ARTICLE IN PRESS

The British Accounting Review xxx (xxxx) xxx

Contents lists available at ScienceDirect

The British Accounting Review

journal homepage: www.elsevier.com/locate/bar

Learning to be green: Accounting comparability and environmental violations

Justin Chircop [a,*], Monika Tarsalewska [b], Agnieszka Trzeciakiewicz [c]

[a] Lancaster University Management School, Lancaster University, Lancaster, LA1 4YX, UK
[b] University of Exeter Business School, Streatham Court, Streatham Campus, Rennes Drive, Exeter, EX4 4PU, UK
[c] School for Business and Society, University of York, York, YO10 5DD, UK

ARTICLE INFO

JEL classification:
G30
G32
G34

Keywords:
Accounting comparability
Environmental violations
Toxic emissions

ABSTRACT

Over recent years there has been an increasing awareness of the costs to the environment of corporate actions. We posit that accounting comparability between a firm and its peers, facilitates firm learning of the impact peer firm activities have on the environment. This learning allows the firm to reduce its own environmental violations. In line with this conjecture, our findings show that accounting comparability is negatively associated with environmental violations. Further, the reduction in firm environmental violations is larger in the presence of comparable peer firms disclosing low toxic releases, suggesting that firms are better able to learn from peer firms with low environmental impact. Our results provide novel evidence that accounting comparability facilitates green learning and therefore benefits society at large by reducing environmental harm.

1. Introduction

Corporations are key actors in environmental degradation. While some of their environmental impacts originate from their ordinary business operations and result in pollution, toxic waste, or wildlife destruction, others go beyond what is perceived as legal and are referred to as environmental violations. These violations occur when firms do not comply with environmental laws and regulations. The United Nations Environment Programme and RHIPTO Rapid Response report that global environmental crime in 2016 was estimated to be ca. 91–258 billion USD and was rising by 5–7% annually (Nellemann et al., 2016).

In response to the recognition that corporations can cause irreparable harm to the environment, many of America's largest firms signed the Statement on the Purpose of a Corporation by the Business Roundtable (BRT) in 2019 in which they committed to running more sustainable businesses and to taking account of important sustainability issues such as the environment in their operations. However, empirical verification of those intentions by Raghunandan and Rajgopal (2022) shows that firms that intended to be more socially responsible had, in fact, more environmental violations.

Operations at the expense of the environment are often optimal from the firm perspective in the short term as gains from engaging in socially irresponsible behaviour are often greater than losses from increased legal liability, increased regulatory oversight, and reputational damage (Shapira & Zingales, 2017). Therefore, the intentions themselves are not a sufficient mechanism to prevent a firm's environmentally harmful actions. Firms rather use the ESG (environmental, social and governance) claims as greenwashing and do not make fundamental changes to be more socially responsible (Financial Times, 2022). In this respect capturing firms'

* Corresponding author.
E-mail addresses: j.chircop1@lancaster.ac.uk (J. Chircop), m.tarsalewska@exeter.ac.uk (M. Tarsalewska), a.trzeciakiewicz@york.ac.uk (A. Trzeciakiewicz).

https://doi.org/10.1016/j.bar.2023.101240
Received 18 July 2022; Received in revised form 4 July 2023; Accepted 27 July 2023
Available online 29 July 2023

Please cite this article as: Justin Chircop et al., *The British Accounting Review*, https://doi.org/10.1016/j.bar.2023.101240

environmental performance through its ESG disclosures is prone to self-selection bias where firms self-select the information that they disclose to stakeholders (Tsang et al., 2023). Hence, in this study, we use environmental violations as a cleaner and more objective measure of a firm's environmental performance. Environmental violations relate to firm activities which have been investigated and found to be in violation of environmental regulations by regulators.

Since environmental violations are costly for both the firm and society at large, the identification of determinants of environmental violations is important. We posit that firm learning about the environmental effects of peer firm activities, allows firms to reduce their environmental violations. Previous literature shows that greater accounting comparability of a subject firm with peer firms facilitates learning, as captured by improved investment decisions and firm productivity (De Franco et al., 2011; Chen et al., 2018; Chircop et al., 2020; Chircop et al., 2021). Accounting comparability captures the similarity with which subject and peer firms map economic events to accounting numbers (De Franco et al., 2011). As greater firm accounting comparability with peer firms facilitates the firm's understanding of peer firms' operations, we propose that greater accounting comparability facilitates the firm's learning about the economic consequences of peer firms' environmental activities. We call this effect the *peer-learning* effect.

However, greater accounting comparability with peer firms exposes firms to enhanced scrutiny by regulators, since regulators are better able to understand the environmental consequences of firm activities. Increased understanding by regulators of the environmental consequences of firm activities facilitates the identification of environmental violations in comparable peers, hence accounting comparability is related to increased environmental violations. We call this effect the *enhanced monitoring* effect.

While we conjecture that the incentives for firms to reduce their environmental impact (Clarkson et al., 2011; Chava, 2014; El Ghoul et al., 2018; Chang et al., 2021) suggests that the peer-learning effect dominates the enhanced monitoring effect, which of the two effects dominates is ultimately an empirical question. This is the empirical question we seek to address in this study.

To address this research question, we examine data on environmental violations sourced from the Violation Tracker database. Violation Tracker is a project of the U.S. organisation Good Jobs First that gathers comprehensive data about corporate misconduct identified by U.S. regulatory agencies. The violations we examine have been identified by regulators and relate to violators that have been sanctioned by U.S. regulatory agencies. After merging this data with firm characteristics, we arrive at a sample of 8,685 firm-year observations for 588 unique firms from 2001 to 2020.

We find that accounting comparability is negatively related to both the number and severity of environmental violations. The number of environmental violations refers to the frequency of environmental violations identified by regulators each year. The severity of environmental violations refers to the size of penalties issued by regulators against the firm. Our results are not only statistically, but also economically significant. Specifically, a one standard deviation increase in our measure of accounting comparability is related to a reduction of 14.3% in the number of violations and 11.8% in the severity of violations.[1]

While our baseline results suggest that on *average* firm accounting comparability with its peers is related to a reduction in firm environmental violations, this relation is likely to be a function of peer firms' environmental impact. Specifically, firms are better able to learn about activities that reduce their environmental impact from peer firms which undertake low environmental impact activities. Conversely, learning from peer firms with high environmental impact activities is limited to ensuring that the firm does not undertake activities similar to peer firms. In this respect, we posit that the presence of comparable peer firms with low environmental impact is associated with a reduction in the firms' environmental impact. To examine this conjecture, we test whether the presence of highly comparable peer firms with low toxic releases is related to a reduction in firm environmental violations and penalties. In line with the notion that accounting comparability facilitates firm learning from peer firm activities, we find that high accounting comparability with peer firms that disclose levels of toxic releases below the industry-year median is negatively related to firm environmental violations.

Since accounting comparability facilitates learning of both activities that reduce the firm's environmental impact and activities that reduce the firm's risk of regulatory scrutiny, without necessarily reducing the firm's environmental impact, we undertake further tests to identify which of the two activities dominates. If the latter activities dominate, we do not expect a significant association between accounting comparability and firm environmental impact. We use the Environmental Protection Agency (EPA) toxic release reports to measure the firm environmental impact and find that accounting comparability with peer firms is negatively related to the firms' EPA toxic releases. This result suggests that accounting comparability facilitates the learning of activities that reduce the firm environmental impact, and this in turn reduces firms' environmental violations.

Finally, we undertake several tests to ensure the robustness of our results. First, to ensure that our results are not a function of research design choices made in computing our independent variable of interest, we run our baseline empirical model using alternative measures of accounting comparability. Second, to ensure that the partial overlap between our measures of accounting comparability and our measures of environmental violations do not bias our results, we run our baseline specification with our independent variable of interest lagged by one period. Third, to ensure that our results are not driven by industry-specific state regulations, we run our baseline analysis using a fixed effect structure, which includes industry-state fixed effects. Fourth, we add controls for CEO incentives to our baseline empirical model to ensure that potentially correlated omitted variables do not drive our results. Fifth, to ensure that our baseline results are not a function of the firms' board characteristics, we run our baseline empirical model including controls for board characteristics. Results for these analyses support our baseline results.

We also undertake further analysis, where we run our baseline empirical model around key regulatory changes that might impact the relation between accounting comparability and environmental violations. Specifically, we run the baseline empirical model for a

[1] Refer to Section 4.2 for a detailed explanation of the calculation of economic significance.

sample period before and after the financial crisis of 2008/2009 and the Paris Climate Accords of 2015/2016. Results for these analyses show that the observed relation between accounting comparability and environmental violations holds irrespective of the sample period used in the analysis. Finally, we run the baseline empirical model on a propensity score matched sample of observations, where we match firms with high accounting comparability with firms with low accounting comparability. Results for this analysis corroborate our baseline results and further mitigate the concern that our results are driven by firm characteristics other than accounting comparability.

Our findings provide novel evidence for the relation between firm accounting comparability with peer firms, a characteristic of the accounting system, and firm environmental impact. Specifically, our results suggest that accounting comparability with peer firms influences firms' environmental violations. When firms produce comparable accounts, they can learn from their peers' disclosures about how to reduce environmental harm. In this respect, regulators should consider peer-learning effects when implementing new regulations intended to protect the environment.

We contribute to several strands of literature. First, we identify a novel link between firm accounting comparability with peer firms and environmental violations. There has been a debate about whether accounting comparability brings positive or negative effects (Schipper, 2003), yet the recommendations by regulators (FASB, 2010; SEC, 2000) suggest that accounting comparability benefits firms. Several papers show that firm accounting comparability with peer firms has a positive effect on capital allocation and productivity (Brochet et al., 2013; Chen et al., 2018; Chircop, 2021; Chircop et al., 2020; De Franco et al., 2011; Horton et al., 2013). We show that by facilitating peer-learning, accounting comparability not only benefits firms but also the environment at large. Specifically, it promotes a reduction of toxic emissions, and ultimately a reduction of environmental violations.

Second, we contribute to a strand of climate finance literature that examines the determinants of environmental practices and misconduct. Previous literature shows that environmental practices are driven by financial constraints (Bartram, et al., 2022; Cohn & Deryugina, 2018; Goetz, 2018; Xu & Kim, 2022), corporate governance and ownership (Akey & Appel, 2019, 2021; Dasgupta et al., 2021; De Villiers et al., 2022; Dyck et al., 2019; Edmans, 2020; Shive & Forster, 2020) and supply chain effects (Dai, et al., 2021; Schiller, 2018). Further, several papers focus on the determinants of environmental misconduct. Abebe and Acharya (2022) show that CEO-led firms have fewer environmental violations and Liu (2018) shows that gender board diversity plays an important role in reducing environmental lawsuits. Finally, Hossain et al. (2022) show that CEO inside debt holdings, a proxy for risk-aversion, are related to higher carbon emissions, while Chircop et al. (2023) show that CEO risk-taking incentives encourage corporate misconduct. Our paper contributes to the literature on the corporate level determinants of environmental misconduct by identifying accounting comparability as a practice that reduces environmental violations and therefore protects the environment.

Third, our paper contributes to the literature on the effects of monitoring and the role of learning from peer firms on corporate misconduct. Previous literature shows that information dissemination and information quality reduce corporate misconduct. For example, Heese et al. (2021) show that a reduction in monitoring due to the closure of local newsagents increases local establishment violations and penalties, as well as leads to an increase in toxic releases. Azar et al. (2021) claim that large investors believe that reducing carbon dioxide emissions increases the value of their portfolio. An analysis of "Big Three" (i.e., BlackRock, Vanguard, and State Street Global Advisors) investments shows that their engagement with portfolio firms in which they hold significant stakes reduces corporate carbon emissions around the world. Cordis et al. (2022) find that higher transparency in the information environment in which firms operate reduces industrial pollution. Hope et al. (2021) show that high quality internal information helps managers make better decisions, and therefore it improves workplace safety while Dasgupta et al. (2021) report that EPA enforcement actions against peer firms reduce emissions of nearby establishments operating in the same product market. We contribute to this literature by showing that accounting comparability allows firms to learn from the information disclosed by peer firms. Therefore, the role of accounting comparability is critical in reducing environmental degradation.

The remainder of the paper is organized as follows. Section 2 presents pertinent literature and sets out the hypothesis. Section 3 describes our research design and data. Section 4 discusses our findings and Section 5 concludes.

