.). You do not have access to any other physical tools or materials. You are a helpful research assistant who wants to label the given text according to the rubric below.”

'## Rubric:##'

'## Cheaptalk'

'Label the given text as Cheaptalk if the text mostly provides unverifiable ESG-related claims that are boastful' 'Do NOT label the text as Cheaptalk if:' ' There are no actual statements in the given text, such as having only a table of contents.'

'## Cheaptalk_informative'

'Label the given text as Cheaptalk_informative if you label the text as Cheaptalk, and the surrounding text provides comparative context with industry peers, making the cheaptalk more evaluable.'

'## Report_bad_ESG'

'Label the given text as Report_bad_ESG if it reports past bad ESG performance.'

'## Anticipate_bad_ESG'

'Label the given text as Anticipate_bad_ESG if it indicates that the firm anticipates having poor ESG-related performance in the future with some certainty, and this anticipation is not attributed to external risk factors.' 'Do NOT label cases as Anticipate_bad_ESG if:' 'The text anticipates bad performance unrelated to ESG issues, such as financial impacts, impacts on physical properties, operational efficiency, macroeconomic factors, or missing data.'

'## Report_good_ESG'

'Label the given text as Report_good_ESG if it reports past good ESG performance.'

'## Qualify_good_ESG'

'Label the given text as Qualify_good_ESG if:' '1. You label the text as Report_good_ESG, and the surrounding text attributes this performance to non-self-initiated factors that mechanically boost ESG performance, or' '2. The firm cautions readers about a one-time or temporary boost in its past good ESG performance.' 'Do NOT label cases as Qualify_good_ESG if:' 'The firm attributes its good ESG performance to its own ESG initiatives, purchases, facilities, or improvement in energy efficiencies.' 'Do NOT label cases as Qualify_good_ESG if:' 'The text is about disclosing past bad ESG performance rather than qualifying past good ESG performance.' 'Do NOT label cases as Qualify_good_ESG if:' 'The text qualifies performance unrelated to ESG issues, such as financial impacts, impacts on physical properties, operational efficiency, macroeconomic factors, or missing data.'

'## Commitment:'

'Label the given text as Commitment if there are explicit or implied targets achieved or set and likely to be implemented.'

'## Specificity:'

'Label the given text as Specificity if there is clear information on past or future events; verifiable goals and how tracked; detailed plans of actions.',
"role":"user","content":prompt]

prompt_template = PromptTemplate.from_template("Read the given statement from the companies' environmental, social, and governance (ESG) report then do three things. 1: Evaluate the Statement: Using the provided rubric, reason step by step to determine whether or not the given text can be classified as cheaptalk, cheaptalk_informative, Report_bad_ESG, Anticipate_bad_ESG, Report_good_ESG, Qualify_good_ESG, commitment, and specific. Read the provided rubric carefully. Report the answer that you think fits best. Do not say NA or skip any task. 2: Given the amount of speculation required in step 1, describe your certainty about the estimate–either high, moderate, or low. 3. Only provide your answers using the following JSON format: (cheaptalk: yes/no, cheaptalk_reason, cheaptalk_certainty; cheaptalk_informative:yes/no, cheaptalk_informative_reason, cheaptalk_informative_certainty; Report_bad_ESG:yes/no, Report_bad_ESG_reason,Report_bad_ESG_certainty; Anticipate_bad_ESG: yes/no, Anticipate_bad_ESG_reason, Anticipate_bad_ESG_ certainty; Report_good_ESG:yes/no, Report_good_ESG_reason,Report_good_ESG_certainty; Qualify_good_ESG: yes/no, Qualify_good_ESG_reason, Qualify_good_ESG_certainty; commitment: yes/no, commitment_reason, commitment_certainty; specific: yes/no, specific_reason, specific_certainty). Provide your reasoning for each of your decisions within 30 words. Make sure every field is answered. The text to be determined is: statement")

Appendix E – Examples of Disclosure Credibility

***Qualify_Good*: Attributed good ESG performance to external factors**

“ ...we reduced our Scope 3 fuel- and energy-related activities emissions by 26,200 metric tons. This represents a 20% decrease from our FY20 baseline. As this category is related to the purchase of fuels and electricity, the emissions follow our total energy consumption trends. We attribute this decrease to lower energy consumption, a significant portion of which is due to the reduced use of office buildings, vehicles and company aircraft due to COVID-19.”

