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Does Carbon Risk Influence Stock Price Crash Risk? International Evidence

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ABSTRACT

This article examines the relationship between carbon risk and future stock price crash risk, focusing on an international sample of firms. Inherently, complex and deep uncertainties of carbon risk limit investors' ability to fully understand and incorporate carbon risk into equity pricing and create room for opportunistic managers to hide bad news about poor carbon performance. Such pricing uncertainties and information asymmetry can result in significant overpricing of stocks (i.e., underpricing of carbon risks), especially for carbon-intensive firms, thereby exposing these stocks to future stock price crash risks. In line with this argument, we find that carbon risk is positively associated with future stock price crash risk. However, we find that better carbon disclosure quality reduces pricing uncertainties and information asymmetry, which attenuates the positive effect of carbon risk on future stock price crash risk. Similarly, internal monitoring (e.g., corporate governance) and external monitoring (e.g., institutional investors and financial analysts) help alleviate information asymmetry related to carbon risk, thus reducing crash risk. In countries with stakeholder-oriented business cultures, high climate change performance, and financial transparency, as well as for companies that link compensation to climate change performance, the positive association between carbon risk and stock price crash risk is weaker.

> "Without the right information, investors and others may incorrectly price or value assets, leading to a misallocation of capital… One of the most significant and perhaps most misunderstood risks organizations face today relates to climate change."
>
> – Task Force on Climate-Related Financial Disclosures

1 | Introduction

It is now widely recognized that greenhouse gas (GHG) emissions are a significant driver of global warming, contributing to both climate change risk and carbon risk, which together can lead to substantial costs for corporations (Intergovernmental Panel on Climate Change [IPCC] 2019). Climate change risk encompasses the broader array of risks associated with climate-related impacts on business, including regulatory, reputational, and physical risks. In contrast, carbon risk refers explicitly to the

The views expressed herein are those of the authors and do not necessarily reflect the views of any employer or other associated entity risks associated with carbon emissions and the potential financial consequences of transitioning to low-carbon operations, which can affect a firm's value and future cash flows (Hoffmann and Busch 2008; Herbohn, Gao, and Clarkson 2019; Jung, Herbohn, and Clarkson 2018).[1] Both climate change and carbon risks include three main components: physical, liability, and transition risks (Carney 2015). Physical risks damage assets and trigger operation and supply chain disruptions. Liability risks exist when investors, consumers, and activists file lawsuits against firms for damages related to climate change. Transition risks are the uncertainties of revising business models, technology, and policies when transitioning into a carbon-constrained economy (e.g., Addoum, Ng, and Ortiz-Bobea 2020; Bergmann, Stechemesser, and Guenther 2016; Huang, Kerstein, and Wang 2018; Schultz and Williamson 2005). Regulators and institutions worldwide have developed rules and initiatives to combat global warming, compelling firms to measure, manage, and report their carbon emissions due to the pervasive impacts of climate change on the ecosystem and the global economy (e.g., Carbon Disclosure Project [CDP] 2018; Task Force on Climate-Related Financial Disclosures [TCFD] 2020).

This article examines whether carbon risk is related to crash risk. We hypothesize a positive relationship between a firm's carbon risk and future stock price crash risk for two reasons. First, the inherent complexity and uncertainty of carbon risk, exacerbated by limitations in scientific models, obscure the financial impact and noncompliance costs for corporations (Barnett, Brock, and Hansen 2020; Berger, Emmerling, and Tavoni 2017; Heal and Millner 2014; Knutti and Sedláček 2013; Knutti, Rugenstein, and Hegerl 2017; Krueger, Sautner, and Starks 2020; Pindyck 2013; Roe and Baker 2007).[2] This complexity leads to underestimated and mispriced carbon risks by investors, especially for carbon-intensive firms, as their stock prices are more vulnerable to carbon-related shocks that cause investors to abruptly correct the stocks' overvaluation to their intrinsic value (Battiston, Dafermos, and Monasterolo 2021; Barnett 2023; Bolton and Kacperczyk 2021; Broeders et al. 2023; Daniel, Litterman, and Wagner 2016; Hong, Li, and Xu 2019).

Second, the complexity of carbon risk incentivizes managerial information withholding. Firms with high emissions may obscure carbon data, increasing information asymmetry and stock price crash risk (Elsbach and Sutton 1992; Fabrizio and Kim 2019; Hart 1995; Walker and Wan 2012). High carbon emissions impair a firm's environmental performance, threatening its competitiveness and resource accessibility along the supply chain (e.g., Hart 1995). Such firms may have incentives not to disclose information about carbon performance or to cloak carbon-related disclosures to manipulate stakeholders' attention (e.g., Elsbach and Sutton 1992; Fabrizio and Kim 2019; Walker and Wan 2012), resulting in higher information asymmetry, which, in turn, increases stock price crash risk.

We use actual carbon emissions as a proxy for carbon risk. High carbon emissions can lead to shocks such as spiking prices for fossil-fuel energy, substitution product threat by low carbon risk competitors, divestment and financing threat by "green" institutional investors or banks, and stricter regulatory policies, penalties, or litigation for heavy carbon emissions (e.g., Bolton and Kacperczyk 2021; Delis, De Greiff, and Ongena 2024; Ginglinger and Moreau 2023; Seltzer, Starks, and Zhu 2021). In the short term, Shapira and Zingales (2017) demonstrate that executives can rationally conclude that violating emissions regulations rather than complying with them is value-maximizing for shareholders; however, this behavior can lead to additional shocks later, which may increase crash risk.

In addition, the study explores whether a firm's transparency about its carbon footprint, assessed through the quality of its carbon disclosures, mitigates the link between carbon risk and stock price crash risk. Carbon disclosure quality is evaluated using the CDP disclosure score, which reflects the depth and thoroughness of a firm's responses to CDP questionnaires. These questionnaires focus on carbon-related issues, including the firm's management methods and initiatives to address them.[3] Using European data, Schiemann and Sakhel (2019) find that the transparent physical risk of carbon disclosure will likely reduce the information asymmetry investors face. Matsumura, Prakash, and Vera-Muñoz (2014) and Bui et al. (2020) show that carbon disclosure alleviates the carbon premium required by investors in the US and cross-country settings, respectively. Lin and Wu (2023) offer empirical insights from China that increased carbon risk disclosures help raise public awareness of climate risk, reducing a firm's stock price crash risk. On the basis of this line of argument, we expect transparent carbon disclosures to reduce pricing uncertainties and discourage managerial bad news hoarding, which may reduce the likelihood of crash risk accrued to carbon risk.

To test our prediction, we follow Chen, Hong, and Stein (2001) and measure crash risk as the conditional skewness of return distribution. Using a sample of 13,165 firm-year observations from 2007 to 2022 across 38 countries, we find that carbon risk is positively associated with future stock price crash risk. However, we also find that more transparent firm-level carbon disclosures alleviate the positive effect of firm carbon risks on its future stock price crash risk. Further analysis shows that the positive association between carbon risk and stock price crash risk is less pronounced for firms linking climate-related issues with incentive contracts and for firms domiciled in countries with stakeholder-orientated business cultures, strong country-level climate change performance, and greater financial transparency. To address potential endogeneity concerns, we use the adoption of mandatory emissions disclosures as an exogenous shock and find that our results hold. Additionally, the positive association between carbon risk and future stock price crash risk is reduced by internal monitoring (e.g., corporate governance) and external monitoring (e.g., high institutional investors and financial analyst coverage).

This study provides three key insights into the link between carbon and crash risks. First, existing literature shows that stock prices are more prone to significant drops than rises, with negative returns impacting investor wealth and financial market stability (e.g., Campbell and Hentschel 1992; Agnes Cheng, Li, and Zhang 2020; French, Schwert, and Stambaugh 1987). Therefore, understanding firm-specific factors and governance issues contributing to crash risk is vital (e.g., Bleck and Liu 2007; Hong, Kim, and Welker 2017; Jin and Myers 2006). Additionally, global regulatory concerns about investors underestimating the financial impacts of carbon risk (Bank for International Settlements

2018; Bank of England 2019; Board of Governors of the Federal Reserve System 2021; International Monetary Fund 2021). Our study uniquely investigates how a firm's carbon risk, indicated by its carbon emissions, affects its stock price crash risk. It also examines country-level factors that might mitigate this crash risk associated with carbon risk.

Second, research indicates that information gaps between managers and investors significantly predict stock price crash risk (Jin and Myers 2006). Enhancing the quality of a firm's carbon disclosures can lessen these gaps and uncertainties related to carbon risks, potentially reducing crash risk. Furthermore, the significant consequences of stock price crashes (Agnes Cheng, Li, and Zhang 2020) highlight the importance of understanding the connection between carbon risks and the financial impacts of crashes. This understanding could motivate financial markets and regulators to implement measures and enforce disclosures to mitigate a firm's carbon risk.