2. Literature review and hypotheses

2.1. Accounting comparability framework

FASB (Financial Accounting Standards Board) Concept Statement No.2 (1980, 40) states that "investing and lending decisions essentially involve evaluations of alternative opportunities, and they cannot be made rationally if comparative information is not available." Accounting comparability between a firm and its peers refers to the similarity of the firms' accounting system to the accounting system of the peer firms. Accounting systems are similar when similar economic events lead to accounting numbers which are similar, while different economic events lead to accounting numbers which are different. Hence, accounting comparability allows for a better understanding of the economic consequences of peer firms' activities. Importantly, accounting comparability does not only facilitate understanding of peer firms' financial statements, but it also facilitates understanding of the mosaic of information disclosed by firms throughout the year.

This understanding allows for more accurate inferences about how an economic event translates into future accounting numbers for comparable firms. In this respect, a firm that wants to evaluate the economic consequences of specific environmental activities can refer to the disclosures of peer firms. If the firm has high accounting comparability with peer firms, then the accounting choices implemented by these firms will be similar. This allows the firm to better identify peer firms' environmental activities, and more importantly to better understand the economic consequences of these environmental activities. Therefore, similarity in accounting policies facilitates the firm interpretation of peer firm disclosures, hence facilitating the comparison of alternative investment opportunities (Bradshaw et al., 2009; Gong et al., 2013). This argumentation suggests that higher accounting comparability lowers the cost of information processing, thus improving firm decision making (De Franco et al., 2011; Kim et al., 2013).

Since the Financial Accounting Standards Board (FASB, 2010) highlighted the importance of accounting comparability in investment decisions, there has been a growing interest in examining accounting comparability and its consequences (e.g., Chen et al., 2018; De Franco et al., 2011). Notwithstanding this, early research in accounting comparability was hampered by the lack of a measure of accounting comparability which captures the accounting system in practice (Chircop et al., 2020). Having such a measure is key to the study of accounting comparability since similarity in accounting rules does not automatically extend to similarity in accounting practice (Petersen, 2015).[2] Specifically, two firms might have similar accounting policies, but these are implemented differently hence, the mapping of economic events into accounting numbers will be different.

To address this concern, in our study we use the De Franco et al. (2011) measure of accounting comparability. Specifically, De Franco et al. (2011) use the parameter estimates from a firm-specific regression of market returns, proxying for economic events, on earnings, that is accounting numbers, to determine the earnings-returns parameter estimates used by the firm. Greater accounting comparability between a firm and its peers arises when the accounting system, as captured by the earnings-returns parameter estimates, gives similar accounting numbers for similar economic events. Unlike other measures (e.g., Peterson et al., 2015), the De Franco et al. (2011) measure captures similarity in accounting policies *and* how such accounting policies are implemented by firms.

Several studies have examined the consequences of accounting comparability and have found that accounting comparability benefits financial market participants (e.g., Choi et al., 2019; De Franco et al., 2011; Shane et al., 2014; Suk & Zhao, 2017; Zhang, 2018) and firms (e.g., Chen et al., 2018; Chircop, 2021; Chircop et al., 2020; Imhof et al., 2017; Kim et al., 2013; Kim et al., 2016; Sohn, 2016; Suk & Zhao, 2017; Zhang et al., 2020). Importantly, while these studies suggest that accounting comparability improves financial market participants' and firms' decision making, no study has to our knowledge yet examined the relation between accounting comparability and the firms' environmental impact. This is surprising given the increasing importance of environmental considerations to firms' operations.

2.2. Environmental practices

Firms are often pressured to change the social and environmental practices that are determinants of their future investments, performance, and survival (Amini et al., 2021; Bolton & Kacperczyk, 2021; Chava, 2014; El Ghoul et al., 2011, 2018; Krueger et al., 2020). Changes to environmental practices can take various forms from greenwashing to more fundamental changes like investments in environmental innovations (Berrone et al., 2013). These changes can be internally or externally driven. For example, firms can transfer their practices towards reducing their environmental footprint onto others along the supply chain, product markets, or internationally through investments in multinational corporations, governance, or direct ownership (Akey & Appel, 2019; Attig et al., 2016; Dai et al., 2021; Dasgupta et al., 2021; Dyck et al., 2019; Li et al., 2018; Peng & Lin, 2008; Schiller, 2018).

The Environmental Protection Agency (EPA) is the primary body responsible for setting up a regulatory framework for environmental monitoring and penalising firms for wrongdoing. To identify potential non-compliance, the EPA monitors regulated firms for deviations from industry norms. The identification of such deviations attracts EPA regulatory scrutiny, and if violations of environmental regulations are identified, the EPA issues some of the largest penalties issued by U.S. regulatory bodies to offending companies.

2.3. Accounting comparability and environmental violations

Accounting comparability facilitates understanding and learning from comparable peer firm disclosures. Specifically, firm accounting comparability with peer firms not only facilitates understanding of peer firms' financial statements but also facilitates understanding of peer firms' disclosures (e.g., earnings announcements, Form 8-K disclosures, EPA and ESG reporting) issued throughout the financial year (Chircop et al., 2020). Therefore, accounting comparability reduces the costs of processing information for firms, investors, and regulators and enables more accurate predictions of future firm performance.

On the one hand, accounting comparability facilitates firm learning of the economic consequences of peer firms' environmental practices, hence enabling the firm to adopt practices that reduce its environmental impact. These environmental spillovers can take place if a firm is able to observe, identify, and understand the environmental practices of peer firms. The application of this learning reduces the number and severity of firm environmental violations. De Franco et al. (2011) argue that accounting comparability reduces the cost of acquiring information. Firms that have higher accounting comparability with peer firms have easier access to information and can better learn from their peers. Previous literature shows that accounting comparability with peer firms is important as it improves corporate investments and productivity through peer firm spillovers (Chen et al., 2018; Chircop, 2021; Chircop et al., 2020). We posit that if firms that make similar accounting choices to their peers can learn about their peers' investments and productivity, they can also better identify the economic consequences of peer firms' environmental activities. This allows firms to replicate those peer firms activities that lower the possibility of violating environmental regulations. We call this the *peer-learning* effect. Firms have incentives to improve environmental performance since it is positively related to financial performance (Clarkson et al., 2011), debt capacity, access to bank credit (Chang et al., 2021), and reduces the overall cost of financing (Chava, 2014; El Ghoul et al., 2018).

[2] Importantly the fact that most firms follow similar ESG standards (e.g., GRI, SASB and UN SDG), and hence adopt similar accounting and disclosure properties, does not automatically translate into similarity (i.e., comparability) in practice since regulations must be interpreted and policies must be implemented. The interpretation and implementation of ESG standards is subjective and firm specific.

On the other hand, accounting comparability facilitates learning by other firm stakeholders such as regulators. Specifically, this learning enables regulators to target their limited resources to monitor firms with a greater likelihood of being violators, hence facilitating the identification of environmental violations. Regulators, often have insufficient information to evaluate the environmental footprint of firms (Berrone et al., 2017; Busch & Hoffmann, 2009; Lyon & Maxwell, 2011). Limited information about a firm's environmental performance or its future environmental impact limits the regulators' ability to identify and penalise the firm for any noncompliance. For example, Yaeger (1991) and Heyes and Rickman (1999) find that EPA resources are limited, and it is not feasible for the agency to detect and prosecute all noncompliant firms. Further, Lyon and Maxwell (2011) add that firms can even strategically disclose misleading information about their environmental practices in the absence of appropriate monitoring. This information asymmetry makes it harder for firms to signal their environmental quality as well as for the environment protection agencies to identify the misbehaving firms and to adequately monitor them. Accounting comparability reduces this information asymmetry by facilitating regulatory monitoring of firms. Therefore, higher accounting comparability leads to more violations and penalties being identified. We call this the *enhanced monitoring* effect.

While the peer-learning and the enhanced monitoring effects are not mutually exclusive, we posit that the incentives for firms to reduce their environmental impact (Clarkson et al., 2011; Chava, 2014; El Ghoul et al., 2018; Chang et al., 2021) suggest that the peer-learning effect dominates the enhanced monitoring effect. Therefore, we formalise our hypothesis as:

H1. *Firm accounting comparability with peer firms is negatively related to firm environmental violations.*

While H1 tests for the *average* effect of accounting comparability on environmental violations, it is likely that the strength of this effect varies as a function of learning from peer firms. While learning from peer firms with low environmental impact facilitates firm learning about activities that if replicated, will reduce the firms' own environmental impact, learning from peer firms with high environmental impact is limited to identifying the peer activities that shouldn't be replicated by the firm. Given the greater scope for learning from peer firms with low environmental impact, we expect that the presence of comparable peer firms with low environmental impact to be negatively related to the firms' own environmental impact. We formalise our hypothesis:

H2. *There is a negative relation between the presence of comparable peer firms with low environmental impact and firm environmental violations.*

3. Research design

3.1. Measuring environmental violations

We source data on environmental violations from the Violation Tracker database maintained by the Corporate Research Project of non-profit organization Good Jobs First.[3] Violation Tracker provides comprehensive coverage of corporate misconduct identified by federal regulatory agencies, state attorney generals, and selected state regulatory agencies since 2000. For our study, we select only violations related to the environment (i.e. offences related to air, land, and water pollution) as regulated by federal laws that include the Clean Air Act, Clean Water Act, Act to Prevent Pollution and Hazardous Waste Management Act among others. The records of the offences originate from 170 different regulators, out of which the Environmental Protection Agency (EPA) is the most active. Our final sample contains 3,765 violations associated with US$4.6 billion in penalties.

3.2. Measuring accounting comparability

Like prior literature examining accounting comparability (e.g., Chircop et al., 2021), we use the De Franco et al. (2011) measure of accounting comparability to examine the relation between accounting comparability and environmental violations. The De Franco et al. (2011) measure of accounting comparability measures the similarity in which economic events are mapped to accounting numbers, where economic events are proxied using market returns and earnings capture accounting numbers.

To calculate accounting comparability for each firm observation in our sample, we first regress earnings on market returns for the 16 quarters[4] prior to the end of financial year *t* as in Eq. (1). As in calculating accounting comparability, we only keep firms with a December 31st year-end, by running Eq. (1) on the 16 quarters prior to quarter *t* we are essentially including data from year *t-3* to year *t*.

$$Earnings_{it} = \alpha_i + \beta_i Returns_{it} + \varepsilon_{it} \quad \text{(Eq. 1)}$$

Earnings is the quarterly net income before extraordinary items scaled by the beginning of the period market value for firm *i* and *Returns* is firm *i* stock returns for the quarter computed as the exponential of the sum of the monthly stock returns in the quarter minus one. The parameter estimates from Eq. (1) gives the firm-specific mapping of economic events in accounting numbers. Hence, the intercept ($\widehat{\alpha}_i$) and the slope coefficient ($\widehat{\beta}_i$) capture the subject firm accounting system.

Similarly, we estimate Eq. (1) for each peer firm, where peer firms are defined as firms operating in the same two-digit SIC code as

[3] Available at https://www.goodjobsfirst.org/violation-tracker.

[4] We require data for at least 14 of the 16 quarters. The choice of using 16 quarters to calculate accounting comparability is in line with De Franco et al. (2011) and Chircop et al. (2021).

the subject firm.[5] Hence, the intercept ($\widehat{\alpha}_j$) and the slope coefficient ($\widehat{\beta}_j$) capture peer firm *j* accounting system. Applying the estimated parameters to the same economic events allows us to calculate the estimated earnings arising from different accounting systems for the same economic events. In Eq. (2) and Eq. (3) we use the estimated parameters from Eq. (1) when economic events as captured by *Returns* are the same. The superscript on *Earnings* in Eq. (2) and Eq. (3) captures the firm whose *Returns* (economic events) are used while the subscript captures the firm whose regression parameters (accounting system) are used.

$$E\left(Earnings^{i}_{i,t}\right) = \widehat{\alpha}_i + \widehat{\beta}_i Returns_{it} \tag{Eq.2}$$

$$E\left(Earnings^{i}_{j,t}\right) = \widehat{\alpha}_j + \widehat{\beta}_j Returns_{it} \tag{Eq.3}$$

We use Eq. (4) to capture the cumulative difference between the estimated earnings from Eq. (2) and Eq. (3). Put differently, $CompAcct_{ijt}$ captures the similarity in earnings arising from the accounting system of firm *i* and peer firm *j* at time *t*, calculated over τ number of quarters, when economic events are the same.

$$CompAcct_{ijt} = \frac{1}{\tau}\sum_{t}^{\tau}\left|E\left(Earnings^{i}_{i,t}\right) - E\left(Earnings^{i}_{j,t}\right)\right| \tag{Eq.4}$$

The smaller the $CompAcct_{ijt}$ the higher the accounting comparability between firm *i* and peer firm *j*. To facilitate interpretation, in line with De Franco et al. (2011) and Chircop (2021), we multiply $CompAcct_{ijt}$ by minus one so that the larger $CompAcct_{ijt}$ the higher accounting comparability. We calculate $CompAcct_{ijt}$ for each firm-peer firm and use the mean and median $CompAcct_{ijt}$ for each firm observation, *Mean_COMP* and *Median_COMP* as our measures of accounting comparability.