***Anticipate_Bad*: Convey a pessimistic future**

“While we have continued to make excellent progress on our waste disposal goal, we anticipate increased waste generation from the air pollution controls being installed in our Franklin and Ville Platte, Louisiana, USA, facilities.”

***Cheaptalk*: Unverifiable claims that are boastful**

“We believe that being a responsible investor begins with being a responsible company, and in 2021 we took great strides to invest in our own corporate responsibility practices and our responsible investing efforts... ”

***Cheaptalk_inform*: Cheaptalk with comparative context**

“...nearly 3 million Americans with celiac disease who must avoid gluten finding affordable, gluten-free foods that taste good can be a challenge [...] The introduction of gluten-free Cheerios followed several years of hard work by hundreds of employees who dedicated thousands of hours to make it happen [...] General Mills is the second-largest U.S. producer of gluten-free products...”

“We placed 63rd out of 874 companies internationally among the top 8% of worldwide participants in the 2018 GRESB assessment...”

"...we maintained our supply chain environmental programs and continued to see progress in the areas of greenhouse gas (GHG) emissions reduction, water stewardship and waste management through partnership with our suppliers. To underscore the positive impact of our supply chain environmental practices, the Institute of Public and Environmental Affairs (IPE) in China ranked Dell Technologies as a Corporate Information Transparency Index (CITI) Master. We are one of only two brands to earn this recognition..."

***Commitment*: Explicit or implied targets achieved or set**

" ...we take great pride in conducting business as an ethical organization. Ethical and trusting relationships have been a core part of who we are for more than a century. Our commitment is about more than legal compliance, it's about upholding high ethical standards and principles. We are committed to winning in the right way and strive to foster a culture where people want to do the right thing..."

***Specific*: Clear information on past or future events**

"As of December 31, 2020, approximately 48% of total annual rental revenue is generated from 78 LEED projects, 23 of which total 3.5 million RSF and are targeting LEED certification..."