Prior studies have shown that firms' climate and carbon risks matter for equity pricing (e.g., Bolton and Kacperczyk 2021; Hsu, Li, and Tsou 2023). For instance, negative environmental and social indicators or climate risk exposure reflect downside risks such as option implied tail risk and increased likelihood of bankruptcy (e.g., Nofsinger, Sulaeman, and Varma 2019; Ilhan, Sautner, and Vilkov 2021). However, our study offers international evidence of the specific impact of a firm's carbon risk on its future stock price crash risk, focusing on the third moment of stock return distribution captured by its skewness. Merton (1978) and Chen, Hong, and Stein (2001) illustrate that as stock returns are less likely to be normally distributed, the third moment of stock return (skewness), distinct from the first and second moments of the return distribution, is essential for equity pricing.

Our study distinguishes itself from two related studies, Ren et al. (2023) and Lin and Wu (2023). Ren et al. (2023) examine the association between stock price crash risk and carbon price uncertainty in China, using the carbon emission allowance (euro index) by S&P DJI. They find that carbon pricing uncertainties lead managers to hide damaging information and increase investor disagreements, thus raising the risk of stock price crashes. Lin et al. (2023) also use data from Chinese companies to analyze firm-level climate risk disclosures through the frequency of climate-related keywords in reports. Their findings suggest that more frequent climate risk disclosures lower stock price crash risk by enhancing awareness of climate risk. In contrast, our study utilizes an international sample of firms and investigates a direct measure of carbon risk and its impact on future stock price crash risk, considering country-specific characteristics. Unlike Ren et al. (2023), who focus on carbon price uncertainty, our study emphasizes the inherent uncertainties of carbon risk and their potential to cause overpricing and subsequent crash risks. Moreover, although Lin et al. (2023) emphasize the quantity of climate risk disclosures in reducing crash risk, our study assesses the quality of carbon disclosures per CDP reporting. High-quality carbon disclosures can lead firms to reduce carbon emissions (Qian and Schaltegger 2017), thus lowering the impact of carbon risk on stock price crash risk by reducing information asymmetry. Our international study provides a broader perspective on the relationship between carbon risk and stock price crash risk by addressing emissions-related carbon risk and the quality of carbon disclosures. Our study also has practical implications. As investors regard crash risk as a crucial concern (e.g., Koonce, Mcanally, and Mercer 2005; Olsen 1997), understanding crash risk informs investment decisions and risk management (e.g., Ghadhab 2019; Kim, Li, and Li 2014). Our study urges investors to be cautious about carbon risk and regulators to increase oversights of high carbon risk firms.

The remainder of the study is structured as follows. Section 2 provides the literature review and develops theoretical hypotheses. Section 3 describes the data sample and variables of interest. Section 4 presents the methodology and results. Section 5 concludes.

2 | Literature Review and Hypothesis Development

2.1 | Pricing and Mispricing of Carbon Risk

Recent research shows carbon risk impacts debt, equity, and options market pricing. Studies indicate that carbon risk affects a firm's future performance and value, leading to a carbon premium in various markets (Barnett, Brock, and Hansen 2020). For instance, in the equity market, Bolton and Kacperczyk (2021, 2023) observe a growing carbon premium across sectors globally. Hsu, Li, and Tsou (2023) find that US firms with higher toxic emissions face a risk premium due to regulatory uncertainty. In the options market, Ilhan, Sautner, and Vilkov (2021) note a higher cost for protection against carbon-intensive firms in the United States. In the debt market, Jung, Herbohn, and Clarkson (2018) and Ehlers, Packer, and de Greiff (2022) find a link between carbon risk and higher borrowing costs.

However, other studies suggest that markets do not fully anticipate the economic impact of carbon risks (Hong, Li, and Xu 2019, Hong, Karolyi, and Scheinkman 2020; Stroebel and Wurgler 2021). Surveys like Krueger, Sautner, and Starks (2020) reveal that institutional investors do not believe climate risk is accurately priced in stocks. Hong, Li, and Xu (2019) show that investors underestimate drought impacts on financial performance in the food sector. Monasterolo and de Angelis (2020) find that investors increasingly consider investing in low-carbon indices but do not penalize carbon-intensive ones post-Paris Agreement. Pankratz, Bauer, and Derwall (2023) observe that analysts and investors fail to anticipate the impacts of heat exposure on earnings. Cuculiza et al. (2023) demonstrate that US equity markets tend to underreact to information about climate change. This underreaction results in the overvaluation of stocks impacted by temperature changes. This overpricing is further influenced by the actions of foreign institutional investors and the less accurate predictions provided by equity analysts.

2.2 | Carbon Risk and Stock Price Crash Risk

We argue that firms with higher carbon risk are more likely to experience future stock price crashes for two main reasons. First, the complexity and uncertainties associated with climate change make it challenging for investors to price a firm's carbon risk accurately. Geoscience studies highlight this difficulty, illustrating the ongoing uncertainty in climate change dynamics and the challenges in predicting climate-related events (Knutti and Sedláček 2013; Knutti, Rugenstein, and Hegerl 2017; Roe and Baker 2007). Furthermore, climate change model simulations have limitations, as shown by Alley et al. (2003), Berger, Emmerling, and Tavoni (2017), and Pindyck (2017), leading to a volatile environment-prone overpricing, which can lead to stock crash risk. The financial and economic models also struggle to effectively capture climate risks characterized by deep uncertainty, nonlinearity, and endogeneity, as suggested by Battiston, Dafermos, and Monasterolo (2021). The underestimation and mispricing of carbon risks (Barnett 2023; Broeders et al. 2023; Daniel, Litterman, and Wagner 2016; Heal and Millner 2014; Krueger, Sautner, and Starks 2020; Pindyck 2013) contribute to significant delays in stock price adjustments, as evidenced by various studies (Cuculiza et al. 2023; Hong, Li, and Xu 2019, Hong, Karolyi, and Scheinkman 2020; Monasterolo and de Angelis 2020).

Second, the inherent complexity and uncertainty about carbon risk create a fertile ground for information asymmetry. Due to internal knowledge and regulatory pressures, managers of high carbon risk firms might obfuscate or delay carbon performance disclosures. This behavior leads to an increased gap in information between the firm and its investors (Elsbach and Sutton 1992; Fabrizio and Kim 2019; Walker and Wan 2012), increasing the risk of stock price crashes when accumulated undisclosed negative information suddenly becomes public.[4]

Moreover, carbon-intensive firms are disproportionately affected by uncertainties and regulatory attention compared to their less carbon-intensive counterparts (Ilhan, Sautner, and Vilkov 2021). These firms are more likely to face unpredicted impacts on compliance costs and operational decisions, exacerbated by investors' inability to fully anticipate the financial impact and timeline of carbon risk materialization (Andersson, Bolton, and Samama 2016; Barnett, Brock, and Hansen 2020). Carbon-related shocks, such as fluctuating energy prices, shifts in consumer preferences, technological innovations by competitors, divestment threats, and stricter emission regulations (Bolton and Kacperczyk 2021; Delis, De Greiff, and Ongena 2024; Fink 2020; Ginglinger and Moreau 2023; Seltzer, Starks, and Zhu 2021), can lead to severe disruptions. These disruptions, in turn, can trigger significant financial shocks like capital loss, asset devaluation, and reduced cash flows, culminating in a stock price crash when investors abruptly readjust their risk assessments and realize the previous mispricing. Sautner et al. (2023) suggest that the risk premium for climate change exposure is an ambiguous concept continuously changing due to uncertainty surrounding the eventual equilibrium. Unsurprisingly, the Task Force on Climate-Related Financial Disclosures (2017, 3) identifies climate change as "one of the most significant, and perhaps most misunderstood, risks organizations face today."

The two preceding arguments lead us to formulate the first hypothesis:

H1. Firm-level carbon risks are positively associated with stock price crash risk.

2.3 | The Mitigating Role of Carbon Risk Disclosures

Annually, the CDP sends questionnaires to large global firms, requesting them to report various aspects of their climate change and carbon risks (CDP 2017). These reports are then assessed for the quality and depth of carbon disclosure. We propose that high-quality CDP disclosures can reduce the likelihood of stock price crash risks linked to carbon risks. This reduction is not only due to the transparency these disclosures provide but also because they supply investors with crucial information to comprehensively evaluate a firm's carbon profile.

High-quality CDP disclosures suggest that a firm is transparent about its carbon risk, which can be instrumental in reducing information asymmetry and potentially mitigating stock price crash risk (Schiemann and Sakhel 2019). Moreover, firms with superior CDP disclosures are often more forward-thinking and better prepared for transitioning to a low-carbon economy, indicating robust carbon governance and strategic planning (Bui et al. 2020; OECD 2017). This preparation may reduce the firm's inherent carbon risk, as reflected in the market valuations (Griffin and Sun 2013; Kim and Lyon 2011; Liesen et al. 2017). Studies in various settings have found that high-quality CDP disclosures can lessen the carbon premium demanded by investors (Bui et al. 2020; Matsumura, Prakash, and Vera-Muñoz 2014). Lin and Wu (2023) find that more frequent climate risk disclosures can reduce a firm's stock price crash risk by raising public awareness of climate risks (Lin and Wu 2023).