3.3. Empirical model

We use Eq. (5) to examine the relation between environmental violations and accounting comparability:

$$\begin{aligned} Env\_Violations_{it} = {} & \beta_0 + \beta_1 COMP_{it} + \beta_2 Size_{it} + \beta_3 Sales\_G_{it} + \beta_4 MB_{it} + \beta_5 Lev_{it} + \beta_6 Cap\_Int_{it} + \beta_7 Q_{it} + \beta_8 CR + \beta_9 Sync_{it} + \beta_{10} IO_{it} \\ & + \beta_{11} Std\_Ocf_{it} + \beta_{12} AQ_{it} + \beta_{13} Corr_{it} + \beta_{14} CC\_Expo_{it} + Industry\ F.E. + Year\ F.E. + State\ F.E. + \varepsilon_{it} \end{aligned} \tag{Eq.5}$$

where $Env\_Violations_{it}$ refers to either the natural logarithm of the number of environmental violations (*ln(Violations)*) or the natural logarithm of the dollar value of penalties for environmental violations (*ln(Penalties)*). The former measure captures the frequency of environmental violations while the latter measure captures the severity of environmental violations. The independent variable of interest is $COMP_{it}$, which refers to either the mean accounting comparability (*Mean_COMP*) or median accounting comparability (*Median_COMP*). We use both *Mean_COMP* and *Median_COMP* to ensure that any skewness in the distribution of the accounting comparability variable does not unduly influence our results. Further, even though both the dependent and the independent variables of interest are measured at time *t* this does not assume that the effect of accounting comparability on environmental violations is immediate since as discussed in Section 3.3, accounting comparability is measured over the previous 16 quarters.

In Eq. (5) we also include a vector of control variables to ensure that the observed effect is driven by accounting comparability and not an omitted correlated variable. Specifically, we include *Size*, the logarithmic transformation of total assets, to control for the possibility that violations are a function of the size of the firms' operations; *Sales_G,* the annual growth in sales, to control for growth in the operations of the firm; *MB,* the market capitalization at the end of the year scaled by the net book value of assets, to control for the firm growth prospects; *Lev,* long-term debt scaled by shareholders' equity, to control for the potential positive relation between financial risk and violations; *Cap_Int,* calculated as the logarithm of total assets scaled by the number of employees, to control for the mix of resources held by the firm; *Q,* computed as the sum of the firm market value and total debt scaled by total assets, to control for the firms' investment opportunity set; *CR,* calculated as current assets scaled by current liabilities, to control for the liquidity risk of the firm; *IO,* the ratio of stock held by institutional holders relative to total outstanding stock, to control for the organisational structure of the firm, and *Std_Ocf,* the coefficient of variation of operating cashflows for the 16 quarters used to calculate *COMP,* ranked into deciles and divided by nine, so this variable takes a value between zero and one. *Std_Ocf* controls for the operating risks of the firm. *AQ,* is accounting quality measured as the standard deviation of the residuals from an OLS regression where the change in working capital and the explanatory variables are from Jones (1991) and the Dechow and Dichev (2002) run over the same 16 quarters used to calculate *COMP*. We multiply the standard deviation of the residuals by minus one, rank the resultant values in deciles and divide by nine so that *AQ* takes a value between zero and one, and higher *AQ* refers to higher accounting quality.

Sync and *Corr,* refer to synchronicity and correlation and are included in Eq. (5) to ensure that accounting comparability does not capture similarity in the operating environment of firms. *Sync* is the adjusted R-squared from a market model estimated over the 16 quarters used to estimate *COMP. Corr* is the mean correlation of the subject firm stock returns with peer firm stock returns, calculated over the 16 quarters used to estimate *COMP. CC_Expo,* climate change exposure measure of Sautner et al. (2021), which is the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls multiplied by 1000. We

[5] In line with De Franco et al. (2011) we require each subject firm to have at least 10 peer firms.

include year, industry, and state fixed effects to control for time trends, structural differences in industries and differences in the state regulatory environment.[6] To ensure outliers do not bias our results, we winsorize all continuous variables at a one percent level. Finally, to ensure that the varying number of observations for each unique firm does not bias our results we cluster standard errors by firm.

3.4. Sample construction

Our sample consists of observations at the intersection of Compustat, the Centre for Research in Security Prices (CRSP) database, Violation Tracker, and data on climate exposure from Sautner et al. (2020, 2021). From our sample we drop observations for financial (SIC codes between 6000 and 6999) and regulated (SIC codes between 4900 and 4999) firms. Further, we drop observations of firms that do not appear in Violation Tracker at any point during our sample period. This ensures that all firms in our sample have an equal chance of appearing in the Violation Tracker database in our sample period.[7] We assume that the number of environmental violations and the value of penalties equals zero for all firms that appear on Violations Tracker but for which there are no records of reported environmental violations in a particular year. Finally, we drop observations with insufficient information to calculate the vector of controls required for the empirical analysis. As shown in Appendix 2, our final sample covers the period from the year 2001–2020 and consists of 8,685 observations for 588 unique firms of which 1,682 relate to firm-year observations of 332 unique firms with identified environmental violations.

4. Findings

4.1. Summary statistics

Table 1 shows the composition of our sample. Panel A reports the distribution of observations per year over the sample period from 2001 to 2020. Other than 2001, which has the smallest number of observations, our sample is relatively balanced. The number of observations gradually increases from 334 in 2002, peaks in 2011 at 504 observations, and then steadily decreases to 459 in 2020. Panel B provides the breakdown of the sample by industry, following the Fama-French Industry Classification. Most of the sectors are represented in our sample suggesting that environmental violations are pervasive across industries. The industry categories with the largest number of observations in our sample are Business Services, Machinery, and Petroleum and Natural Gas with 10.74%, 7.47%, and 7.45% respectively. The industry categories with the smallest number of observations in our sample are Textiles, Coal, and Candy & Soda, and Fabricated products representing 0.03%, 0.16%, 0.23% and 0.30% respectively.

Table 2 presents summary statistics for the dependent and explanatory variables used in the main analysis. First, we present the key variables of interest, *ln(Violations)* and *ln(Penalties)*, capturing the frequency and severity of environmental violations. The mean *ln (Violations)* is 0.196 while the mean *ln(Penalties)* is 2.161. By construction, these variables are truncated at zero and are negatively skewed (given that environmental offences are present in the top two deciles of the sample). These values suggest that the average firm in our sample commits 0.424 environmental violations and pays US$524,000 of associated penalties per year.

The sample contains records of 3,679 environmental violations and US$4.6 billion worth of associated penalties. The violations are spread across several industry categories with the Petroleum and Natural Gas, Chemicals, and Steel Works containing 35.55%, 11.36%, and 6.88% of all environmental violations in our sample respectively. Sectors associated with the largest damage to the environment, captured by the total value of penalties, are Petroleum and Natural Gas, Chemicals, and Transportation contributing 61.76%, 4.68% and 4.51% worth of penalties, which translates into an average penalty of $7.24 million, $4.33 million, and $3.73 million, respectively. Further details on the distribution of environmental violations and associated penalties are presented in Appendix 3.

We also report summary statistics for all the explanatory variables. *COMP,* our independent variable of interest in Eq. (5), is either mean accounting comparability, *Mean_Comp* or median accounting comparability, *Median_Comp.* The former (latter) captures the mean (median) accounting comparability of firms with peers. While the mean might better capture the distribution of accounting comparability for firms, it is susceptible to outliers, hence we supplement *Mean_Comp* with *Median_Comp.* The mean *Mean_Comp (Median_Comp)* is −2.894 (−1.868) and the median *Mean_Comp (Median_Comp)* is −2.600 (−1.330). These values are comparable to Chircop et al. (2021) that report mean (median) *COMP* (our *Mean_Comp*) of −3.037 (−2.63).

The average firm size (*Size)* is $3.21 billion (8.077) while the median is $2.98 billion (7.999). The mean (median) growth of sales (*Sales_G*) is 8.3% (6.1%). The mean values of market-to-book ratio (*MB*), leverage (*Lev*), and capital intensity (*Cap_Int*) are 3.414, 0.702, and 5.922, while the medians are 2.423, 0.434, and 5.873, respectively. The mean (median) of Tobin's Q (*Q),* current ratio (*CR),* and synchronicity *(Sync)* are 1.727 (1.352), 12.095 (8.19), and 0.292 (0.287). Further, 48.5% (63.7%) of shares in the average (median) firm in our sample are held by institutional owners. The mean (median) operating cash flow volatility (*Std_Ocf*), accounting quality (*AQ*), and correlation of returns (*Corr*) are 0.553 (0556), 0.775 (0.778), and 0.262 (0.253) respectively. These statistics are generally in line with Chircop et al. (2020) and Chircop (2021). Finally, similar to Sautner et al. (2021) the mean (median) climate change exposure (*CC_Expo*) is 0.807 (0.383).

Table 3 reports pairwise correlations between all variables used in the baseline model. We find a significant positive correlation

[6] More details on the variables used in the analysis are provided in Appendix 1.

[7] This attenuates the concern that a firm does not appear in the Violations Tracker database simply because it is not covered by Violations Tracker and not because it has not been identified as a violator by a regulatory agency.

Table 1
Sample composition.

Panel A. Sample Composition by Year		
Year	*Freq.*	*Percent*
2001	77	0.89
2002	334	3.85
2003	370	4.26
2004	385	4.43
2005	405	4.66
2006	419	4.82
2007	429	4.94
2008	442	5.09
2009	466	5.37
2010	495	5.70
2011	504	5.80
2012	501	5.77
2013	497	5.72
2014	498	5.73
2015	491	5.65
2016	481	5.54
2017	485	5.58
2018	480	5.53
2019	467	5.38
2020	459	5.28
Panel B. Sample Composition by Industry		
Industry Name	*Freq.*	*Percent*
Food Products	246	2.83
Candy & Soda	20	0.23
Beer & Liquor	70	0.81
Recreation	76	0.88
Entertainment	126	1.45
Printing and Publishing	51	0.59
Consumer Goods	245	2.82
Apparel	76	0.88
Healthcare	177	2.04
Medical Equipment	378	4.35
Pharmaceutical Products	307	3.53
Chemicals	373	4.29
Rubber and Plastic Products	76	0.88
Textiles	3	0.03
Construction Materials	251	2.89
Construction	52	0.60
Steel Works Etc	218	2.51
Fabricated Products	26	0.30
Machinery	649	7.47
Electrical Equipment	167	1.92
Automobiles and Trucks	301	3.47
Aircraft	144	1.66
Shipbuilding, Railroad Equipment	45	0.52
Defense	31	0.36
Precious Metals	83	0.96
Non-Metallic and Industrial Metal Mining	46	0.53
Coal	14	0.16
Petroleum and Natural Gas	647	7.45
Communication	246	2.83
Personal Services	54	0.62
Business Services	933	10.74
Computers	304	3.50
Electronic Equipment	567	6.53
Measuring and Control Equipment	334	3.85
Business Supplies	186	2.14
Shipping Containers	62	0.71
Transportation	163	1.88
Wholesale	523	6.02
Retail	168	1.93
Restaurants, Hotels, Motels	214	2.46
Other	33	0.38

This table reports the composition of the sample by fiscal year in Panel A and by industry (following the Fama-French Industry Classification Type-48) in Panel B.

Table 2
Summary statistics.