Figures

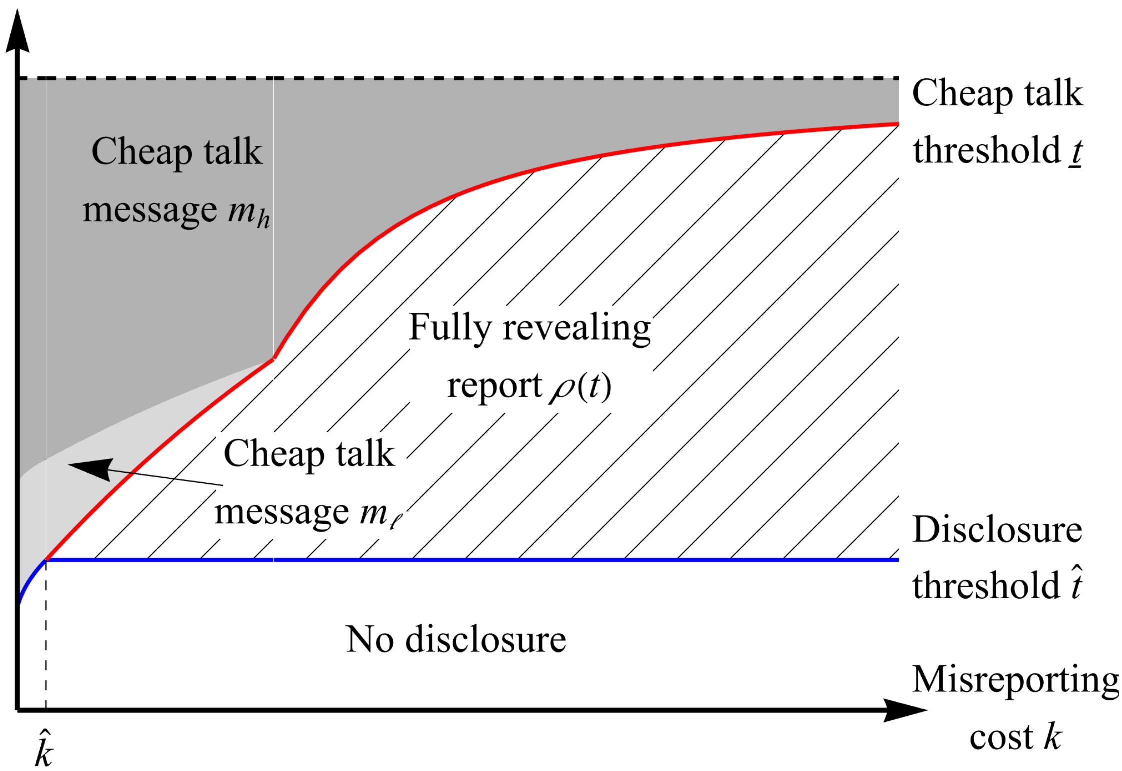

Figure 2.1: Reporting thresholds as a function of misreporting cost

Figure 2.1 plots the disclosure thresholds $\hat{t}$, $\hat{t}_c$ (blue) and cheap-talk threshold $\underline{t}$ (red) as a function of the misreporting cost k. When $k < \hat{k}$, firms with $t < \hat{t}_c$ do not disclose, and firms with $t > \hat{t}_c$ claim to be type 1 and issue one of two cheap talk reports m_ℓ or m_h. When $k > \hat{k}$, firms with $t < \hat{t}$ do not disclose, firms with $t \in (\hat{t}, \underline{t})$ issue an exaggerated but fully revealing report $\rho(t)$, and firms with $t > \underline{t}$ claim to be type 1.