It is crucial to recognize the dual role of CDP disclosures. As Qian and Schaltegger (2017) suggest, transparent CDP reporting may induce firms to reduce their carbon emissions actively, implying that these disclosures could proxy for a firm's transparency and commitment to reducing carbon risk. Therefore, the moderating effect of CDP disclosure on the relationship between carbon risk and stock price crash risk may reflect firms' actual actions in carbon risk management alongside the reduction in information asymmetry.

The research on corporate social responsibility (CSR) adds more depth to this topic. Kim, Li, and Li (2014) found that companies with greater transparency in their CSR performance often face a reduced risk of stock price crashes. This observation is complex, as transparent CSR reporting might reflect true corporate responsibility (Gelb and Strawser 2001), or managers could use it to divert attention from other problems (Hemingway and Maclagan 2004). On the basis of this intricate relationship, we formulate the following hypothesis:

H2. The positive relationship between corporate carbon risk and stock price crash risk is weaker in firms with more transparent CDP disclosures, possibly reflecting enhanced transparency and active management of their carbon risks.

3 | Data

Our sample consists of all firms responding to the CDP[5] questionnaire from 2006 to 2022.[6] We collect carbon risk, quality of carbon disclosures, and climate incentives data from the CDP database. We also collect financial and nonfinancial data from Worldscope and the Refinitiv environmental, social, and governance (ESG) database. The stock market, analyst coverage, and institutional investor ownership data are collected from the DataStream, Institutional Brokers' Enterprise Systems (I/B/E/S), and FactSet LionShare databases. We collect climate change performance and risk index data from Germanwatch and Climate Action Network. Other country-level data are collected from the World Bank database. After merging all databases and excluding incomplete observations, we obtain an initial sample of 13,165 firm-year observations with 2258 unique firms from 38 countries. Panel A of Table 1, shows the sample-selection procedure.

Panels B and C of Table 1 show the distribution of sample firms by industry and year, respectively. Panel B shows that our samples are dominated by firms operating in the computer industry (10.23%), followed by transportation (8.51%), and the services industry (8.01%). Panel C shows that 2022 accounts for the highest number of observations (12.65%), followed by 2021 (12.01%), whereas 2007 (1.50%) shows the lowest number of observations. Further, Panel D of Table 1 shows that the United States (24.82%) and Japan (15.56%) account for the highest number of observations, followed by the United Kingdom (11.52%). We also show the average carbon emissions by country and find that Russia (24.350 million CO_2-e) has the highest level of carbon emissions, whereas Luxembourg (0.048 million CO_2-e) has the lowest emissions.

3.1 | Variables of Interest

To examine the relationship between carbon risk and stock price crash risk, we collect data from DataStream to calculate the exact measures of stock price crash risk shown in Chen, Hong, and Stein (2001), *NCSKEW*, and down-to-up volatility *(DUVOL)*. Table 2 presents descriptive statistics for each crash risk measure split on whether the firm has high or low carbon risk. High carbon risk is defined as a firm with a carbon risk higher than or equal to the country-industry-year adjusted median level of carbon risks, and vice versa. *NCSKEW* represents the negative skewness of firm-specific weekly returns over the fiscal year. *DUVOL* represents the natural logarithm of the standard deviation of down-week to up-week firm-specific weekly returns, respectively. For both variables, a higher value indicates greater crash risk. The mean (median) value for *NCSKEW* is 0.142 (0.102) and 0.075 (0.056) for high and low-carbon risk firms, respectively, significantly different at the 1% level. The mean (median) value for *DUVOL* is 0.055 (0.047) and 0.031 (0.027) for high and low-carbon risk firms, respectively, significantly different at the 1% level. The correlation between the two measures of crash risk is 0.872, a value similar to that of Chen, Hong, and Stein (2001). Though the range of values is generally consistent with the literature (e.g., Kim, Li, and Zhang 2011; Kim, Li, and Li 2014), the mean values for both *NCSKEW* and *DUVOL* in our sample are higher than Chen, Hong, and Stein (2001), suggesting higher stock price crash risk.

Following Bolton and Kacperczyk (2021), we use the natural logarithm of the total amount of carbon emissions measured in millions of metric tons of CO_2-e as a measure of carbon risk (*CRISK*).[7] The carbon emissions data are sourced from the CDP database.[8]

The carbon disclosure score (*CCDS*) data are also sourced from the CDP database, which measures the quality of the carbon disclosures. The score consists of the firm-level disclosures of information from a questionnaire. It covers carbon-related risks and opportunities, business strategy, climate governance, climate change-related targets, performance, firm initiatives about reducing carbon emissions, verification, carbon pricing, and firm-level engagement with value chain partners regarding carbon-related activities (CDP 2017). The historical data for *CCDS* are inconsistent year-over-year and have been calculated as either a score ranging from 0 to 100 (pre-2015) or a letter signifying a performance band. Therefore, rather than using a continuous measure of performance, we measure the quality of carbon disclosures (*HIGH_CDISC*) as an indicator variable based on the yearly country and industry median value of carbon disclosure, which ensures that the annual measurement is consistent. Thus, *HIGH_CDISC* takes a value of one if the firm-level quality of carbon disclosures (*CCDS*) is higher than the country-industry-year adjusted median and zero otherwise. This measure is used to control for differences across firms in reporting transparency, which can mitigate the likelihood of stock price crash risk.

4 | Methodology

We first examine the relationship between carbon risk and stock price crash risk via an ordinary least squares (OLS) lead-lag model and then perform robustness analyses confirming the documented relationships. Finally, we use two-stage least squares (2SLS) with an instrumental variables approach and exogenous shocks to test and control for potential endogeneity.

In each of the regressions, we examine versions of the following lead-lag specification:

$$Crash\ Risk_{i,j,t+1} = \propto + \beta_1 \times CRISK_{i,j,t} + \beta_2 \times Crash\ Risk_{i,j,t} + \beta_3 \times Firm\ Controls_{i,j,t} + k_{i,t} + \upsilon_t + \theta_{i,t} + \varepsilon_{i,j,t} \quad (1)$$

We use robust standard errors clustered at the country level to address potential heteroskedasticity and serial correlation. Furthermore, we include country fixed effects ($k_{i,t}$), year fixed effects (υ_t), and industry fixed effects ($\theta_{i,t}$) to capture any potential omitted variable bias. Subscript *i,j,t* represents firm *i*, located in country *j*, for year *t*. Appendix A describes the variables in detail. Firm controls include size, market-to-book (MB), leverage (LEV), return on assets, detrended turnover, mean return, standard deviation of return, earnings management (EM), firm Herfindahl, and industry Herfindahl. Crash risk variables include *NCSKEW* or *DUVOL*. We run lead-lag regression models to ensure that reverse causality does not influence the results.

Each control variable has been shown to affect future stock price crash risk (e.g., Defond et al. 2015; Kim, Li, and Zhang 2011; Kim, Li, and Li 2014). The value of the current year's crash risk (*CRISK*) is included as it captures the potential serial correlation associated with crash risk for the sample firms (Kim, Li, and Li 2014). We control for firm size (*SIZE*), the average of

TABLE 1 | Sample selection and distribution.

Panel A: Sample selection	Observations
CDP carbon emissions data coverage from 2006 to 2022	33,268
Less: Firm-year observations with missing data due to merging with World scope, DataStream, FactSet, IBES, and ESG databases	(14,354)
Less: Firms dropped due to missing control variables	(3491)
Less: Firms dropped due to lead-lag model	(2258)
Final Test Sample from 2007–2018	**13,165**

Panel B: Industry distribution of sample firms

Name of Industry	Observations	% of observations
Mining/Construction	1041	7.91
Food	749	5.69
Textiles/Print/Publish	470	3.57
Chemicals	671	5.10
Pharmaceuticals	405	3.08
Extractive	428	3.25
Manufacturing: Rubber/glass/etc.	340	2.58
Manufacturing: Metal	311	2.36
Manufacturing: Machinery	691	5.25
Manufacturing: Electrical equipment	391	2.97
Manufacturing: Transport equipment	598	4.54
Manufacturing: Instruments	464	3.52
Manufacturing: Miscellaneous	26	0.20
Computers	1347	10.23
Transportation	1120	8.51
Utilities	948	7.20
Retail: Wholesale	255	1.94
Retail: Miscellaneous	697	5.29
Retail: Restaurant	58	0.44
Financial	432	3.28
Insurance/Real estate	652	4.95
Services	1054	8.01
Others	17	0.13
Total sample	**13,165**	**100**

Panel C: Year distribution of sample firms

Year	Observations	% of observations
2006	197	1.50
2007	297	2.26
2008	435	3.30

(Continues)

TABLE 1 | (Continued)

Panel C: Year distribution of sample firms		
Year	**Observations**	**% of observations**
2019	489	3.71
2010	565	4.29
2011	628	4.77
2012	706	5.36
2013	774	5.88
2014	879	6.68
2015	948	7.20
2016	776	5.89
2017	960	7.29
2018	1073	8.15
2019	1192	9.05
2020	1581	12.01
2021	1665	12.65
Total	**13,165**	**100**