Variable	Mean	Std.dev.	10th	Median	90th	N
ln(Violations)	0.196	0.451	0.000	0.000	0.693	8,685
ln(Penalties)	2.161	4.505	0.000	0.000	10.621	8,685
Mean_Comp	−2.894	1.658	−4.480	−2.600	−1.390	8,685
Median_Comp	−1.868	1.779	−3.420	−1.330	−0.640	8,685
Size	8.077	1.652	5.951	7.999	10.506	8,685
Sales_G	0.083	0.255	−0.120	0.061	0.291	8,685
MB	3.414	4.133	1.002	2.423	6.616	8,685
Lev	0.702	1.573	0.000	0.434	1.675	8,685
Cap_Int	5.922	1.115	4.746	5.837	7.267	8,685
Q	1.727	1.294	0.719	1.352	3.104	8,685
CR	12.095	14.535	2.349	8.019	24.429	8,685
Sync	0.292	0.144	0.103	0.287	0.507	8,685
IO	0.485	0.389	0.000	0.637	0.935	8,685
Std_Ocf	0.553	0.245	0.222	0.556	0.889	8,685
AQ	0.775	0.212	0.444	0.778	1.000	8,685
Corr	0.262	0.121	0.109	0.253	0.433	8,685
Cc_Expo	0.807	1.297	0.000	0.383	1.900	8,685

The table presents summary statistics (i.e. mean, standard deviation, 10th percentile, median, 90th percentile) for the sample containing 8,685 observations for the period 2001–2020. The definitions of all variables are provided in Appendix 1.

between *ln(Violations)* and *ln(Penalties)* suggesting that the incidence of violations is related to the severity of penalties. In line with our expectations, we find negative and significant correlations between the measures of environmental violations and the measures of accounting comparability. We note that the correlation coefficients are of a similar magnitude for both the frequency and severity of environmental violations for each of the employed measures of accounting comparability, i.e., *Mean_Comp* and *Median_Comp*. The reported coefficients provide preliminary evidence for a negative relation between accounting comparability and environmental violations. Next, we report the correlation coefficients for all control variables and find that both measures of environmental misconduct are significantly positively related to size, leverage, capital intensity, synchronicity, accounting quality, correlation of returns, and climate change exposure. Further, leverage, Tobin's Q, current ratio, and operating cash flow volatility are significantly negatively correlated with the number and severity of violations.

4.2. Findings

4.2.1. Accounting comparability and environmental violations

Table 4 presents the results for testing H1, where we examine the relation between accounting comparability, and environmental violations using OLS regressions. In the first two regressions, presented in columns (1) and (2), *ln(Violations)* is the dependent variable, while in regressions (3) and (4), *ln(Penalties)* is the dependent variable. We find that the coefficients on measures of accounting comparability, *Mean_Comp* and *Median_Comp*, are negative and significant in all four specifications. Specifically, the coefficient on *Mean_Comp* when *ln(Violations)* (*ln(Penalties)*) is the dependent variable is −0.017 [t-stat.: -3.13] (−0.154 [t-stat.: -3.10]) and the coefficient on *Median_Comp* when *ln(Violations)* (*ln(Penalties)*) is the dependent variable is −0.013 [t-stat.: -2.56] (−0.141 [t-stat.: -3.16]). These results, indicating that firms with greater accounting comparability commit fewer violations and receive smaller penalties, are not only statistically significant but also economically significant. Specifically, a one standard deviation increase in *Mean_Comp (Median_Comp)* is associated with a reduction in *ln(Violations)* of −0.03 (−0.02) and a reduction in *ln(Penalties)* of −0.26 (−0.25). This corresponds to a reduction of 14.3% (11.8%) in *ln(Violations)* and a reduction of 11.8% (11.6%) in *ln(Penalties)* when accounting comparability is measured using *Mean_Comp (Median_Comp)*. Taken together these results suggest that in line with H1 the peer-learning effect dominates the enhanced monitoring effect.

In all specifications, the size of the firm is positive and significant at the 1% level, suggesting that the larger the firm the greater the incidence and severity of environmental violations. Further, investment opportunities *(Q)* and current ratio *(CR)*, also play an important role. Specifically, firms with more investment opportunities and firms with a better ability to cover their short-term obligations with current assets violate less. Lastly, firms that are perceived to have greater exposure to climate risk, as proxied by *CC_Expo*, violate more.

4.2.2. Comparable peers with low environmental impact and environmental violations

We posit that accounting comparability does not only facilitate learning from the financial statements but also facilitates learning from the various disclosures that the firm makes throughout the financial period, since these disclosures are at least partly a product of the firm accounting system. Disclosures which are particularly pertinent to our setting are EPA disclosures.[8] These public disclosures provide information about the firm's environmental impact.

[8] Refer to Section 3.2 for a more detailed description of EPA disclosures.

Table 3
Correlations matrix.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	*ln(Violations)*	1.000															
(2)	*ln(Penalties)*	0.926*	1.000														
(3)	*Mean_Comp*	−0.065*	−0.059*	1.000													
(4)	*Median_Comp*	−0.044*	−0.045*	0.935*	1.000												
(5)	*Size*	0.270*	0.262*	0.209*	0.253*	1.000											
(6)	*Sales_G*	−0.010	−0.008	0.007	0.025*	0.028*	1.000										
(7)	*MB*	−0.033*	−0.018	0.124*	0.125*	0.294*	0.054*	1.000									
(8)	*Lev*	0.031*	0.041*	−0.017	−0.032*	0.072*	−0.018	0.487*	1.000								
(9)	*Cap_Int*	0.255*	0.232*	−0.101*	−0.093*	0.346*	0.073*	−0.039*	0.051*	1.000							
(10)	*Q*	−0.117*	−0.113*	0.157*	0.176*	0.284*	0.126*	0.504*	−0.091*	−0.073*	1.000						
(11)	*CR*	−0.026*	−0.029*	0.013	0.016	0.016	0.328*	0.045*	0.028*	0.144*	0.103*	1.000					
(12)	*Sync*	0.096*	0.091*	0.066*	0.071*	0.189*	−0.104*	−0.041*	0.012	0.113*	−0.117*	−0.050*	1.000				
(13)	*IO*	0.001	0.013	0.113*	0.104*	0.046*	−0.016	0.024*	0.006	−0.152*	−0.022*	0.015	0.128*	1.000			
(14)	*Std_Ocf*	−0.034*	−0.030*	−0.041*	−0.043*	−0.193*	0.008	−0.072*	−0.020	−0.098*	−0.131*	−0.035*	0.038*	0.018	1.000		
(15)	*AQ*	0.083*	0.084*	−0.022*	−0.010	0.193*	−0.052*	0.083*	0.058*	0.256*	0.035*	0.045*	0.203*	−0.035*	−0.057*	1.000	
(16)	*Corr*	0.131*	0.123*	−0.057*	−0.089*	0.026*	−0.056*	−0.117*	0.043*	0.202*	−0.205*	−0.007	0.498*	−0.008	0.007	0.006	1.000
(17)	*CC_Expo*	0.056*	0.050*	−0.020	−0.008	−0.077*	0.015	−0.076*	−0.036*	0.012	−0.103*	0.005	0.157*	0.032*	0.093*	0.095*	0.125*

This table presents the matrix of correlations coefficients. * indicates the significance of the correlation coefficient at 5% level. Definitions of all variables are provided in Appendix 1.

Table 4
The association between the accounting comparability and environmental violations and penalties.

	(1)	(2)	(3)	(4)
	ln(Violations)	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp	−0.017***		−0.154***	
	(-3.13)		(-3.10)	
Median_Comp		−0.013**		−0.141***
		(-2.56)		(-3.16)
Size	0.092***	0.092***	0.876***	0.883***
	(9.06)	(9.20)	(10.98)	(11.04)
Sales_G	−0.015	−0.016	−0.048	−0.048
	(-0.82)	(-0.85)	(-0.26)	(-0.26)
MB	−0.004**	−0.004**	−0.028	−0.028
	(-2.16)	(-2.19)	(-1.43)	(-1.45)
Lev	0.008*	0.008*	0.090**	0.089**
	(1.90)	(1.91)	(2.21)	(2.20)
Cap_Int	−0.001	−0.001	−0.039	−0.044
	(-0.05)	(-0.07)	(-0.32)	(-0.35)
Q	−0.037***	−0.037***	−0.382***	−0.380***
	(-5.56)	(-5.53)	(-6.25)	(-6.24)
CR	−0.001***	−0.001***	−0.011***	−0.011***
	(-3.09)	(-3.07)	(-3.12)	(-3.10)
Sync	−0.063	−0.064	−0.742	−0.693
	(-0.73)	(-0.74)	(-0.91)	(-0.85)
IO	−0.047	−0.048	−0.418*	−0.422*
	(-1.53)	(-1.55)	(-1.76)	(-1.77)
Std_Ocf	−0.035	−0.034	−0.381	−0.370
	(-1.38)	(-1.34)	(-1.61)	(-1.57)
Aq	0.087	0.088	0.730	0.741
	(1.01)	(1.02)	(1.10)	(1.11)
Corr	−0.042	−0.042	−0.002	−0.032
	(-0.36)	(-0.36)	(-0.00)	(-0.03)
Cc_Expo	0.018***	0.018***	0.139***	0.143***
	(2.60)	(2.65)	(2.60)	(2.67)
Constant	−0.241	−0.218	−1.084	−0.983
	(-1.15)	(-1.06)	(-0.41)	(-0.37)
R-squared	0.319	0.319	0.286	0.286
Observations	8,685	8,685	8,685	8,685
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

This table reports the estimation results for four models. Columns (1) and (2) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (3) and (4) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of penalties plus one. All independent variables are measured contemporaneously. The definitions of all variables are provided in Appendix 1. The sample spans the period 2001–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at the firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

We obtain annual total toxic releases information from the Toxic Release Inventory (TRI) database,[9] previously examined within the context of corporate finance by Akey and Appel (2021), Chang et al. (2021), and Clarkson et al. (2013) among others. The TRI database, created in 1986 by Congress through Section 313 of the Emergency Planning and Community Right-to-Know Act (EPCRA), is one way through which EPCRA provides the public with important information on the hazardous and toxic chemicals in their communities. This information is useful in preparing for and protecting from chemical accidents. This database links establishment-level emissions data to the parent company, which is the level at which we aggregate and undertake our analysis. Following Heath et al. (2023) we create measures of pollution using data from Form R of the TRI database. Toxic releases measure the total on-site and off-site emissions of firms, as captured by item 103 of Form R Report. Our study utilises the data on toxic releases resulting from ordinary production activities hence, emissions resulting from accidents or catastrophic events are excluded from our measures.

[9] Available at https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-data-files-calendar-years-1987-present.

Given that the nominal value of total toxic releases is likely a function of size, we scale total toxic releases by the firm total assets[10], and use this scaled measure of toxic releases to identify peer firms with toxic releases below the median for the industry-year. As in H2 we conjecture that comparable peer firms with low environmental impact provide greater scope for firm learning, in line with prior literature,[11] we construct an indicator variable, *Low_Peer_TR*. This variable takes the value of one if at least one of the four firms with the highest accounting comparability with the subject firm has scaled toxic releases below the median for the industry-year, and zero otherwise. We include *Low_Peer_TR,* in the vector of independent variables in Eq. (5). If accounting comparability with peer firms with low environmental impact is associated with a reduction in firm environmental violations, we expect the coefficient on *Low_Peer_TR* to be significant and negative, hence providing support to H2. In Eq. (5), we still include our measure for accounting comparability, *COMP*, since we recognise that learning from peer firm environmental disclosures is one of the multiple ways in which accounting comparability facilitates learning that results in a reduction in subject firm violations.

Table 5 presents the results of this analysis. Specifications (1) and (2) show the results when *Mean_Comp* and *Median_Comp* respectively, is our measure of accounting comparability and *ln(Violations)* is the dependent variable, while specifications (3) and (4) show the results when *Mean_Comp* and *Median_Comp* respectively, is our measure of accounting comparability and *ln(Penalties)* is the dependent variable. In all specifications, the coefficient on *Low_Peer_TR* is negative and significant, hence providing support to H2. These results suggest that the presence of comparable peer firms with low environmental impact is negatively related to firms' environmental violations. In all specifications the coefficient on our measure of accounting comparability is negative and significant, buttressing the negative relation between accounting comparability and environmental violations. The fact that our measures of accounting comparability remain significant in all specifications suggests that learning from peer firm EPA toxic release disclosures is one out of potentially several channels that drive the negative relation between accounting comparability and environmental violations.

It is pertinent to note that in these specifications, the effect of accounting comparability comes into each specification twice. It comes into the specification indirectly since *Low_Peer_TR* is a function of accounting comparability and directly through *Mean_Comp* and *Median_Comp*. Further, the results in Table 5 are not directly comparable to our baseline results, since in constructing *Low_Peer_TR* we require at least one of the four peer firms with the highest accounting comparability with the subject firm to report EPA total toxic releases.