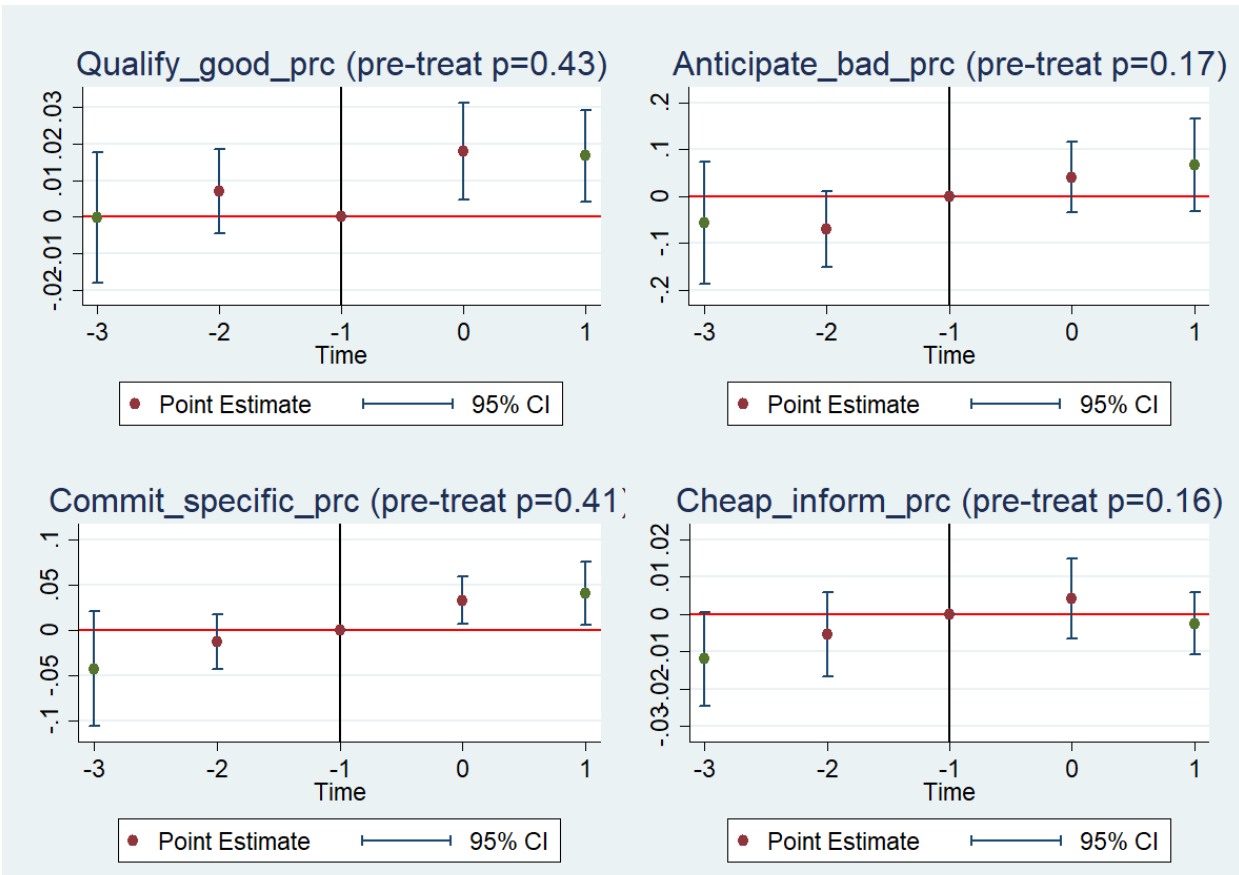

Figure 2.2: Parallel Trends

Figure 2.2 presents the diagnostic parallel trends, along with the p-values of the joint test for pre-treatment significance. We use the *Eventdd* package in Stata for the graphs and joint tests.

Tables

Table 2.1: Propensity score matching

Table 2.1 documents the propensity score matching regression and the covariate match amongst matched observations within the same two digit SIC code. The sample includes all US-incorporated firms with Compustat and Asset4 data available at the beginning of 2018.Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

Panel A. First Stage Logistic Regression Results for PSM

	ESG_Linked
Size	0.403***
	(4.17)
ESG_score	0.034***
	(4.41)
Leverage	-0.283
	(-0.41)
Profitability	1.104***
	(2.79)
Constant	-6.325***
	(-7.38)
Observations	1,508
Industry FE	Yes
Pseudo R-squared	0.293
Area under ROC curve	0.888

Panel B. Covariate Balance

	ESG-linked	Control	Difference	P-value
Size	9.42	9.37	0.05	0.80
ESG_score	54.47	53.58	0.89	0.76
Leverage	0.624	0.622	0.002	0.95
Profitability	0.04	0.028	0.012	0.27

Table 2.2: Sample Composition

Panel A. Industry Distribution					
SIC	Description	Linked	Matched	Reports	Pages
10	Metal Mining	1	1	8	1,162
13	Oil and Gas Extraction	2	2	19	1,175
20	Food and Kindred Products	3	3	25	1,844
28	Chemicals and Allied Products	2	2	18	1,112
33	Primary Metal Industries	1	1	5	204
34	Fabricated Metal Products	3	3	15	631
35	Industrial and Commercial Machinery & Computer Equipment	9	9	67	5,206
36	Electronic & Other Electrical Equipment& Components	4	4	32	2,342
37	Transportation Equipment	2	2	17	1,515
44	Water Transportation	3	3	15	306
45	Transportation by Air	1	1	9	344
49	Electric, Gas and Sanitary Services	11	11	76	6,198
51	Wholesale Trade - Nondurable Goods	1	1	5	274
62	Security & Commodity Brokers, Dealers,Exchanges & Services	2	2	11	366
63	Insurance Carriers	3	3	26	1,523
65	65 Real Estate	1	1	10	918
67	Holding and Other Investment Offices	40	40	253	11,458
73	Business Services	3	3	27	1,596
87	Engineering, Accounting, Research,and Management Services	3	3	19	847
Total		95	95	657	39,021