Panel D: Country descriptive			
Country	**Observations**	**%**	**Emission (CO_2-e million)**
Argentina	5	0.04	4.880
Australia	406	3.08	2.884
Belgium	56	0.43	0.141
Bermuda	8	0.06	0.139
Brazil	231	1.75	1.747
Canada	710	5.39	2.257
Chile	11	0.08	4.846
China	63	0.48	0.308
Denmark	64	0.49	5.305
Finland	178	1.35	0.830
France	641	4.87	4.910
Germany	588	4.47	5.724
Greece	12	0.09	0.737
Hong Kong	104	0.79	10.181
India	311	2.36	4.048
Ireland	44	0.33	0.168
Italy	200	1.52	5.787
Japan	2048	15.56	2.175
Luxembourg	5	0.04	0.048
Malaysia	24	0.18	2.723
Mexico	65	0.49	6.746
Netherlands	61	0.46	0.105
New Zealand	65	0.49	0.314
Norway	163	1.24	1.308
Philippines	11	0.08	4.069

(Continues)

TABLE 1 | (Continued)

Panel D: Country descriptive			
Country	**Observations**	**%**	**Emission (CO_2-e million)**
Poland	10	0.08	9.059
Russia	36	0.27	24.350
Singapore	70	0.53	1.075
South Africa	399	3.03	0.991
South Korea	439	3.33	3.726
Spain	176	1.34	5.533
Sweden	345	2.62	0.363
Switzerland	379	2.88	3.263
Thailand	50	0.38	5.690
Turkey	79	0.6	0.741
Taiwan	324	2.46	1.488
United Kingdom	1516	11.52	1.389
United States	3268	24.82	4.752
Total/Average	**13,165**	**100**	**3.258**

Note: This table presents the descriptive statistics of our sample. Panel A presents the sample formation steps. Panel B shows the sample firms' industry distribution, whereas Panel C shows the year-wise distribution. Panel D shows the country-level breakout and the country-level carbon emissions.
Abbrviations: CDP, Carbon Disclosure Project; ESG, environmental, social, and governance.

TABLE 2 | Descriptive statistics.

	HIGH_CRISK ($N = 7033$)		***LOW_CRISK*** ($N = 6132$)		**Mean-test**	**Median-test**
	Mean	**Median**	**Mean**	**Median**	**(p value)**	**(p value)**
NCSKEW	0.142	0.102	0.075	0.056	0.000***	0.000***
DUVOL	0.055	0.047	0.031	0.027	0.000***	0.000***
HIGH_CDISC	0.757	1.000	0.598	1.000	0.000***	0.000***
SIZE	9.119	9.121	8.424	8.401	0.000***	0.000***
MB	2.925	1.911	3.481	2.176	0.004***	0.000***
LEV	0.284	0.273	0.254	0.236	0.000***	0.000***
ROA	0.050	0.043	0.057	0.048	0.000***	0.000***
DTURN	−0.007	−0.001	−0.007	−0.001	0.964	0.354
MEAN_RET	−0.047	−0.076	−0.005	−0.002	0.451	0.443
SD_RET	0.032	0.028	0.033	0.030	0.000***	0.000***
EM	0.032	0.017	0.035	0.019	0.000***	0.017**
IND_HERF	0.307	0.228	0.269	0.183	0.000***	0.000***
FIRM_HERF	0.061	0.026	0.055	0.020	0.003***	0.000***

Note: This table presents the descriptive statistics of variables used in Equation (1). It shows the mean and median test between high and low carbon risk firms. High versus low carbon risk firms are defined on the basis of whether the firm's carbon risk is higher than or equal to the country-industry-year adjusted median level of carbon risks and zero otherwise. The superscripts *** and ** correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.
Abbreviations: DUVOL, down-to-up volatility; EM, earnings management; LEV, leverage; MB, market-to-book.

firm-specific weekly returns (*MEAN_RET*), and the standard deviation of firm-specific weekly returns (*SD_RET*) because prior studies document that larger firms or firms with higher or riskier returns are prone to higher future stock price crash risk (e.g., Defond et al. 2015; Kim, Li, and Zhang 2011; Kim, Li, and Li 2014). We control for the MB ratio, financial performance (ROA), and LEV because stocks with low ratios of book value to market value, higher performance, or more debt are more likely to have lower stock price crash risk (Defond et al. 2015; Kim, Li, and Zhang 2011; Kim, Li, and Li 2014). We include changes in trading volume (*DTURN*) to capture the differences in opinion among investors (e.g., Defond et al. 2015; Kim, Li, and Zhang 2011; Kim, Li, and Li 2014). We also control for EM as higher EM is related to higher stock price crash risk (e.g., Defond et al. 2015; Hutton, Marcus, and Tehranian 2009; Kim, Li, and Zhang 2011; Kim, Li, and Li 2014). Finally, we control for industry Herfindahl–Hirschman index (*IND_HERF*) calculated using two-digit SIC industry sales revenue and firm Herfindahl–Hirschman index (*FIRM_HERF*) calculated based on individual firm sales revenue to control for product market competition following Ben-Nasr and Ghouma (2018). Table 3 shows the correlation matrix. Overall, we find that the proxy for carbon emissions positively correlates with crash risk, which provides initial support for our first hypothesis (H1). Carbon disclosure is negatively related to crash risk, which supports our second hypothesis (H2). Further, the correlation matrix shows no high correlations among variables.

4.1 | Carbon Risk and Crash Risk

In Panel A of Table 4, we show the multivariate estimation of Equation (1), where the dependent variable is either skewness (*NCSKEW*) or *DUVOL*. We control for the country, industry, and year-fixed effects and cluster the standard errors by country. We report the *t*-statistics in parentheses. Our variable of interest is carbon risk (*CRISK*). Columns (1) and (2) show the regression results of only control variables, whereas the remaining columns show the regression results, including carbon risk.

Columns (1) and (2) indicate that the value of the current year's stock price crash risk is positive and significant in both regressions with coefficients of 0.027 and 0.021 (significant at the 1% level), respectively. There is a positive relationship between stock price crash risk and size (coefficient of 0.037 in Column (1) and 0.013 in Column (2), significant at the 1% level). Further, higher profitability and detrended turnovers are associated with higher levels of stock price crash risk (coefficients of 0.303 and 0.173 in Column (1) and coefficients of 0.091 and 0.064 in Column (2), significant at 5% or higher levels). Finally, firms with higher competition have higher stock price crash risk (coefficients of 0.053 in Column (1), significant at 5%). Each of these relationships is consistent with the literature (e.g., Defond et al. 2015; Kim, Li, and Zhang 2011; Kim, Li, and Li 2014).

We next examine the relationship between carbon risk and stock price crash risk by adding the carbon risk variable into Columns (3) and (4) of Table 4. Column (3) uses *NCSKEW* as the dependent variable, and Column (4) uses *DUVOL* as the dependent variable. The control variables remain similar in both qualitative and quantitative conclusions. The coefficient on *CRISK* is positive and statistically significant in Columns (3) and (4), suggesting that increased carbon risks are positively associated with one year-ahead crash risk proxied by *NCSKEW* and *DUVOL*. This finding is interpreted as firms with higher carbon risk levels also have higher crash risk. In terms of economic significance, the estimated coefficient in Columns (3) and (4) suggests that an increase of one standard deviation in *CRISK* is associated with a 6.32% (2.28%) increase in *NCSKEW* (*DUVOL*).[9]

The R^2 value is 0.046 in both Columns (3) and (4), suggesting that the independent variables collectively capture 4.60% of the variation in crash risk measured by *NCSKEW* and *DUVOL*, respectively. To assess the incremental contribution of *CRISK* to the explanatory power of our regression analysis, we follow Gujarati and Porter (2009) and compare the explanatory power to the regressions excluding the primary test variable, *CRISK*. The results from this regression show that the explanatory power decreases to 3.6% and 3.5%, respectively, as reported in Table 4, Columns (1) and (2). We then compute the *F*-statistic, as demonstrated by Gujarati (2003), using the R^2 statistics reported for the regressions with and without *CRISK* to test the null hypothesis that the inclusion of *CRISK* as an explanatory variable does not affect the explanatory power (R^2) of our regression model. Gujarati and Porter's (2009) *F*-statistic, reported at the bottom of Table 4 in Columns (3) and (4), is 61.20 and 65.16, respectively, and is significant at a 1% level, suggesting that *CRISK* significantly increases the explanatory power of the regression models. Overall, we find that *CRISK* is incrementally informative in explaining the variation of crash risk over our base estimations. These results confirm that carbon risk reduces transparency and increases long-term uncertainty, leading to higher future stock price crash risk.