4.3. Further analysis

As discussed in Section 2.3, the negative relation between accounting comparability and environmental violations may be driven by two non-mutually exclusive types of learning. Accounting comparability facilitates firm learning about both peer firm activities that reduce environmental impact and peer firm activities that reduce the probability of being subject to regulatory scrutiny without necessarily reducing environmental impact. To examine which type of learning dominates, we use EPA data on firm toxic releases. First, we examine whether firm accounting comparability with peer firms is negatively related to firm toxic releases. A negative relation between accounting comparability and firm toxic releases suggests that firms learn and implement activities that reduce their impact on the environment. Second, we examine whether toxic releases are related to environmental violations. While toxic releases are reported by firms, environmental violations are the product of regulatory scrutiny and action.

To test for the relation between firm accounting comparability with peers and firm toxic releases, we substitute our measures for environmental violations in Eq. (5) with subject firm toxic releases. *Toxic_Releases* refers to the total amount of toxic releases reported by the firm to the EPA. Note, we do not scale subject firm toxic releases by total assets, since in Eq. (5) we already control for the size of the subject firm.[12] Specifications (1) and (2) of Table 6 show the results of this analysis. The coefficients on both *Mean_Comp* (Specification (1)) and *Median_Comp* (Specification (2)) are −0.294 and −0.261, respectively, and significant at the 1% level indicating a significant negative relation between accounting comparability and firm toxic releases. These results suggest that accounting comparability facilitates firm learning about activities that ultimately reduce its toxic releases.

To test for the relation between toxic releases and environmental violations, we include our measure for toxic releases in Eq. (5). Specifications (3)–(6) of Table 6 show the results of this analysis. Specifications (3) and (4) show the results when *ln(Violations)* is the dependent variable and specifications (5) and (6) show the results when *ln(Penalties)* is the dependent variable. As expected, in all specifications, the coefficient on *Toxic_Releases* is positive and significant at the 1% level suggesting a positive relation between firm-reported toxic releases and firm environmental violations identified by regulators. In all specifications our measures for accounting comparability remain negative and significant, suggesting that firm toxic releases do not fully capture the effect of accounting comparability on environmental violations.

[10] We obtain similar results when we scale by sales instead of total assets.

[11] While we recognise that the choice of considering the four firms with the highest accounting comparability with the subject firm is ad-hoc, this choice is motivated by De Franco et al. (2011) and Chircop (2021). Both these studies consider the four firms with the highest accounting comparability with the subject firm in their analysis.

[12] We obtain qualitatively similar results if we scale the subject firm total toxic releases by the total assets of the subject firm.

Table 5
The association between peer firms toxic releases and environmental violations and penalties.

	(1)	(2)	(3)	(4)
	ln(Violations)	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp	−0.035***		−0.308***	
	(-3.46)		(-3.21)	
Median_Comp		−0.031***		−0.304***
		(-3.32)		(-3.45)
Low_Peer_TR	−0.050***	−0.049***	−0.370**	−0.359**
	(-2.94)	(-2.89)	(-2.25)	(-2.18)
R-squared	0.467	0.467	0.351	0.352
Observations	3,206	3,206	3,206	3,206
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

This table reports the estimation results for four models. Columns (1) and (2) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (3) and (4) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of penalties plus one. All independent variables are measured contemporaneously. All models include a set of control variables i.e. *Sales_G, MB, Lev, Cap_Int, Q, CR, Sync, IO, Std_Ocf, AQ, Corr, CC_Expo*, and a set of industry, time and state fixed effects. The definitions of all variables are provided in Appendix 1. The sample spans the period 2001–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

Table 6
Subject firm cuts to total releases of toxic emissions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Toxic_Releases	*Toxic_Releases*	*ln(Violations)*	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp	−0.294***		−0.019**		−0.160**	
	(-5.55)		(-2.30)		(-2.09)	
Median_Comp		−0.261***		−0.014*		−0.144**
		(-5.39)		(-1.79)		(-2.12)
Toxic_Releases			0.030***	0.030***	0.242***	0.242***
			(4.56)	(4.53)	(5.52)	(5.48)
R-squared	0.547	0.547	0.443	0.443	0.346	0.346
Observations	3,850	3,850	3,850	3,850	3,850	3,850
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the estimation results for four OLS regressions. Columns (1) and (2) report the coefficients of regressions, where the dependent variable is the natural logarithm of toxic releases plus one. Columns (3) and (4) report the coefficients of regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (5) and (6) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of penalties plus one. All independent variables are measured contemporaneously. All models include a set of control variables i.e. *Sales_G, MB, Lev, Cap_Int, Q, CR, Sync, IO, Std_Ocf, AQ, Corr, CC_Expo*, and a set of industry, time and state fixed effects. The definitions of all variables are provided in Appendix 1. The sample spans the period 2001–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at the firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

4.4. Robustness tests

4.4.1. Alternative measures of accounting comparability

In computing our measure of accounting comparability, in line with De Franco et al. (2011) we assume a linear relation between economic events as captured by returns, and accounting earnings, as captured by earnings. However, due to accounting conservatism, such a relation might be asymmetric between periods of positive returns and periods of negative returns. To ensure that the potential asymmetric relation between earnings and returns does not bias our results, in line with the Basu (1997) methodology, we include an indicator variable *Neg* in Eq. (1). Specifically, *Neg* takes the value of one when returns are negative and zero otherwise. We estimate *Mean_Comp1* and *Median_Comp1* using Eqs. (2)–(4) but using the regression parameters from the adjusted Eq. 1.

Further, to control for the possibility that prices lead earnings (Collins et al., 1994) we compute an alternative measure of accounting comparability. We start from the adjusted Eq. (1) used to compute *Mean_Comp1* and *Median_Comp1,* and add variables *Return_lag, Neg_lag* and an interaction between *Return_lag* and *Neg_lag. Return_lag* refers to lagged firm returns (i.e., at *t-1*) while *Neg_lag* is an indicator variable that takes the value of one if lagged returns are negative and zero otherwise. We run Eqs. (2)–(4) using the regression parameters from the adjusted Eq. (1) to compute *Mean_Comp2* and *Median_Comp2.*

Panel A of Table 7 shows the results when we use alternative measures of accounting comparability. Irrespective of which measure of accounting comparability we use, the coefficient on accounting comparability is negative and significant at the 1% level. Specifically, when *ln(Violations)* is the dependent variable the coefficients on *Mean_Comp1 (Median_Comp1)* and *Mean_Comp2 (Median_Comp2)* are −0.018 (−0.014) and −0.019(−0.015) respectively. Similarly, when *ln(Penalties)* is the dependent variable the coefficients on *Mean_Comp1 (Median_Comp1)* and *Mean_Comp2 (Median_Comp2)* are −0.168 (−0.151) and −0.179 (−0.167) respectively.

4.4.2. *Lagged accounting comparability*

As explained in Section 3.3, our measure of accounting comparability is computed over the 16 quarters from *t-3* to *t.* As our measures of environmental violations are measured at *t,* there is a one-year overlap between our measures of accounting comparability and environmental violations. This raises the concern that environmental violations might influence our measure of accounting comparability. To assuage this concern, we lag our measures of accounting comparability by one period, such that our measures of accounting comparability are computed over the 16 quarters from *t-4* to *t-1.* In this way, there is no overlap between our independent variable of interest and our dependent variables.

Panel B of Table 7 shows the results of this analysis. In line with our baseline results, the coefficient on our measures for accounting comparability is negative and significant irrespective of whether our dependent variable captures the number or severity of environmental violations. These results assuage the concern that our results are driven by the potential effect of environmental violations on our measures of accounting comparability.

4.4.3. *Controlling for differences in state-level regulations*

In our baseline model, Eq. (5), we include industry and state fixed effects to control for time-invariant industry and state characteristics which might influence the relation between accounting comparability and environmental violations, and year fixed effects to control for time trends in our measure of accounting comparability. The inclusion of cross-sectional fixed effects, namely industry and state fixed effects, is particularly important in our setting since the environmental footprint of companies tends to be a function of their industry. Further, while federal regulations such as the Clean Air Act and Clean Water Act set the minimum standards to be maintained to safeguard the environment, states might go over and above these standards. Further states play an important role in enforcing environmental regulations. For example, the Emergency Planning and Community Right to Know Act provides states with the authority to collect information about hazardous material in the local community. As different industries tend to concentrate in different states and the importance of industries in each state tends to vary, state environmental regulations and enforcement tend to vary. To ensure that industry-state differences do not drive our results, we run Eq. (5) including interactions between industry and state fixed effects.

Panel C of Table 7 shows the results of this analysis. In line with our baseline results, the coefficients on our accounting comparability measures are negative. Specifically, the coefficient on *Mean_Comp (Median_Comp)* is −0.011 (−0.008) when *ln(Violations)* is the dependent variable and −0.094 (−0.081) when *ln(Penalties)* is the dependent variable. These results are significant at the 5% level

Table 7a
Panel A: Alternative measures of accounting comparability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Violations)	*ln(Violations)*	*ln(Violations)*	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp1	−0.018***				−0.168***			
	(-3.57)				(-3.62)			
Median_Comp1		−0.014***				−0.151***		
		(-2.81)				(-3.43)		
Mean_Comp2			−0.019***				−0.179***	
			(-3.53)				(-3.89)	
Median_Comp2				−0.015***				−0.167***
				(-2.94)				(-3.69)
R-squared	0.321	0.32	0.327	0.326	0.287	0.287	0.293	0.292
Observations	8,543	8,543	8,274	8,274	8,543	8,543	8,274	8,274
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the OLS estimation results for four models. Columns (1)–(4) report the coefficients of regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (5)–(8) report the coefficients of regressions, where the dependent variable is the natural logarithm of penalties plus one. All models include a set of control variables measured contemporaneously, i.e. *Sales_G, MB, Lev, Cap_Int, Q, CR, Sync, IO, Std_Ocf, AQ, Corr, CC_Expo*, and a set of industry, time and state fixed effects. The definitions of all variables are provided in Appendix 1. The sample spans the period 2001–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at the firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

Table 7b
Panel B: Lagged accounting comparability.

	(1)	(2)	(3)	(4)
	ln(Violations)	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp$_{t-1}$	−0.016***		−0.140***	
	(-2.83)		(-2.64)	
Median_Comp$_{t-1}$		−0.012**		−0.127***
		(-2.29)		(-2.67)
R-squared	0.323	0.322	0.288	0.288
Observations	7,952	7,952	7,952	7,952
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

This table reports the estimation results for four models. Columns (1) and (2) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (3) and (4) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of penalties plus one. All models include a set of control variables measured contemporaneously, i.e. *Sales_G, MB, Lev, Cap_Int, Q, CR, Sync, IO, Std_Ocf, AQ, Corr, CC_Expo*, and a set of industry, time and state fixed effects. The definitions of all variables are provided in Appendix 1. The sample spans the period 2001–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

Table 7c
Panel C: Alternative fixed effect structure.

	(1)	(2)	(3)	(4)
	ln(Violations)	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp	−0.011**		−0.094**	
	(-2.44)		(-2.17)	
Median_Comp		−0.008*		−0.081**
		(-1.77)		(-2.11)
R-squared	0.447	0.446	0.389	0.389
Observations	8,685	8,685	8,685	8,685
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry* State FE	Yes	Yes	Yes	Yes

This table reports the OLS estimation results for four models. Columns (1) and (2) report the coefficients of regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (3) and (4) report the coefficients of regressions, where the dependent variable is the natural logarithm of penalties plus one. All models include a set of control variables measured contemporaneously, i.e. *Sales_G, MB, Lev, Cap_Int, Q, CR, Sync, IO, Std_Ocf, AQ, Corr, CC_Expo*, and a set of time fixed effects and interacted industry and state fixed effects. The definitions of all variables are provided in Appendix 1. The sample spans the period 2001–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at the firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

except for the coefficient on *Median_Comp* when *ln(Violations)* is the dependent variable which is significant at the 10% level.

4.4.4. Controlling for CEO incentives

As CEO incentives might be correlated with both accounting comparability and environmental violations, hence representing a potentially correlated omitted variable, in robustness tests, we include controls for CEO incentives. Specifically, Lobo et al. (2018) and Choi and Suh (2019) find that accounting comparability increases the prevalence of CEO equity-based compensation and increases the pay-performance sensitivity of CEO compensation. Further, Chircop et al. (2023) find a relation between characteristics of CEO equity-based compensation and violations.