Table 2.2: Sample Composition (Continued)

Panel B: Characteristics of ESG-linked loan contracts	
External_verify	% of ESG-linked firms
KPI auditor, assurance provider, or external reviewer	34.74%
Other third party certificates	11.58%
Total	46.32%
ESG_Linked_Category	% of ESG-linked firms*
Environmental	85.26%
Social	20.00%

* Does not add to 100% because firms may have KPIs in multiple categories

Table 2.3: Descriptive statistics

variable	obs	mean	sd	p10	p50	p90
Qualify_good_prc	657	0.03	0.05	0.00	0.00	0.09
Anticipate_bad_prc	657	0.13	0.37	0.00	0.00	0.50
commit_specific_prc	657	0.85	0.17	0.73	0.89	0.96
cheap_inform_prc	657	0.01	0.03	0.00	0.00	0.04
ESG_linked	657	0.29	0.45	0.00	0.00	1.00
Swing	657	1.29	3.01	0.00	0.00	8.00
KPI	657	0.39	0.77	0.00	0.00	2.00
External_verify	657	0.14	0.34	0.00	0.00	1.00
ESG_score	657	65.16	14.57	43.60	67.18	82.31
Size	657	9.57	1.24	7.93	9.52	11.25
Profitability	657	0.04	0.06	0.00	0.03	0.12
Leverage	657	0.63	0.18	0.42	0.61	0.87

Table 2.4: Pairwise Pearson correlations

Bold values indicate statistical significance at the 0.10 level or lower.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Qualify_good_prc (1)	1.00								
Anticipate_bad_prc (2)	**0.16**	1.00							
Commit_specific_prc (3)	**0.14**	**0.12**	1.00						
Cheap_inform_prc (4)	-0.02	0.04	**0.10**	1.00					
ESG_linked (5)	**0.07**	**0.12**	**0.14**	0.04	1.00				
ESG_score (6)	**0.10**	**0.09**	**0.26**	0.01	0.03	1.00			
Size (7)	-0.05	-0.05	**0.22**	0.03	-0.02	**0.45**	1.00		
Profitability (8)	-0.01	-0.01	0.00	-0.04	0.00	**0.09**	-0.02	1.00	
Leverage (9)	0.02	-0.03	**0.10**	**-0.09**	-0.03	**0.16**	**0.30**	**-0.14**	1.00

Table 2.5: ESG-Linked Loans and Qualifications of Good News

Table 2.5 reports the estimated effect of ESG-linked loans on the qualifications of good ESG news. Column (1) presents the results from a Poisson model, where the dependent variable is the total count of qualifications of good news ($Qualify\_good$). Column (2) presents the results from a fractional logistic model, where the dependent variable is the percentage of qualifications of good news ($Qualify\_good\_prc$). Columns (3) and (4) present the results of running the same regression using OLS, with and without controls. The variable *ESG_linked* is the staggered difference-in-difference indicator that equals 1 if the report is issued after entering into ESG-linked loans. All variables are winsorized at the 1st and 99th percentiles. Robust z-statistics are reported in parenthesis. Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

	(1)	(2)	(3)	(4)
VARIABLES	Qualify_good	Qualify_good_prc	Qualify_good_prc	Qualify_good_prc
TREAT	0.702***	0.581***	0.018**	0.015**
	(4.43)	(2.65)	(2.59)	(2.28)
Size	-0.060	-0.480***		0.004
	(-0.48)	(-3.83)		(0.44)
Profitability	-2.516	-2.113		-0.059
	(-1.59)	(-1.06)		(-0.75)
Leverage	-1.745	-1.736		-0.043
	(-1.35)	(-1.17)		(-0.83)
ESG_score	0.022*	0.018		0.000
	(1.91)	(1.30)		(1.26)
Observations	657	657	629	629
Log pseudolikelihood	-643.75			
(Pseudo) R-squared		0.114	0.413	0.417
FE	Firm	Firm	Firm	Firm
Cluster	Pair	Pair	Pair	Pair