In Columns (3) and (4), we measure the carbon risk using the natural logarithm of the total amount of carbon emissions measured in millions of metric tons of CO_2-e following Bolton and Kacperczyk (2021). In Columns (5) and (6), we show our regression results for Equation (1) using carbon intensity as the measure of carbon risk. We measure carbon intensity as the ratio of the total carbon emissions measured in millions of metric tons of CO_2-e to total sales revenue. Using this alternative measure of carbon risk, the coefficient on *CRISK* remains positive and statistically significant at the 1% level (coefficients of 0.034 and 0.014 in Columns (5) and (6), respectively). As we find similar results using both carbon intensity and the natural logarithm of carbon emissions, we use the latter for the rest of the analyses.

Beyond the previously discussed themes of information asymmetry and agency conflicts, it is plausible that firms with elevated carbon risk may be more susceptible to sudden, dramatic adverse shocks, leading to an increased propensity for stock price crashes compared to those firms that experience a low level of carbon risk. This inherent risk could stem from heightened regulatory scrutiny, shifts in consumer preferences toward sustainability, technological advancements in cleaner alternatives, and increased exposure to environmental liabilities. These factors, intrinsic to the operations and market positioning of high-carbon-risk firms, could naturally predispose them to more volatile market reactions and sudden shifts in investor sentiment. Using the entropy balancing method, we randomize our sample firms to mitigate this firm-level observable heterogeneity in our sample. Several studies have adopted the entropy balancing

TABLE 3 | Correlation matrix.

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
NCSKEW	[1]	1.000													
DUVOL	[2]	0.872***	1.000												
CRISK	[3]	0.125***	0.122***	1.000											
HIGH_CDISC	[4]	−0.119***	−0.100***	0.007	1.000										
SIZE	[5]	0.113***	0.105***	0.430***	0.117***	1.000									
MB	[6]	0.026***	0.029***	−0.119***	0.001	0.254***	1.000								
LEV	[7]	0.002	0.012	0.156***	0.025***	0.029***	0.052***	1.000							
ROA	[8]	0.044***	0.038***	−0.109***	0.003	0.232***	0.349***	−0.290***	1.000						
DTURN	[9]	0.004	0.004	0.016*	−0.012	−0.038***	−0.051***	0.031***	−0.081***	1.000					
MEAN_RET	[10]	−0.001	−0.002	−0.004	0.002	0.005	0.000	−0.013	0.002	−0.003	1.000				
SD_RET	[11]	−0.055***	−0.044***	−0.067***	−0.025***	−0.325***	−0.093***	0.036***	−0.289***	0.103***	−0.032***	1.000			
EM	[12]	0.006	−0.002	−0.068***	−0.024***	0.039***	0.055***	0.014*	0.036***	−0.013	−0.010	0.123***	1.000		
IND_HERF	[13]	−0.019**	−0.021**	−0.015*	0.057***	−0.127***	−0.059***	0.034***	−0.040***	0.007	−0.017**	0.006	−0.097***	1.000	
FIRM_HERF	[14]	−0.052***	−0.045***	−0.016*	0.039***	−0.101***	−0.079***	−0.010	−0.031***	−0.006	−0.005	0.042***	−0.062***	0.219**	1.000

Note: This table presents Pearson's correlation matrix. The superscripts ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.
Abbreviations: DUVOL, down-to-up volatility; EM, earnings management; LEV, leverage; MB, market-to-book.

TABLE 4 | Carbon risk and crash risk.

Panel A: Full sample

	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$	Entropy balancing sample DV = $NCSKEW_{t+1}$	Entropy balancing sample DV = $DUVOL_{t+1}$
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
CRISK			0.025***	0.009***	0.034***	0.014***	0.027***	0.010***
			(7.486)	(7.441)	(7.178)	(6.720)	(6.949)	(6.877)
NCSKEW/DUVOL	0.027***	0.021***	0.029***	0.024***	0.027***	0.021***	0.022**	0.021***
	(2.981)	(4.040)	(3.205)	(4.406)	(2.907)	(4.041)	(2.140)	(2.861)
SIZE	0.037***	0.013***	0.015***	0.005**	0.037***	0.013***	0.017***	0.005*
	(8.180)	(7.160)	(2.800)	(2.222)	(8.182)	(7.267)	(3.011)	(1.767)
MB	−0.002*	−0.000	0.001	0.001	−0.001	−0.000	0.000	0.000
	(−1.725)	(−0.588)	(1.040)	(1.414)	(−1.310)	(−0.231)	(0.008)	(0.152)
LEV	−0.003	0.002	−0.040	−0.011	−0.001	0.003	−0.030	−0.001
	(−0.062)	(0.139)	(−1.035)	(−0.787)	(−0.013)	(0.206)	(−0.674)	(−0.046)
ROA	0.303**	0.091**	0.389***	0.122***	0.321***	0.099**	0.537***	0.186***
	(2.654)	(2.313)	(3.599)	(3.299)	(2.773)	(2.458)	(5.168)	(5.142)
DTURN	0.173**	0.064**	0.170**	0.063**	0.170**	0.063**	0.191*	0.066*
	(2.217)	(2.147)	(2.286)	(2.204)	(2.182)	(2.106)	(1.861)	(1.706)
MEAN_RET	−0.001	−0.000	−0.001	−0.000	−0.001	−0.000	−0.002	−0.001
	(−0.534)	(−0.323)	(−0.543)	(−0.322)	(−0.572)	(−0.352)	(−1.506)	(−1.150)
SD_RET	−0.010	0.111	−0.272	0.015	−0.069	0.086	−0.168	0.077
	(−0.021)	(0.630)	(−0.592)	(0.087)	(−0.140)	(0.484)	(−0.334)	(0.414)
EM	−0.057	−0.058	−0.029	−0.047	−0.057	−0.057	0.039	−0.034
	(−0.529)	(−1.552)	(−0.276)	(−1.293)	(−0.528)	(−1.551)	(0.386)	(−0.883)
IND_HERF	0.053**	0.013	0.044*	0.009	0.052**	0.012	0.066**	0.018
	(2.112)	(1.305)	(1.721)	(0.913)	(2.139)	(1.308)	(2.522)	(1.586)
FIRM_HERF	−0.039	0.020	−0.046	0.017	−0.045	0.017	−0.069	0.034
	(−0.679)	(1.217)	(−0.796)	(1.119)	(−0.790)	(1.053)	(−1.186)	(1.452)
Intercept	−0.354***	−0.044*	−0.452***	−0.080***	−0.424***	−0.074***	−0.901***	−0.404***
	(−5.570)	(−1.893)	(−7.404)	(−3.632)	(−6.132)	(−2.818)	(−13.427)	(−14.329)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 4 | (Continued)

Panel A: Full sample

	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$	Entropy balancing sample DV = $NCSKEW_{t+1}$	Entropy balancing sample DV = $DUVOL_{t+1}$
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,165	13,165	13,165	13,165	13,165	13,165	13,165	13,165
R-squared	0.036	0.035	0.046	0.046	0.043	0.044	0.054	0.054
Gujarati (2003) ΔR^2-F-statistic	61.20***	65.16***	23.05***	33.50***				

Panel B: Sample split by time

	POST COVID		COVID		PRE COVID	
	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CRISK	0.021***	0.007***	0.033***	0.011***	0.023***	0.009***
	(3.886)	(3.297)	(4.374)	(3.146)	(5.346)	(5.313)
Intercept	0.225*	0.081	−0.145	−0.029	−0.368	−0.069
	(1.740)	(1.672)	(−0.363)	(−0.474)	(−1.092)	(−0.639)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1665	1665	1581	1581	9919	9919
R-squared	0.084	0.073	0.109	0.099	0.049	0.051

Note: This table presents OLS regression results in which we examine the effect of carbon risk on firm-level stock price crash risk. Panel A is for the entire sample, whereas Panel B segments by pre- (2006–2019), during (2020), and post-COVID (2021–2022). In Panel A, Models (1) and (2) show the regression results of only control variables using *NCSKEW* and *DUVOL* as dependent variables, respectively. Models (3) and (4) show the regression results of the effect of carbon risks (*CRISK*) using *NCSKEW* and *DUVOL* as dependent variables and the natural logarithm of carbon emissions as a proxy for carbon risk. Models (5) and (6) show the regression results of the effect of carbon risks (*CRISK*) using *NCSKEW* and *DUVOL* as dependent variables and carbon emissions intensity as a proxy for carbon risk. Models (7) and (8) show the regression results using an entropy-balancing sample. We show the Gujarati statistical difference between Models (1) and (2) versus Models (3) and (4) (or Models (5) and (6)). In Panel B, *CRISK* is the natural logarithm of carbon emissions as a proxy for carbon risk. All coefficient values (robust t-statistics) are shown with standard errors clustered at the country level. The superscripts ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Abbreviations: DUVOL, down-to-up volatility; EM, earnings management; LEV, leverage; MB, market-to-book.

technique to address similar concerns, including Ashraf, Michas, and Russomanno (2020), Cepni, Şensoy, and Yılmaz (2024), Fang et al. (2024), and Hanlon et al. (2024). This technique mitigates the effects of imbalances in firm characteristics, thereby reducing the likelihood that our results would relate to these imbalances rather than carbon risks. The entropy balancing assigns weights to adjust for the sample's distribution of control observations (Hainmueller and Xu 2013). This adjustment reweighs each observation in the control group; therefore, all covariates' mean, variance, and skewness are balanced between the treatment and control groups. The procedure assigns more weight to under-represented observations and less to over-represented observations, resulting in a "pseudo" control group that mitigates the risk that design choices could affect our study's results. We split firm-year observations into a high carbon treatment group (*HIGH_CRISK* = 1) and a low carbon control group (*HIGH_CRISK* = 0) based on the country-industry-year adjusted median value of firm-level carbon risks. For the sake of brevity, we do not report the matching results. However, the unreported results suggest that all covariates' mean, variance, and skewness are balanced between the treatment and control groups. Columns (7) and (8) of Table 4 show the second-stage regression results generated by estimating Equation (1) on the entropy-balanced samples. The coefficient of *CRISK* is positive and statistically significant. These entropy-balanced sample-based findings confirm that imbalances in firm characteristics do not drive the positive association of *CRISK* with both *NCSKEW* and *DUVOL*.