To control for CEO incentives, we follow Armstrong et al. (2013) and include in our baseline specification variables *CEO_Vega*, which captures CEO pay sensitivity to a 1% change in the volatility of the share price, *CEO_Delta* that captures CEO pay sensitivity to a 1% change in share price and *CEO_Cash_Comp* that captures CEO cash compensation received during the year. *CEO_Vega* and *CEO_Delta* are computed like Coles et al. (2013) and capture characteristics of the CEO equity based compensation. Including these three variables in our model ensures that we comprehensively control for the CEO compensation structure.

Panel D, Table 7 shows the results of this test. Out of the three control variables capturing CEO incentives, only the coefficients on *CEO_Cash_Comp* load suggesting a positive relation between CEO cash compensation and environmental violations. This positive relation is likely driven by the insensitivity of cash compensation to the costs of environmental violations. More importantly, in line with our baseline results, the coefficients on our measures of accounting comparability are negative and significant at the 5% level irrespective of our measure of environmental violations. Taken together, these results suggest that CEO incentives do not drive our baseline results.

Table 7d
Panel D: The association between the accounting comparability and environmental violations and penalties after controlling for CEO incentives.

	(1)	(2)	(3)	(4)
	ln(Violations)	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp	−0.017**		−0.146**	
	(-2.47)		(-2.32)	
Median_Comp		−0.014**		−0.141**
		(-2.19)		(-2.50)
CEO_Vega	−0.011	−0.011	−0.061	−0.063
	(-1.30)	(-1.33)	(-1.12)	(-1.15)
CEO_Delta	0.008	0.009	0.002	0.012
	(0.81)	(0.89)	(0.03)	(0.14)
CEO_Cash_Comp	0.057**	0.057**	0.481**	0.479**
	(2.49)	(2.49)	(2.50)	(2.48)
Constant	−1.027***	−1.025***	−7.144**	−7.175**
	(-3.22)	(-3.25)	(-2.25)	(-2.28)
R-squared	0.344	0.344	0.301	0.302
Observations	6,186	6,186	6,186	6,186
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

This table reports the estimation results for four models. Columns (1) and (2) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (3) and (4) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of penalties plus one. All independent variables are measured contemporaneously. All models include a set of control variables i.e. *Sales_G, MB, Lev, Cap_Int, Q, CR, Sync, IO, Std_Ocf, AQ, Corr, CC_Expo*, and a set of industry, time and state fixed effects. The definitions of all variables are provided in Appendix 1. The sample spans the period 2001–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

Table 7e
Panel E: The association between the accounting comparability and environmental violations and penalties after controlling for board characteristics.

	(1)	(2)	(3)	(4)
	ln(Violations)	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp	−0.017**		−0.150**	
	(-2.11)		(-2.15)	
Median_Comp		−0.011		−0.128**
		(-1.51)		(-1.99)
CEO_Board_Member	−0.027	−0.027	−0.264	−0.260
	(-1.16)	(-1.14)	(-1.43)	(-1.41)
Staggered_Board	−0.004	−0.004	−0.010	−0.007
	(-0.40)	(-0.39)	(-0.10)	(-0.07)
Board_Independence	0.002**	0.002**	0.023***	0.023***
	(2.18)	(2.17)	(2.76)	(2.77)
Board_Size	0.094	0.095	0.878*	0.872*
	(1.57)	(1.59)	(1.82)	(1.81)
Board_Meetings	0.010	0.010	0.187	0.174
	(0.37)	(0.35)	(0.78)	(0.72)
Constant	−0.750***	−0.687***	−7.861***	−7.340***
	(-3.50)	(-3.30)	(-4.08)	(-3.94)
R-squared	0.368	0.367	0.327	0.327
Observations	4,969	4,969	4,969	4,969
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

This table reports the estimation results for four models. Columns (1) and (2) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (3) and (4) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of penalties plus one. All independent variables are measured contemporaneously. All models include a set of control variables i.e. *Sales_G, MB, Lev, Cap_Int, Q, CR, Sync, IO, Std_Ocf, AQ, Corr, CC_Expo*, and a set of industry, time and state fixed effects. The definitions of all variables are provided in Appendix 1. The sample spans the period 2001–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

Table 7f

Panel F: The association between the accounting comparability and environmental violations and penalties before and after the financial crisis of 2008/2009.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Violations)	*ln(Violations)*	*ln(Violations)*	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp$_{t-1}$	−0.021**	−0.014**			−0.152*	−0.135**		
	(-2.16)	(-2.04)			(-1.71)	(-2.19)		
Median_Comp$_{t-1}$			−0.016*	−0.010*			−0.152*	−0.121**
			(-1.79)	(-1.68)			(-1.82)	(-2.30)
Constant	−0.240	−0.347*	−0.236	−0.315*	0.031	−0.296	0.032	−0.118
	(-1.47)	(-1.93)	(-1.46)	(-1.82)	(0.02)	(-0.18)	(0.02)	(-0.07)
R-squared	0.350	0.328	0.349	0.327	0.317	0.298	0.317	0.298
Observations	2,419	5,358	2,419	5,358	2,419	5,358	2,419	5,358
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	Before	After	Before	After	Before	After	Before	After

This table reports the estimation results for four models. Columns (1)–(4) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (5)–(8) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of penalties plus one. All independent variables are measured contemporaneously. All models include a set of control variables i.e. *Sales_G, MB, Lev, Cap_Int, Q, CR, Sync, IO, Std_Ocf, AQ, Corr, CC_Expo*, and a set of industry, time and state fixed effects. The definitions of all variables are provided in Appendix 1. The period 'before' the financial crisis includes the years 2001–2007. The period 'after' the financial crisis includes the years 2010–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

Table 7g

Panel G: The association between the accounting comparability and environmental violations and penalties before and after the paris climate accords 2015/2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(Violations)	*ln(Violations)*	*ln(Violations)*	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp$_{t-1}$	−0.017***	−0.027**			−0.149***	−0.277**		
	(-2.88)	(-2.39)			(-2.65)	(-2.55)		
Median_Comp$_{t-1}$			−0.012**	−0.020**			−0.129***	−0.242***
			(-2.35)	(-2.04)			(-2.59)	(-2.59)
Constant	−0.442**	−0.001	−0.417**	−0.389	−1.585	0.152	−1.480	−5.414
	(-2.23)	(-0.00)	(-2.12)	(-1.16)	(-0.86)	(0.05)	(-0.80)	(-1.60)
R-squared	0.341	0.311	0.340	0.310	0.303	0.293	0.303	0.293
Observations	5,822	1,891	5,822	1,891	5,822	1,891	5,822	1,891
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	Before	After	Before	After	Before	After	Before	After

This table reports the estimation results for four models. Columns (1) and (2) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (3) and (4) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of penalties plus one. All independent variables are measured contemporaneously. All models include a set of control variables i.e. *Sales_G, MB, Lev, Cap_Int, Q, CR, Sync, IO, Std_Ocf, AQ, Corr, CC_Expo*, and a set of industry, time and state fixed effects. The definitions of all variables are provided in Appendix 1. The period 'before' the Paris Climate Accords includes the years 2001–2014. The period 'after' the Paris Climate Accords includes the years 2017–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

4.4.5. Controlling for board characteristics

If as suggested by Zhang et al. (2020), accounting comparability is an effective internal monitoring tool, then the effect of accounting comparability on environmental violations is likely a function of other internal monitoring mechanisms within the firm. An internal monitoring mechanism particularly pertinent to our study, since it has previously been linked to firm environmental performance, is board monitoring (de Villiers et al., 2011). To ensure that our baseline results are not simply capturing the effect of board monitoring on environmental violations, we augment our baseline model, Eq. (5), with variables capturing board monitoring.

To Eq. (5), we add *CEO_Board_Member,* an indicator variable that takes the value of one when the CEO is a board member and zero otherwise; *Staggered_Board,* an indicator variable that takes the value of one if the firm has a staggered board structure and zero

Table 7h
Panel H: Effect of accounting comparability on environmental violations: Propensity score matched sample.

Panel H1. PSM covariance balance for *Mean_Comp*

Dependent Variable	Treated (Mean)	Control (Mean)	Difference in means between treated and control groups	t-stat
Size	7.92	8.00	−0.08	−1.43
MB	2.94	3.10	−0.17	−1.42
Loss	0.18	0.16	0.02	1.58
ROA	0.05	0.05	0.00	−0.91
Big4	0.92	0.93	0.00	−0.50

Panel H2. PSM covariance balance for *Median_Comp*

Dependent Variable	Treated (Mean)	Control (Mean)	Difference in means between treated and control groups	t-stat
Size	8.00	8.00	−0.01	−0.14
MB	3.04	3.17	−0.13	−1.09
Loss	0.12	0.11	0.01	0.90
ROA	0.06	0.06	0.00	−0.39
Big4	0.93	0.93	0.00	0.13

Panel H3. Regressions on matched sample

	(1)	(2)	(3)	(4)
	ln(Violations)	*ln(Violations)*	*ln(Penalties)*	*ln(Penalties)*
Mean_Comp	−0.020**		−0.176***	
	(-2.57)		(-2.75)	
Median_Comp		−0.017**		−0.194***
		(-2.14)		(-2.75)
Size	0.107***	0.104***	−0.176***	0.988***
	(6.89)	(7.29)	(-2.75)	(8.70)
Sales_G	−0.016	−0.020	0.998***	0.043
	(-0.40)	(-0.55)	(9.19)	(0.12)
MB	−0.009***	−0.006**	0.228	−0.046*
	(-2.66)	(-2.32)	(0.61)	(-1.67)
Lev	0.016**	0.011*	−0.076***	0.114**
	(2.16)	(1.84)	(-2.68)	(2.03)
Cap_Int	0.002	0.001	0.201***	−0.040
	(0.12)	(0.07)	(3.00)	(-0.25)
Q	−0.043***	−0.043***	−0.049	−0.437***
	(-4.02)	(-4.42)	(-0.31)	(-5.10)
CR	−0.002***	−0.002***	−0.394***	−0.012***
	(-3.20)	(-2.95)	(-4.37)	(-2.60)
Sync	−0.127	−0.039	−0.016***	−0.335
	(-0.99)	(-0.35)	(-3.38)	(-0.31)
IO	−0.058	−0.051	−1.697	−0.496
	(-1.29)	(-1.20)	(-1.48)	(-1.61)
Std_Ocf	−0.056	−0.055	−0.490	−0.602*
	(-1.43)	(-1.61)	(-1.53)	(-1.91)
Aq	0.134	0.083	−0.477	0.519
	(1.14)	(0.81)	(-1.45)	(0.62)
Corr	−0.088	−0.055	0.660	−0.255
	(-0.55)	(-0.40)	(0.73)	(-0.23)
Cc_Expo	0.026**	0.026***	−0.388	0.195***
	0.107***	(2.92)	(-0.31)	(2.75)
Constant	−0.702***	−0.802***	−0.717***	−4.789**
	(-3.52)	(-2.63)	(-3.33)	(-2.21)
R-squared	0.362	0.343	0.323	0.300
Observations	3,466	3,776	3,466	3,776
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

This table presents the analysis on propensity score matched sample. Panel H1 and panel H2 show the mean comparisons. Panel H3 shows the estimation results for four models on the matched sample. Columns (1) and (2) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of violations plus one. Columns (3) and (4) report the coefficients of OLS regressions, where the dependent variable is the natural logarithm of penalties plus one. All independent variables are measured contemporaneously. The definitions of all variables are provided in Appendix 1. The sample spans the period 2001–2020. The values reported in parentheses below coefficients represent t-statistics. Standard errors are clustered at the firm level. *, **, *** represent significance at 10%, 5%, and 1% respectively.

otherwise; *Board_Independence,* defined as the relative number of independent board members on the firms' board of directors, *Board_Size,* defined as the number of members forming the board of directors and *Board_Meetings,* defined as the number of board meetings held during the year.

Panel E, Table 7 shows the results for this test. The coefficients on the controls for board monitoring are generally insignificant; the only exceptions being the coefficients for *Board_Independence* which are positive and significant irrespective of the specification and the coefficients for *Board_Size* which are positive and significant when *ln(Penalties)* is the dependent variable. These results provide support to Friess (2022) argument that corporate governance mechanisms such as the board of directors, created to address the agency conflict between shareholders and managers, are not meant to address conflicts between the firm and stakeholders other than shareholders. The results for the relation between accounting comparability and environmental violations are in line with our baseline results suggesting that our results are not driven by the effects of board monitoring on environmental violations.