Table 2.6: ESG-Linked Loans and forthcoming of bad News

Table 2.6 reports the estimated effect of ESG-linked loans on the forthcoming of bad ESG news. Column (1) presents the results from a Poisson model, where the dependent variable is the total count of forthcoming bad news (*Anticipate_bad*). Column (2) and (3) present the results from the OLS model, where the dependent variable is (*Anticipate_bad_prc*), with and without controls. The variable *ESG_linked* is the staggered difference-in-difference indicator that equals 1 if the report is issued after entering into ESG-linked loans. All variables are winsorized at the 1st and 99th percentiles. Robust z-statistics are reported in parenthesis. Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

	(1)	(2)	(3)
VARIABLES	Anticipate_bad	Anticipate_bad_prc	Anticipate_bad_prc
ESG_linked	0.570***	0.103***	0.083**
	(2.69)	(2.93)	(2.48)
Size	-0.424		0.007
	(-1.52)		(0.10)
Profitability	-0.364		-0.278
	(-0.11)		(-0.80)
Leverage	-3.854		-0.655**
	(-1.62)		(-2.00)
ESG_score	0.020		0.004*
	(1.13)		(1.89)
Observations	657	629	629
Log pseudolikelihood	-261.75		
(Pseudo) R-squared		0.543	0.550
FE	Firm	Firm	Firm
Cluster	Pair	Pair	Pair

Table 2.7: ESG-Linked Loans and the specificity of ESG commitment

Table 2.7 reports the estimated effect of ESG-linked loans on the specificity of ESG commitments. Column (1) presents the results from a Poisson model, where the dependent variable is the total count of specific commitment (*Commit_specific*). Column (2) presents the results from a fractional logistic model, where the dependent variable is the percentage of specific commitment (*Commit_specific_prc*). Columns (3) and (4) present the results of running the same regression using OLS, with and without controls. The variable *ESG_linked* is the staggered difference-in-difference indicator that equals 1 if the report is issued after entering into ESG-linked loans. All variables are winsorized at the 1st and 99th percentiles. Robust z-statistics are reported in parenthesis. Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

VARIABLES	(1) Commit_specific	(2) Commit_specific_prc	(3) Commit_specific_prc	(4) Commit_specific_prc
ESG_linked	0.211***	0.471***	0.052***	0.048***
	(3.04)	(3.42)	(3.51)	(3.11)
Size	0.342***	0.196*		0.023
	(9.21)	(1.76)		(0.64)
Profitability	-0.372	-1.520		-0.168
	(-0.67)	(-0.65)		(-0.61)
Leverage	-0.102	1.796		0.205
	(-0.20)	(1.18)		(1.16)
ESG_score	0.015***	0.005		0.001
	(4.96)	(0.54)		(0.65)
Observations	657	657	629	629
Log pseudolikelihood	-2889.03			
(Pseudo) R-squared		0.116	0.462	0.468
FE	Firm	Firm	Firm	Firm
Cluster	Pair	Pair	Pair	Pair

Table 2.8: ESG-Linked Loans and informativeness of cheap talk

Table 2.8 reports the estimated effect of ESG-linked loans on the informativeness of cheap talk. Column (1) presents the results from a Poisson model, where the dependent variable is the total count of informative cheap talk ($Cheap\_inform$). Column (2) presents the results from a fractional logistic model, where the dependent variable is the percentage of informative cheap talk ($Cheap\_inform\_prc$). Columns (3) and (4) present the results of running the same regression using OLS, with and without controls. The variable *ESG_Linked* is the staggered difference-in-difference indicator that equals 1 if the report is issued after entering into ESG-linked loans. All variables are winsorized at the 1st and 99th percentiles. Robust z-statistics are reported in parenthesis. Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