In Panel B of Table 4, we split our sample into three periods: pre-COVID (2006–2019), COVID (2020), and post-COVID (2021). The study by Demers et al. (2021) motivates us to segment the sample into pre-COVID, COVID, and post-COVID periods to examine the impact of carbon risk on stock price crash risk during these distinct phases of the pandemic. Demers et al. (2021) find that ESG performance is not an effective shield against share price declines during crises. Instead, factors like liquidity, *LEV*, financial performance, supply chain management, intangible assets, industry affiliation, and traditional equity risk measures are more explanatory of stock returns in these periods. We find that our results do not change during these subperiods. Our findings, indicating that carbon risk significantly impacts crash risk during the COVID-19 period, offer a nuanced perspective that complements the broader findings of Demers et al. (2021). Although Demers et al. (2021) observed that overall ESG performance did not protect against share price declines during the pandemic, our research highlights the importance of considering specific ESG components individually. This distinction underscores the multifaceted nature of ESG factors, where certain aspects, such as carbon risk, may exhibit a more pronounced influence on market behaviors, even when the broader ESG spectrum does not. Our results thus contribute to a more granular understanding of ESG impacts, particularly under crisis conditions, emphasizing the need to analyze ESG components, like carbon risk, in their specific contexts and implications.

4.2 | Role of Quality of Carbon Disclosures

In our second hypothesis, we predict that the quality of carbon disclosure can alleviate some uncertainty and improve transparency, which may reduce carbon risk's positive impact on crash risk. In Panel A of Table 5, we interact the quality of carbon disclosures with carbon risks to understand their role in the crash risk. Using this *CCDS* variable, we create an indicator, *HIGH_CDISC*, that equals one when the firm-level *CCDS* is higher than the country-year-industry adjusted score and zero otherwise.

To test H2, the variable of interest is the interaction term *CRISK* × *HIGH_CDISC*. In Columns (1) and (2) of Table 5, the negative coefficients of *CRISK* × *HIGH_CDISC* indicate that the average increase in crash risk associated with carbon risk is attenuated for firms with a higher quality of carbon disclosures, controlling for other factors. In terms of economic magnitude, combining the main effect and the interaction effect in Column (1), a one standard deviation increase in the carbon risks leads to a 5.56% (1.77%) decrease in crash risk for firms with a higher quality of carbon disclosures, compared to 10.37% (3.54%) increase in carbon risk for firms with lower quality of carbon disclosures using *NCSKEW* and *DUVOL* measures of crash risk, respectively.[10] Overall, our results support the second hypothesis and show that firms with high carbon risk can reduce their information asymmetry and alleviate investors' pricing uncertainties, leading to lower future crash risk if they are transparent in managing that risk.

In Panel B of Table 5, we implement change-specific model specifications that enable us to control for time-invariant factors affecting both carbon and crash risks. To implement the change regression, we regress the change in our crash risk on the change in carbon risk and control variables. The coefficients on *ΔCRISK* are positive and statistically significant in Columns (1) and (3), thus corroborating our findings. Additionally, the coefficients on Δ*CRISK* × *HIGH_CDISC* are negative and statistically significant in Columns (2) and (4), corroborating our findings in Panel A of Table 5. The conclusions of the change regression suggest that our findings are unaffected by reverse causality issues.

4.3 | Internal and External Influences

In this section, we investigate the role of external and internal monitoring mechanisms and country and industry factors that may influence the relationship between carbon risk and future stock price crash risk. In Table 6, we examine the influence of the following on crash risk: (i) firm-level institutional ownership, analyst coverage, corporate governance performance, and climate-linked incentives; (ii) country-level stakeholder orientation, climate change performance, financial opaqueness, pollution, and environmental values; and (iii) industry-level pollution. We present results using *NCSKEW* as the dependent variable but note that results are qualitatively similar when using *DUVOL*.

Institutional investors and financial analysts provide external monitoring, whereas corporate governance provides internal monitoring of managers (Kim, Li, and Li 2014), which may alleviate the relationship between carbon risk and crash risk. We measure institutional investors' monitoring using the percentage of ownership held by the institutional investors. We create an indicator variable of *HIGH_INSTOWN* that takes a value of one if the institutional investor ownership percentage is greater than

TABLE 5 | Carbon risk, crash risk, and the role of carbon disclosure quality.

Panel A: OLS estimates

	DV = $NCSKEW_{t+1}$	DV = $DUVOL_{t+1}$
	(1)	(2)
CRISK	0.041***	0.014***
	(7.876)	(6.145)
CRISK × *HIGH_CDISC*	−0.022***	−0.007***
	(−4.976)	(−3.124)
HIGH_CDISC	0.091	0.032
	(1.650)	(1.277)
Intercept	−0.493***	−0.095***
	(−6.852)	(−3.383)
Controls	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Observations	13,165	13,165
R-squared	0.064	0.060

Panel B: Change-specific regression results between crash risk and carbon risk

	DV = $\Delta NCSKEW_{t+1}$		DV = $\Delta DUVOL_{t+1}$	
	(1)	(2)	(3)	(4)
ΔCRISK	0.068***	0.103***	0.018***	0.033***
	(4.294)	(5.375)	(3.055)	(3.645)
ΔCRISK × *HIGH_CDISC*		−0.037*		−0.016**
		(−1.897)		(−1.993)
HIGH_CDISC		−0.133***		−0.035***
		(−5.373)		(−3.947)
Intercept	0.511***	0.594***	0.112***	0.134***
	(5.936)	(6.154)	(3.671)	(4.043)
Controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	10,148	10,148	10,148	10,148
R-squared	0.257	0.262	0.257	0.261

Note: This table presents OLS regression results in which we examine the effect of carbon emissions on firm-level stock price crash risk by adding two control variables: *HIGH_CDISC* and the interaction of carbon risk and *HIGH_CDISC*. The *HIGH_CDISC* variable takes the value of 1 when the firm-level carbon disclosure quality score is above the median country-year-industry value. Panel A shows the OLS estimates. Column (1) shows the regression results using *NCSKEW* as a dependent variable. Column (2) shows the regression results using *DUVOL* as a dependent variable. Panel B uses first-order change estimation to calculate the first-order change for all variables. Columns (1) and (2) use Δ*NCSKEW*, whereas Columns (3) and (4) use Δ*DUVOL*. All coefficient values (robust *t*-statistics) are shown with standard errors clustered at the country level. We use the same controls as in Table 4. The superscripts ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.
Abbreviations: DUVOL, down-to-up volatility; OLS, ordinary least squares.

TABLE 6 | Internal and external environment.