4.4.6. The influence of regulatory changes

Notwithstanding that the inclusion of year fixed effects in our empirical analysis controls for time-trends in our sample, we recognise that during our sample period, several major events occurred that resulted in significant changes to the sampled firms' regulatory framework. Two such events were the 2008/2009 financial crisis and the 2015/2016 Paris climate accords. While the former gave rise to significant changes in financial regulations, the latter provided the impetus to initiatives intended to reduce the environmental impact of corporations. To examine whether the observed relation between accounting comparability and environmental violations has been affected by these events, we run Eq. (5) for the period before and after each event separately.

Panel F, Table 7 presents the results of an analysis in which we separately run our baseline model for the period before and the period after the 2008/2009 financial crisis. Irrespective of the sample period used, we find that accounting comparability is negatively related to environmental violations suggesting that the regulatory changes following the 2008/2009 did not significantly alter the relation between accounting comparability and environmental violations.

In a similar vein, Panel G, Table 7, presents the results of an analysis in which we separately run our baseline model for the period before and after the 2015/2016 Paris Climate Accord. Irrespective of the sample period used, results suggest a negative and significant relation between accounting comparability and environmental violations. Taken together our results show that the relation between accounting comparability and violations is not sensitive to the identified regulatory events.

4.4.7. Selection bias – propensity score matching

While the inclusion of controls in our specification addresses one source of endogeneity, correlated omitted variables, another source of endogeneity is selection bias (Wooldridge, 2010).[13] In our case, selection bias arises if firms self-select in having high or low accounting comparability. To address this concern, we implement propensity score matching (PSM). To perform propensity score matched tests, we follow Rosenbaum and Rubin (1983) and compare treated firms with a control sample of firms that are similar across covariates other than accounting comparability. First, we estimate propensity scores for all firms in our sample by estimating a probit model where *High_Acctcomp*, an indicator variable that equals to one if *Mean_Comp* is above median value and zero otherwise, is the dependent variable and variables capturing company characteristics, industry and year fixed effects are the independent variables. Following Zhang (2018) and Zhang et al. (2020) we match on the following covariates: market-to-book value (*MTB*), firm size (*Size*), an indicator variable that is equal to one if firm ROA is negative and zero otherwise (*Loss*), and a Big4 indicator variable that is equal to one if the firm is audited by a "Big Four" auditor, and zero otherwise (*Big4*). Second, based on the estimated propensity scores we create a matched sample of treated firms, with above median *Mean_Comp*, and a control sample of firms with below median *Mean_Comp*. Finally, we estimate an OLS regression using the matched sample of high comparability and low comparability firms.

Panel H, Table 7 presents the results of this analysis. In Panel H1 and Panel H2 we present the covariance balance for *Mean_Comp* and *Median_Comp*, respectively. In Panel H3 we present the results from estimating the OLS regression for the matched sample with the one-to-one nearest neighbour with a caliper of one percent. The coefficients on the accounting comparability measures are negative and significant in line with our baseline results. Taken together, this analysis suggests that our baseline results are not driven by selection bias.

5. Conclusion

While prior literature has shown that accounting comparability improves the market conditions for the firm (e.g., De Franco et al., 2011) and improves corporate decision making, (e.g., Chen et al., 2018; Chircop et al., 2021) this is the first study that to our knowledge examines the relation between firm accounting comparability with peer firms and firm environmental performance. Specifically, we show that accounting comparability facilitates firm learning from peer firms such that firms reduce the number and severity of environmental violations. We find that high comparability with peer firms disclosing low toxic releases is related to a

[13] Another source of endogeneity that might influence our results is reverse causality, i.e., the possibility that environmental violations influence accounting comparability. Notwithstanding that this is unlikely due to (a) the way the variables of interest are constructed, where like De Franco et al. (2011) our measure of accounting comparability is essentially the average of the previous 16 quarters and environmental violations are captured at time *t*; and (b) in previous robustness tests (refer to Section 4.4.2) the results hold when we lag accounting comparability by one year, we address this potential problem by applying dynamic GMM (Zhang et al., 2020). Results from this analysis are similar to our baseline results and inferences are unchanged.

reduction in firm environmental violations, suggesting that one source of firm learning is peer firm EPA toxic release disclosures. Further, we find a negative relation between accounting comparability and firm toxic releases suggesting that accounting comparability facilitates learning that reduces the firm environmental impact.

This study contributes to three streams of extant literature: a) it informs the accounting comparability literature by providing initial evidence that accounting comparability not only benefits financial market participants and firms, but it also benefits the general environment through a reduction in environmental violations; b) it informs literature on the corporate level determinants of environmental practices and misconduct by identifying accounting comparability as a practice that reduces environmental violations and therefore protects the environment; and c) it contributes to the literature on the effects of monitoring and the role of learning from peer firms on corporate misconduct, by showing that accounting comparability facilitates firm learning from peer firms that ultimately results in a reduction in firms' environmental violations. Taken together these results support initiatives encouraging greater accounting comparability between firms.

Data availability

Data will be made available on request.

Acknowledgements

We are grateful to Philip Mattera of 'Good Jobs First' for giving us access to the data on environmental violations. We thank Stella Huiying Wu (discussant) and participants at the 6th Shanghai-Edinburgh-London Green Finance Conference for their comments and suggestions. Finally, we thank the reviewers and editors of the British Accounting Review for their feedback and suggestions.

APPENDIX 1

Definitions of Variables

Variable	Definition	Source
Violations	The total number of environmental violations per year.	Violation Tracker
Penalties	The total value of penalties for environmental violations per year.	Violation Tracker
ln(Violations)	Natural logarithm of one plus the number of environmental violations.	Violation Tracker
ln(Penalties)	Natural logarithm of one plus the value of penalties for environmental violations per year.	Violation Tracker
Mean_Comp	Mean accounting comparability calculated as in De Franco et al. (2011).	CRSP, Compustat
Median_Comp	Median accounting comparability calculated as in De Franco et al. (2011).	CRSP, Compustat
Mean_Comp1	The adjusted mean measure of accounting comparability measured similarly to COMP but allows for asymmetric earnings-return relation between periods when the firm exhibits positive market returns and periods when the firm exhibits negative market returns.	CRSP, Compustat
Median_Comp1	Adjusted median measure of accounting comparability measured similar to COMP but allows for asymmetric earnings-return relation between periods when the firm exhibits positive market returns and periods when the firm exhibits negative market returns.	CRSP, Compustat
Mean_Comp2	Adjusted mean measure of accounting comparability measured similar to Mean_COMP1 but allows for the possibility that prices lead earnings.	CRSP, Compustat
Median_Comp2	Adjusted median measure of accounting comparability measured similar to Median_COMP1 but allows for the possibility that prices lead earnings.	CRSP, Compustat
Size	Natural logarithm of market value.	Compustat
Sales_G	Sales growth, end of fiscal year sales minus beginning of fiscal year sales, divided by beginning of fiscal year sales.	Compustat
MB	Market-to-book ratio, calculated as the firm market capitalization at financial year-end scaled by net assets.	Compustat
Lev	Leverage, computed as long-term debt scaled by total shareholders' equity.	Compustat
Cap_Int	Capital intensity, calculated as the log of total assets scaled by the number of employees.	Compustat
Q	The sum of firm market value and total debt scaled by total assets	Compustat
CR	Current ratio, calculated as current assets scaled by current liabilities.	Compustat
Sync	Synchronicity, calculated as the adjusted r-squared from a market model OLS regression run over the same 16 quarters used to compute COMP	Compustat
IO	Institutional ownership, calculated as the number of shares held by institutional owners scaled by the number of outstanding shares at financial year end.	Compustat
Std_Ocf	Operating cash flow volatility, calculated as the coefficient of variation for the same 16-quarters used to calculate COMP.	Compustat
AQ	Accounting quality, calculated as the standard deviation of residuals from an OLS regression where change in working capital is a function of lag operating cash flows, operating cash flows, lead operating cash flows, change in sales and property plant and equipment. The regression is run by a 4-digit NAICS industry.	Compustat
Corr	Correlation, calculated as the average correlation of a subject firm return with peer firm returns. Correlation is calculated for all subject firm-peer firm combination within the same 4-digit NAICS industry over the same 16-quarters used to calculate COMP.	Compustat

(*continued on next page*)

(*continued*)

Variable	Definition	Source
Cc_Expo	Climate change risk exposure, measured by Sautner et al. (2021) as the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls multiplied by 1000.	Sautner et al. (2021)
Low_Peer_TR	Peer with a low level of toxic releases, an indicator variable that takes the value of one when at least one of the four peer firms with the highest accounting comparability with the subject firm has toxic releases scaled by total assets lower than the median for the industry-year, and zero otherwise.	Compustat, EPA
Toxic_Releases	Toxic releases, proxied by the natural logarithm of one plus the total on-site and off-site releases.	EPA TRI
CEO_Vega	CEO vega, calculated as the natural logarithm of one plus the sensitivity of the CEO's equity portfolio to 0.01 change in volatility (Coles et al., 2013).	Compustat, CRSP
CEO_Delta	CEO delta, calculated as the natural logarithm of one plus the sensitivity of the CEO's equity portfolio to 0.01 change in stock prices (Coles et al., 2013).	Compustat, CRSP
CEO_Cash_Comp	CEO cash compensation, calculated as the natural logarithm of one plus the total cash compensation received by the CEO during the year.	Compustat
CEO_Board_Member	CEO board membership, proxied by an indicator variable that takes the value of one when the CEO is a board member and zero otherwise.	Refinitiv
Staggered_Board	Staggered board, proxied by an indicator variable that takes the value of one if the firm has a staggered board structure and zero otherwise.	Refinitiv
Board_Independence	Board independence, proxied by the relative number of independent board members of the firms' board of directors.	Refinitiv
Board_Size	Board size, proxied by the number of members forming the board of directors.	Refinitiv
Board_Meetings	Board meetings, calculated as the number of board meetings held during the year.	Refinitiv

APPENDIX 2

Sample Selection

This table reports sample selection.

	# firm/year observations
Number of firms available on Compustat between 1998 and 2021	184,357
Less:	
SIC <6000; 6999>	45,979
SIC<4900; 4999>	7,363
lack of coverage by Violation Tracker	109,565
missing data to construct the vector of control variables	12,765
Final sample	8,685

APPENDIX 3

Distribution of Violations and Penalties

This table presents the distribution of environmental violations across industries following the Fama-French Type 48 Industry Classification. The reported figures represent the total number of offences (*Env_Violations*) and the total value of penalties (*Env_Penalties*) across industries.

	Env_Violations	*Env_Penalties*
Food Products	147	62,200,000
Candy & Soda	14	539,797
Beer & Liquor	40	8,042,091
Recreation	3	13,000,000
Entertainment	7	8,640,018
Consumer Goods	98	19,200,000
Apparel	3	277,880
Healthcare	48	17,100,000
Medical Equipment	30	2,168,671
Pharmaceutical Products	88	45,100,000
Chemicals	418	213,000,000
Rubber and Plastic Products	4	442,600

(*continued on next page*)

(*continued*)

Textiles	1	14,512
Construction Materials	124	6,161,249
Construction	33	4,124,350
Steel Works Etc	253	71,900,000
Fabricated Products	1	96,307
Machinery	151	78,000,000
Electrical Equipment	20	1,024,066
Automobiles and Trucks	93	34,800,000
Aircraft	81	60,600,000
Shipbuilding, Railroad Equipment	3	176,671
Defense	13	5,501,994
Precious Metals	25	181,000,000
Non-Metallic and Industrial Metal Mining	79	20,200,000
Coal	2	23,000
Petroleum and Natural Gas	1,308	2,810,000,000
Communication	42	115,000,000
Business Services	34	15,800,000
Computers	6	421,440
Electronic Equipment	74	195,000,000
Measuring and Control Equipment	45	7,848,434
Business Supplies	143	195,000,000
Shipping Containers	27	927,889
Transportation	55	205,000,000
Wholesale	64	3,092,050
Retail	27	17,000,000
Restaraunts, Hotels, Motels	15	377,945
Other	60	135,000,000