VARIABLES	(1) Cheap_inform_prc	(2) Cheap_inform_prc	(3) Cheap_inform_prc	(4) Cheap_inform_prc
ESG_linked	0.220	0.389	0.039	0.067
	(0.85)	(1.22)	(0.61)	(1.03)
Size	-0.293*	-0.579***		-0.196
	(-1.81)	(-3.14)		(-1.60)
Profitability	0.514	1.433		0.073
	(0.12)	(0.29)		(0.16)
Leverage	2.513	2.378		0.441
	(1.31)	(1.06)		(1.09)
ESG_score	-0.006	-0.032		-0.001
	(-0.28)	(-1.54)		(-0.25)
Observations	657	657	629	629
Log pseudolikelihood	-240.63			
(Pseudo) R-squared		0.193	0.345	0.350
FE	Firm	Firm	Firm	Firm
Cluster	Pair	Pair	Pair	Pair

Table 2.9: External KPI verification and the credibility of ESG disclosures

Table 2.9 reports the OLS estimation of the incremental effects of external KPI verification requirements on the credibility of ESG disclosures. Robust z-statistics are reported in parenthesis. Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

VARIABLES	(1) Qualify_good_prc	(2) Anticipate_bad_prc	(3) Commit_specific_prc	(4) Cheap_inform_prc
ESG_linked	0.009	0.087	0.041**	0.000
	(1.35)	(1.54)	(2.27)	(0.07)
ESG_linked x External_verify	0.013	-0.007	0.014	0.008
	(0.91)	(-0.10)	(0.44)	(1.10)
Size	0.002	0.008	0.021	-0.010*
	(0.28)	(0.11)	(0.60)	(-1.70)
Profitability	-0.061	-0.277	-0.169	0.011
	(-0.76)	(-0.80)	(-0.61)	(0.43)
Leverage	-0.041	-0.656**	0.207	0.020
	(-0.80)	(-2.00)	(1.17)	(0.88)
ESG_score	0.001	0.004*	0.001	-0.000
	(1.36)	(1.84)	(0.67)	(-1.23)
Observations	629	629	629	629
R-squared	0.419	0.550	0.468	0.404
FE	Firm	Firm	Firm	Firm
Cluster	Pair	Pair	Pair	Pair

Table 2.10: ESG-Linked margin adjustments and the credibility of ESG disclosures

Table 2.10 reports the OLS estimation of the incremental effects of the magnitudes of ESG-Linked margin adjustment on the credibility of ESG disclosures. Robust z-statistics are reported in parenthesis. Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

VARIABLES	(1) Qualify_good_prc	(2) Anticipate_bad_prc	(3) Commit_specific_prc	(4) Cheap_inform_prc
ESG_linked	0.024***	0.079	0.044**	0.001
	(2.72)	(1.39)	(2.38)	(0.12)
ESG_linked x Swing	-0.002	0.001	0.001	0.001
	(-1.16)	(0.15)	(0.22)	(0.98)
Size	0.005	0.007	0.022	-0.010
	(0.54)	(0.09)	(0.63)	(-1.63)
Profitability	-0.054	-0.281	-0.171	0.009
	(-0.70)	(-0.81)	(-0.62)	(0.37)
Leverage	-0.046	-0.654**	0.207	0.020
	(-0.88)	(-1.99)	(1.17)	(0.90)
ESG_score	0.000	0.004*	0.001	-0.000
	(1.27)	(1.89)	(0.65)	(-1.44)
Observations	629	629	629	629
R-squared	0.421	0.550	0.468	0.403
FE	Firm	Firm	Firm	Firm
Cluster	Pair	Pair	Pair	Pair

Table 2.11: Number of KPIs and the credibility of ESG disclosures

Table 2.11 reports the OLS estimation of the incremental effects of the number of KPIs on the credibility of ESG disclosures. Robust z-statistics are reported in parenthesis. Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