	DV = $NCSKEW_{t+1}$									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
CRISK	0.035***	0.046***	0.042***	0.025***	0.027**	0.037***	−0.022***	0.021***	0.052***	0.018***
	(5.972)	(4.311)	(4.164)	(7.123)	(2.360)	(6.484)	(−4.304)	(6.448)	(2.496)	(4.875)
CRISK × HIGH_INSTOWN	−0.016***									
	(−3.717)									
HIGH_INSTOWN	0.047									
	(0.675)									
CRISK × HIGH_ANALYST		−0.027***								
		(−2.728)								
HIGH_ANALYST		0.153								
		(1.449)								
CRISK × HIGH_CGOV			−0.023**							
			(−2.348)							
HIGH_CGOV			0.075							
			(0.625)							
CRISK × CLIMATE_INCENTIVE				−0.019**						
				(−2.378)						
CLIMATE_INCENTIVE				−0.333***						
				(−3.557)						
CRISK × STAKE					−0.029**					
					(−2.690)					
STAKE					−0.782***					
					(−5.262)					
CRISK × HIGH_CCPI						−0.029***				
						(−4.792)				
HIGH_CCPI						−0.003				
						(−0.054)				
CRISK × HIGH_OPAQUE							0.066***			
							(13.770)			

(Continues)

TABLE 6 | (Continued)

	DV = $NCSKEW_{t+1}$									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
HIGH_OPAQUE							0.856***			
							(11.718)			
CRISK × DIRTY_COUNTRY								0.009*		
								(1.698)		
DIRTY_COUNTRY								−0.068		
								(−0.951)		
CRISK × HIGH_EVAL									−0.052**	
									(−2.520)	
HIGH_EVAL									0.613**	
									(2.450)	
CRISK × DIRTY_INDUSTRY										0.015***
										(3.420)
DIRTY_INDUSTRY										−0.356***
										(-1.816)
Intercept	−0.392***	−0.703***	−0.487***	−0.422***	−0.654***	−0.665***	−1.589***	−0.383***	−0.218	−0.211
	(−5.336)	(−6.414)	(−4.926)	(−5.624)	(−5.776)	(−11.576)	(−11.694)	(−4.049)	(−0.948)	(−1.218)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,165	13,165	13,165	13,165	13,165	13,165	13,165	13,165	5587	13,165
R-squared	0.059	0.055	0.067	0.195	0.239	0.110	0.182	0.047	0.058	0.047

Note: This table presents the results of the internal and external environment using *NCSKEW* as a dependent variable. Column (1) shows institutional investors' ownership, Column (2) shows analysts' coverage, Column (3) shows corporate governance performance, Column (4) shows climate-linked incentives, Column (5) shows country-level stakeholder-orientation, Column (6) shows country-level climate change performance, Column (7) shows country-level financial opaqueness, Column (8) shows dirty-countries, Column (9) shows country-level environmental culture, and Column (10) shows dirty-industries. All coefficient values (robust *t*-statistics) are shown with standard errors clustered at the country level. We use the same controls as in Table 4. The superscripts ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

the country and yearly median value of institutional investor ownership and zero otherwise. We measure financial analysts' coverage using the total number of analysts covering a firm. We create an indicator variable of *HIGH_ANALYST* that takes a value of one if the total number of analysts' coverage is greater than the country and yearly median value of the total number of analysts' coverage and zero otherwise. The interaction terms' coefficients for external monitoring measures are significantly negative (i.e., *CRISK* × *HIGH_INSTOWN* and *CRISK* × *HIGH_ANALYST* in Columns 1 and 2, respectively). These results show that where external monitoring improves transparency, carbon risks become more transparent, weakening the relationship with crash risk.

Bae, Lim, and Wei (2006) find that well-governed firms have better risk management and more information transparency, resulting in lower crash risk. We measure corporate governance performance rated by Refinitiv ESG to proxy for the effectiveness of corporate governance.[11] We create an indicator variable of *HIGH_CGOV* that takes a value of one if the corporate governance performance is greater than the country and yearly median value of corporate governance performance and zero otherwise. We interact *HIGH_CGOV* with *CRISK* and report the regression results in Column (3). The coefficient on *CRISK* × *HIGH_CGOV* is significantly negative, suggesting that good governance attenuates the relationship between crash risk and carbon risk.

Similarly, we examine whether the relationship between carbon risk and crash risk varies when CEO compensation is tied to the firm's carbon performance. Prior studies find that sustainability-linked CEO compensation is positively associated with nonfinancial performance, including carbon performance (Bose et al. 2023; Haque and Ntim 2020; Ikram, Li, and Minor 2019). Data on climate change incentives are obtained from the CDP database.[12] We create an indicator variable, *CLIMATE_INCENTIVE*, equal to one if the CEO receives climate-linked incentives and zero otherwise. We interact *CLIMATE_INCENTIVE* with *CRISK* and find that crash risk declines when CEO compensation is tied to carbon risk in Column (4).

As considerable variation is evident among country characteristics, we next segment our analysis into five country-level institutional factors that may influence the impact of carbon risk on crash risk. Prior studies show that country-level business culture influences firm-level sustainability activities (e.g., Simnett, Vanstraelen, and Chua 2009). In this study, we argue that the impact of carbon risk on crash risk may be influenced by country-level business culture. To test this conjecture, we follow Simnett, Vanstraelen, and Chua (2009) and classify countries with code law as stakeholder-oriented business culture (*STAKE* = 1) and countries with common law as stakeholder-oriented business culture (*STAKE* = 0). More specifically, we interact *STAKE* with *CRISK* in Column (5) and find that *CRISK* × *STAKE* is significantly negative, suggesting that the impact of carbon risk on crash risk is weakened in the stakeholder-oriented business culture countries. Firms operating in these countries will likely have developed a greater awareness of managing and reporting carbon risk to minimize its adverse impacts on stakeholders, thereby mitigating the crash risk induced by carbon-related shocks.

Bose, Minnick, and Shams (2021) show that country-level climate change performance influences the impact of carbon risk on firm performance. Therefore, we examine the role of country-level climate change performance in the association between carbon risk and crash risk. We measure country-level climate change performance using the country-level performance score developed by Germanwatch and Climate Action Network (2019). We create an indicator variable of *HIGH_CCPI* that takes a value of one if the country-level climate change performance score exceeds the median value of the climate change performance score and zero otherwise. We interact *HIGH_CCPI* with *CRISK* and report the regression results in Column (6). The coefficient on *CRISK* × *HIGH_CCPI* is significantly negative, suggesting that a higher country-level climate change performance score can attenuate carbon-related shocks and pricing uncertainties, which mitigates the positive association between carbon risk and stock price crash risk.

Next, we investigate whether the association between carbon and crash risks varies with country-level informational environment. We measure country-level financial opaqueness using the country-level financial opacity score developed by Dhaliwal et al. (2012). We create an indicator variable of *HIGH_OPAQUE* that takes a value of one if the country-level financial opaqueness is greater than the median value of financial opaqueness and zero otherwise. The coefficient on *CRISK* × *HIGH_OPAQUE* is significantly positive, as shown in Column (7). The results indicate that the positive relationship between carbon risk and crash risk is more (less) pronounced for firms operating in countries with opaque (transparent) informational environments.

Countries with higher pollution levels may find it more challenging to improve their climate performance. We define more polluted countries as those where the country-level carbon emissions exceed the yearly median of a country's emissions. To test this conjecture, we use country-level carbon emissions data from the OECD database and label them as *DIRTY_COUNTRY* if the country-level carbon emissions are higher than the median value of each year.[13] We find that the coefficient of *CRISK* × *DIRTY_COUNTRY* is positive and significant in Column (8). In other words, the positive relationship between carbon and crash risk is more pronounced for firms operating in more polluted countries.

Similarly, prior studies show that country-level environmental culture moderates the impact of carbon risk on firm performance (Bose, Minnick, and Shams 2021). In this study, we argue that the effects of carbon risk on crash risk may be influenced by country-level environmental culture. We use country-level environmental culture scores from the World Survey database to test this conjecture. We partition our sample based on the median country-level environmental culture value. Specifically, *HIGH_EVAL* equals one (zero) if the country-level environmental culture value is above (below) the median. Regression results reported in Column (9) show that the coefficient on *CRISK* × *HIGH_EVAL* is positive and significant. Higher carbon risks in countries with stronger environmental values are potentially positively related to crash risk because the firm is misaligned with the government (i.e., strong environmental culture with high carbon risk).

Furthermore, firms operating in carbon-sensitive industries face significant uncertainty and risk that push them to invest in carbon management that enhances other costs, including clean-up, compliance, litigation costs, and reputation damage (e.g., Griffin, Lont, and Sun 2017; Matsumura, Prakash, and Vera-Muñoz 2014). We refer to firms operating in carbon-intensive industries as being dirty industries. On the basis of the CDP (2018) classifications, we include mining and construction, textiles, printing and publishing, chemicals and pharmaceuticals, extractive, manufacturing, transportation, and utilities as dirty industries (*DIRTY_INDUSTRY* = 1), whereas the remaining industries are classified as clean industries (*DIRTY_INDUSTRY* = 0). Regression results reported in Column (10) show a positive and significant coefficient on *CRISK* × *DIRTY_INDUSTRY*, suggesting an increased crash risk for carbon-intensive firms operating in carbon-sensitive industries.

4.4 | Robustness Tests

To check the robustness of our main results, we conduct five tests: (i) using a Heckman (1979) two-stage analysis, (ii) using an instrumental variable approach, (iii) performing a quasi-experiment using the adoption of country-level GHG emissions disclosure, (iv) using a machine learning approach to identify significant predictors, and (v) using the US sample only, including additional fixed effects, and subsamples of firms with and without financial constraint.

4.4.1 | Results Using Heckman Correction

Our sample is based on firms that self-report their carbon risk data to the CDP. Therefore, there is a possibility of a sample selection bias if firms that report information to CDP differ from those that do not. We employ a Heckman (1979) two-stage selection model to address the sample selection bias that firms self-select into reporting their carbon risks by modeling the likelihood of firms' response to the CDP questionnaire in the first stage. In the second stage, we examine the effect of carbon risk on crash risk using Equation (1) and address selection bias using the inverse Mills ratio (*IMR*) estimated from the first stage model. Specifically, we employ a probit model for the first stage, where the dependent variable, *CDP_DISC*, is an indicator equal to one if a firm responds to the CDP questionnaire and zero otherwise.