References

Abebe, M. A., & Acharya, K. (2022). Founder CEOs and corporate environmental violations: Evidence from S&P 1500 firms. *Business Strategy and the Environment, 31*(3), 1204–1219.
Akey, P., & Appel, I. (2019). *Environmental externalities of activism*. Available at SSRN 3508808.
Akey, P., & Appel, I. (2021). The limits of limited liability: Evidence from industrial pollution. *The Journal of Finance, 76*(1), 5–55.
Amini, S., Johan, S., Kashefi-Pour, E., & Mohamed, A. (2021). *Employee welfare, social capital, and IPO survival*. Available at SSRN 3938945.
Armstrong, C. S., Larcker, D. F., Ormazabal, G., & Taylor, D. J. (2013). The relation between equity incentives and misreporting: The role of risk-taking incentives. *Journal of Financial Economics, 109*(2), 327–350.
Attig, N., Boubakri, N., El Ghoul, S., & Guedhami, O. (2016). Firm internationalization and corporate social responsibility. *Journal of Business Ethics, 134*(2), 171–197.
Azar, J., Duro, M., Kadach, I., & Ormazabal, G. (2021). The big three and corporate carbon emissions around the world. *Journal of Financial Economics, 142*(2), 674–696.
Bartram, S. M., Hou, K., & Kim, S. (2022). Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics, 143*(2), 668–696.
Basu, S. (1997). The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics, 24*(1), 3–37.
Berrone, P., Fosfuri, A., & Gelabert, L. (2017). Does greenwashing pay off? Understanding the relationship between environmental actions and environmental legitimacy. *Journal of Business Ethics, 144*(2), 363–379.
Berrone, P., Fosfuri, A., Gelabert, L., & Gomez-Mejia, L. R. (2013). Necessity as the mother of 'green' inventions: Institutional pressures and environmental innovations. *Strategic Management Journal, 34*(8), 891–909.
Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics, 142*(2), 517–549.
Bradshaw, M. T., Miller, G. S., & Serafeim, G. (2009). *Accounting method heterogeneity and analysts' forecasts*. University of Chicago, University of Michigan, and Harvard University. Unpublished paper.
Brochet, F., Jagolinzer, A. D., & Riedl, E. J. (2013). Mandatory IFRS adoption and financial statement comparability. *Contemporary Accounting Research, 30*(4), 1373–1400.
Busch, T., & Hoffmann, V. H. (2009). Ecology-driven real options: An investment framework for incorporating uncertainties in the context of the natural environment. *Journal of Business Ethics, 90*(2), 295–310.
Chang, X., Fu, K., Li, T., Tam, L., & Wong, G. (2021). *Corporate environmental liabilities and capital structure*. Available at SSRN 3200991.
Chava, S. (2014). Environmental externalities and cost of capital. *Management Science, 60*(9), 2223–2247.
Chen, C. W., Collins, D. W., Kravet, T. D., & Mergenthaler, R. D. (2018). Financial statement comparability and the efficiency of acquisition decisions. *Contemporary Accounting Research, 35*(1), 164–202.
Chircop, J. (2021). The relation between accounting comparability and firm productivity. *Journal of Accounting.* Auditing & Finance, 0148558X211046221.
Chircop, J., Collins, D. W., Hass, L. H., & Nguyen, N. N. Q. (2020). Accounting comparability and corporate innovative efficiency. *The Accounting Review, 95*(4), 127–151.
Chircop, J., Tarsalewska, M., & Trzeciakiewicz, A. (2023). *CEO risk taking equity incentives and workplace misconduct*. Available at SSRN 3511638.
Choi, J. H., Choi, S., Myers, L. A., & Ziebart, D. (2019). Financial statement comparability and the informativeness of stock prices about future earnings. *Contemporary Accounting Research, 36*(1), 389–417.
Choi, H., & Suh, S. (2019). The effect of financial reporting quality on CEO compensation structure: Evidence from accounting comparability. *Journal of Accounting and Public Policy, 38*(5), Article 106681.
Clarkson, P. M., Fang, X., Li, Y., & Richardson, G. (2013). The relevance of environmental disclosures: Are such disclosures incrementally informative? *Journal of Accounting and Public Policy, 32*(5), 410–431.
Clarkson, P. M., Li, Y., Richardson, G. D., & Vasvari, F. P. (2011). Does it really pay to be green? Determinants and consequences of proactive environmental strategies. *Journal of Accounting and Public Policy, 30*(2), 122–144.
Cohn, J., & Deryugina, T. (2018). *Firm-level financial resources and environmental spills*. NBER Working Paper No. w24516, Available at SSRN 3163297.
Coles, J., Daniel, N., & Naveen, L. (2013). *Calculation of Compensation Incentives and Firm-Related Wealth using Execucomp: Data, Program, and Explanation*. Temple University Working paper.

Collins, D. W., Kothari, S. P., Shanken, J., & Sloan, R. G. (1994). Lack of timeliness and noise as explanations for the low contemporaneous return-earnings association. *Journal of Accounting and Economics, 18*(3), 289–324.
Cordis, A. S., Hsu, P. H., & Zhang, J. (2022). *Freedom of information and industrial pollution*. Available at SSRN 3995477.
Dai, R., Liang, H., & Ng, L. (2021). Socially responsible corporate customers. *Journal of Financial Economics, 142*(2), 598–626.
Dasgupta, S., Huynh, T., & Xia, Y. (2021). *Joining forces: The spillover effects of EPA enforcement actions and the role of socially responsible investors*. Available at SSRN 3930776.
De Franco, G., Kothari, S. P., & Verdi, R. S. (2011). The benefits of financial statement comparability. *Journal of Accounting Research, 49*(4), 895–931.
De Villiers, C., Jia, J., & Li, Z. (2022). Are boards' risk management committees associated with firms' environmental performance? *The British Accounting Review, 54*(1), Article 101066.
De Villiers, C., Naiker, V., & Van Staden, C. J. (2011). The effect of board characteristics on firm environmental performance. *Journal of Management, 37*(6), 1636–1663.
Dyck, I. J., Lins, K., Roth, L., & Wagner, H. (2019). Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics, 131*(3), 693–714.
Edmans, A. (2020). *Grow the pie: How great companies deliver both purpose and profit*. Cambridge University Press.
El Ghoul, S., Guedhami, O., Kim, H., & Park, K. (2018). Corporate environmental responsibility and the cost of capital: International evidence. *Journal of Business Ethics, 149*(2), 335–361.
El Ghoul, S., Guedhami, O., Kwok, C. C., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance, 35*(9), 2388–2406.
Financial Accounting Standards Board (FASB). (1980). *Statement of financial accounting concepts No. 2: Qualitative characteristics of accounting information*.
Financial Accounting Standards Board (FASB). (2010). *Statement of financial accounting concepts No. 8: Conceptual framework for financial reporting*.
Financial Times. (2022). Asset managers told to clean up greenwashing and net zero claims. June 20, 2022 https://www.ft.com/content/f1367ab4-ac6f-486d-8bd2-e7659448055d.
Friess, J. C. (2022). *ESG's democratic deficit: Why corporate governance cannot protect stakeholders*. Available at SSRN 4136714.
Goetz, M. R. (2018). *Financial constraints and corporate environmental responsibility*. Available at SSRN 3230344.
Gong, G., Li, L. Y., & Zhou, L. (2013). Earnings non-synchronicity and voluntary disclosure. *Contemporary Accounting Research, 30*(4), 1560–1589.
Heath, D., Macciocchi, D., Michaely, R., & Ringgenberg, M. C. (2023). *Does socially responsible investing change firm behavior? Review of finance* (in press).
Heese, J., Pérez-Cavazos, G., & Peter, C. D. (2021). When the local newspaper leaves town: The effects of local newspaper closures on corporate misconduct. *Journal of Financial Economics, 145*(2), 445–463.
Heyes, A. G., & Rickman, N. (1999). Regulatory dealing – revisiting the Harrington paradox. *Journal of Public Economics, 72*(3), 361–378.
Hope, O. K., Wang, D., Yue, H., & Zhao, J. (2021). Information quality and workplace safety. *Journal of Management Accounting Research, 34*(1), 133–162.
Horton, J., Serafeim, G., & Serafeim, I. (2013). Does mandatory IFRS adoption improve the information environment? *Contemporary Accounting Research, 30*(1), 388–423.
Hossain, A., Saadi, S., & Amin, A. S. (2022). Does CEO risk-aversion affect carbon emission? *Journal of Business Ethics*, 1–28.
Imhof, M. I., Seavey, S. E., & Smith, D. B. (2017). Comparability and cost of equity capital. *Accounting Horizons, 31*(2), 125–138.
Kim, S., Kraft, P., & Ryan, S. G. (2013). Financial statement comparability and credit risk. *Review of Accounting Studies, 18*(3), 783–823.
Kim, J.-B., Leye, L., Lu, L. Y., & Yu, Y. (2016). Financial statement comparability and expected crash risk. *Journal of Accounting and Economics, 61*(2–3), 294–312.
Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *Review of Financial Studies, 33*(3), 1067–1111.
Liu, C. (2018). Are women greener? Corporate gender diversity and environmental violations. *Journal of Corporate Finance, 52*, 118–142.
Li, Q., Xue, Q., Truong, Y., & Xiong, J. (2018). MNCs' industrial linkages and environmental spillovers in emerging economies: The case of China. *International Journal of Production Economics, 196*, 346–355.
Lobo, G. J., Neel, M., & Rhodes, A. (2018). Accounting comparability and relative performance evaluation in CEO compensation. *Review of Accounting Studies, 23*(3), 1137–1176.
Lyon, T. P., & Maxwell, J. W. (2011). Greenwash: Corporate environmental disclosure under threat of audit. *Journal of Economics and Management Strategy, 20*(1), 3–41.
Nellemann, C., Henriksen, R., Kreilhuber, A., Stewart, D., Kotsovou, M., Raxter, P., Mrema, E., & Barrat, S. (2016). The rise of environ mental crime – a growing threat to natural resources peace, development and security. *A UNEPINTERPOL Rapid Response Assessment. United Nations Environment Programme and RHIPTO Rapid Response–Norwegian Center for Global Analyses*.
Peng, Y. S., & Lin, S. S. (2008). Local responsiveness pressure, subsidiary resources, green management adoption and subsidiary's performance: Evidence from Taiwanese manufacturers. *Journal of Business Ethics, 79*(1), 199–212.
Peterson, K., Schmardebeck, R., & Wilks, T. J. (2015). The earnings quality and information processing effects of accounting consistency. *The Accounting Review, 90*(6), 2483–2514.
Raghunandan, A., & Rajgopal, S. (2022). *Do socially responsible firms walk the talk?*. Available at SSRN 3609056.
Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.
Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2020). Data for 'firm-level climate change exposure. https://doi.org/10.17605/OSF.IO/FD6JQ.
Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2021). *Firm-level climate change exposure*. European Corporate Governance Institute–Finance Working Paper (686), Available at SSRN 3642508.
Schiller, C. (2018). April. Global supply-chain networks and corporate social responsibility. In *13th annual mid-atlantic research conference in finance (MARC) paper*. Available at SSRN 3089311.
Schipper, K. (2003). Principles-based accounting standards. *Accounting Horizons, 17*(1), 61–72.
SEC. (2000). SEC Concept release: International accounting standards. http://www.sec.gov/rules/concept/34-42430.htm.
Shane, P. B., Smith, D. B., & Zhang, S. (2014). *Financial statement comparability and valuation of seasoned equity offerings*. Available at SSRN 12372965.
Shapira, R., & Zingales, L. (2017). *Is pollution value-maximizing? The DuPont case*. NBER Working Paper No. w23866, Available at SSRN 3046380.
Shive, S. A., & Forster, M. M. (2020). Corporate governance and pollution externalities of public and private firms. *Review of Financial Studies, 33*(3), 1296–1330.
Sohn, B. C. (2016). The effect of accounting comparability on the accrual-based and real earnings management. *Journal of Accounting and Public Policy, 35*(5), 513–539.
Suk, I., & Zhao, Y. (2017). *Does financial statement comparability deter aggressive tax avoidance*. Available at SSRN 3065250.
Tsang, A., Frost, T., & Cao, H. (2023). *Environmental, social, and governance (ESG) disclosure: A literature Review*. The British Accounting Review, Article 101149.
Xu, Q., & Kim, T. (2022). Financial constraints and corporate environmental policies. *Review of Financial Studies, 35*(2), 576–635.
Yaeger, P. (1991). *The limits of the law: The public regulation of private pollution*. Cambridge: Cambridge University Press.
Zhang, J. H. (2018). Accounting comparability, audit effort, and audit outcomes. *Contemporary Accounting Research, 35*(1), 245–276.
Zhang, Z., Ntim, C. G., Zhang, Q., & Elmagrhi, M. H. (2020). Does accounting comparability affect corporate employment decision-making? *The British Accounting Review, 52*(6), Article 100937.