	(1)	(2)	(3)	(4)
VARIABLES	Qualify_good_prc	Anticipate_bad_prc	Commit_specific_prc	Cheap_inform_prc
ESG_linked	0.027***	0.095	0.056**	0.002
	(3.23)	(1.60)	(2.43)	(0.35)
ESG_linked x KPI_num	-0.008*	-0.009	-0.006	0.002
	(-1.74)	(-0.31)	(-0.38)	(0.51)
Size	0.004	0.008	0.023	-0.009
	(0.48)	(0.11)	(0.65)	(-1.59)
Profitability	-0.054	-0.273	-0.164	0.011
	(-0.70)	(-0.79)	(-0.60)	(0.41)
Leverage	-0.043	-0.656**	0.205	0.019
	(-0.86)	(-2.00)	(1.15)	(0.85)
ESG_score	0.000	0.004*	0.001	-0.000
	(1.21)	(1.90)	(0.64)	(-1.43)
Observations	629	629	629	629
R-squared	0.420	0.550	0.468	0.401
FE	Firm	Firm	Firm	Firm
Cluster	Pair	Pair	Pair	Pair

Table 2.12: ESG-Linked Loans and ESG-related Media Coverage

Table 2.12 reports the staggered difference-in-difference results of the impact of ESG-linked loans on ESG-related news coverage, measured semiannually using Factiva. Columns (1) and (2) present results from an OLS model, while Column (3) shows the dynamics in ESG_news around the inception of ESG-linked loans. *Relative_year* indicates years relative to the treatment of ESG-linked loans, with the year immediately preceding the treatment serving as the benchmark period. Robust z-statistics are reported in parenthesis. Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

	(1)	(2)	(3)
VARIABLES	ESG_news	ESG_news	ESG_news
ESG_linked	2.337***	1.564***	
	(3.82)	(3.71)	
Relative_year_-2			-0.626
			(-1.59)
Relative_year_0			1.788***
			(3.50)
Relative_year_1			2.077***
			(2.91)
Relative_year_2			4.923**
			(2.08)
Size		3.957***	3.115***
		(3.60)	(3.32)
Profitability		-7.408*	-7.602**
		(-1.98)	(-2.32)
Leverage		-10.556**	-9.940**
		(-2.39)	(-2.28)
ESG_score		-0.016	-0.030
		(-0.60)	(-1.01)
Constant			-19.015**
			(-2.35)
Observations	1,520	1,132	1,132
R-squared	0.665	0.742	0.749
FE	Firm	Firm	Firm
Cluster	Pair	Pair	Pair

Table 2.13: Alternative estimator: Stacked difference-in-difference

Table 2.13 reports the estimated effect of ESG-linked loans on the credibility of ESG disclosures using stacked regression. All variables are winsorized at the 1st and 99th percentiles. Robust z-statistics are reported in parenthesis. Appendix C provides variable definitions. Two-tailed significance levels are denoted by: *** 1%, ** 5%, and * 10%.

	(1)	(2)	(3)	(4)
VARIABLES	Qualify_good_prc	Anticipate_bad_prc	Commit_specific_prc	Cheap_inform_prc
ESG_linked	0.013*	0.074**	0.056***	0.005
	(1.96)	(2.19)	(3.15)	(1.36)
Size	0.014	0.079	-0.007	-0.007
	(1.24)	(0.75)	(-0.13)	(-1.24)
Profitability	-0.087	-0.427	-0.056	-0.006
	(-0.97)	(-1.05)	(-0.18)	(-0.25)
Leverage	-0.070	-0.591	0.455*	0.018
	(-1.58)	(-1.60)	(1.69)	(1.05)
ESG_score	0.001	0.005	-0.000	-0.001**
	(1.48)	(1.63)	(-0.13)	(-2.23)
Observations	1,599	1,599	1,599	1,599
R-squared	0.455	0.482	0.514	0.509
FE	Firm	Firm	Firm	Firm
Cluster	Pair	Pair	Pair	Pair

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