We include two variables to satisfy the "exclusion restrictions" criteria in the Heckman (1979) two-stage model following Bose, Minnick, and Shams (2021) and Matsumura, Prakash, and Vera-Muñoz (2014). These variables are industry pressure to respond to the CDP questionnaire (*PROPDISC)* and whether the firm responded to the CDP questionnaire in prior years (*CDP_DISC_LAG)*. We measure *PROPDISC* as the proportion of firms in an industry that respond to the CDP questionnaire to total firms in the industry at a country-year level. *CDP_DISC_LAG* is an indicator equal to one if the firm responded to the CDP questionnaire in the prior year and zero otherwise. We expect a positive coefficient on *PROPDISC* and *CDP_DISC_LAG*. These variables will likely influence whether a firm self-selects into reporting but are unlikely to impact crash risk in later years. Differences in means (unreported) show that firms that responded to the CDP questionnaire have higher industry pressure and prior response rates than CDP non-responding firms. In the second stage, we employ the exact estimation as in Table 4 but include *IMR* from the first stage of the Heckman (1979) two-stage regression.

Table 7 reports the results. Column (1) shows the first-stage regression results. Consistent with our expectation, the coefficients of *PROPDISC* and *CDP_DISC_LAG* are both positive and statistically significant. The model has a pseudo-R^2 value of 64.10% and the partial R^2 values (unreported) for *PROPDISC* and *CDP_DISC_LAG* of 14.36% and 38.78%, respectively, statistically significant at a 1% level, suggesting that *PROPDISC* and *CDP_DISC_LAG* are reasonable exogenous variables. Columns (2–5) report the second-stage regression results. The results indicate that the coefficient on *CRISK* is positive and statistically significant in both Columns (2) and (4), and the coefficient on *CRISK* × *HIGH_CDISC* is negative and statistically significant in both Columns (3) and (5). Furthermore, the coefficient on *IMR* is statistically insignificant across all models, suggesting that selection bias does not affect our findings.

4.4.2 | Instrumental Variable Analysis

This study finds that firms with higher carbon risk levels have greater crash risk. However, it is reasonable to argue that omitted variables may influence crash and carbon risks. We employ 2SLS regression with instrumental variables to address the potential endogeneity. We use two instrumental variables related to carbon risk but not to crash risk: country-level carbon emissions (*EMI_COUNTRY*) and country-level renewable energy production (*RENEW*). The rationale for selecting country-level carbon emissions (*EMI_COUNTRY*) is that firm-level carbon risk is likely to be correlated with a country's output of carbon emissions. The rationale for choosing country-level renewable energy consumption (*RENEW*) is that if a country prioritizes investment in renewable energy to reduce its carbon footprint, its firms will also reduce their carbon risk. We expect a positive coefficient on *EMI_COUNTRY* and a negative coefficient on *RENEW*.

Table 8 reports the regression results. We regress carbon risk (*CRISK*) in the first stage on *EMI_COUNTRY, RENEW*, and other control variables from Equation (1). We report the results of the first stage in Table 8, Columns (1) and (3), where the coefficient of *EMI_COUNTRY* is positive and statistically significant, and the coefficient on *RENEW* is negative and statistically significant, consistent with our expectation. Furthermore, Shea's partial R^2 value varies between 1.8% and 3.4%, whereas the partial F-statistic values vary between 48.727 and 226.975 in the first-stage models. On the basis of the analysis by Stock, Wright, and Yogo (2002), this high value for the F-statistic suggests that our instrument is not weak. More importantly, the *CRISK_PREDICTED* variable's coefficients are positive and statistically significant in Columns (2) and (4), thus corroborating our main findings. Therefore, our instrumental regression provides further assurance of the primary evidence documented in our study on the impact of carbon risk on crash risk.

TABLE 7 | Heckman two-stage analysis.

		DV = $NCSKEW_{t+1}$		DV = $DUVOL_{t+1}$	
	(1)	(2)	(3)	(4)	(5)
CRISK		0.028***	0.044***	0.010***	0.016***
		(5.924)	(6.527)	(5.920)	(5.870)
CRISK × HIGH_CDISC			−0.022***		−0.008***
			(−4.420)		(−3.703)
HIGH_CDISC			0.099		0.047*
			(1.430)		(1.914)
NCSKEW/DUVOL		0.020**	0.016*	0.022***	0.019***
		(2.454)	(1.820)	(4.107)	(3.298)
PROPDISC	3.230***				
	(40.522)				
CDP_DISC_LAG	2.088***				
	(66.968)				
SIZE	0.091***				
	(5.552)				
ROA	0.063				
	(0.360)				
MB	0.001				
	(0.149)				
LEV	0.182				
	(2.022)				
FAGE	0.042				
	(1.306)				
FOREIGN	0.089***				
	(2.623)				
CAPEX	0.056				
	(0.756)				
RISK	0.030				
	(0.292)				
ANALYST	0.089***				
	(3.685)				
ENV_PERF	1.196***				
	(18.938)				
IMR	—	0.023	0.022	0.008	0.008
		(1.445)	(1.488)	(1.154)	(1.168)
Intercept	−3.542***	−0.640***	−0.746***	−0.234***	−0.277***
	(−8.900)	(−11.809)	(−8.375)	(−14.999)	(−11.052)
Control variables	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	29,665	9813	9813	9813	9813
Pseudo-R^2/R^2	0.641	0.046	0.064	0.047	0.059

(Continues)

TABLE 7 | (Continued)

Note: This table presents the results of Heckman's (1979) two-stage analysis. Column (1) shows the first stage probit regression results. Columns (2–5) present the Heckman (1979) second-stage regression results. Models (1) and (2) show the regression results of the effects of carbon risks on the firm-level stock price crash risk and the moderating role of carbon disclosure quality using *NCSKEW* as a dependent variable. Models (3) and (4) show the regression results of the effects of carbon risks on the firm-level stock price crash risk and the moderating role of carbon disclosure quality using *DUVOL* as a dependent variable. All coefficient values (robust *t*-statistics) are shown with standard errors clustered at the country level. The superscripts ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Abbreviations: CDP, Carbon Disclosure Project; IMR, inverse Mills ratio; LEV, leverage; MB, market-to-book.

4.4.3 | Quasi-Experimental Analysis

To address endogeneity in our findings, we used a quasi-experimental approach, focusing on introducing mandatory carbon disclosure regulation in the United Kingdom (UKCDR) in October 2013 as an exogenous event affecting carbon risks. This regulation required UK-listed companies to report their direct (Scope 1) and indirect (Scope 2) GHG emissions from fiscal years ending after September 30, 2013. We hypothesized that this increased transparency would lead to a greater firm-level crash risk following the UKCDR introduction.

We applied a difference-in-difference (DiD) methodology over the period 2008–2017 to compare the crash risk changes in a treatment group of UK-listed firms subject to the UKCDR against a control group of firms from other countries not subject to the UKCDR (identified with an indicator variable, *TREAT*, that equals one for these firms and zero otherwise). We also used a variable (*POST*) to indicate financial years ending after September 30, 2013. By examining the interaction between *TREAT* and *POST* variables, we isolated the DiD effect to understand how the regulation impacted crash risk in the treated firms compared to the control group. We argue that if this regulation increases the transparency about the firm's "carbon footprint," firm-level crash risk will be greater following the introduction of the UKCDR. Specifically, we employ the following model:

$$\begin{aligned} NCSKEW/DUVOL_{i,t+1} &= \beta_0 + \beta_1 TREAT \times POST_{i,t} + \beta_2 POST_{i,t} \\ &+ \beta_3 NCSKEW/DUVOL_{i,t} + \beta_4 SIZE_{i,t} \\ &+ \beta_5 MB_{i,t} + \beta_6 LEV_{i,t} + \beta_7 ROA_{i,t} + \beta_8 DTURN_{i,t} \\ &+ \beta_9 MEAN\_RET_{i,t} + \beta_{10} SD\_RET_{i,t} + \beta_{11} EM_{i,t} \\ &+ \beta_{12} IND\_HERF_{i,t} + \beta_{13} FIRM\_HERF_{i,t} \\ &+ \sum FIRM_{i,t} + \sum YEAR + \varepsilon_{i,j,t} \end{aligned}$$

Our interaction of interest is $TREAT \times POST$, which measures the change in crash risk for UK firms subject to the UKCDR relative to firms in the control group. This variable is essential for evaluating the impact of the UKCDR on crash risk. If the $TREAT \times POST$ coefficient is positive, it would indicate that the UKCDR significantly heightened crash risk for UK-listed firms compared to their counterparts not subjected to the regulation. This finding would support our hypothesis that increased transparency about firms' carbon footprints due to the UKCDR is associated with an increased crash risk. All other variables and their definitions are provided in Appendix A.

To ensure our treatment and control samples are comparable and address potential nonrandom sample selection, we combine the DiD analysis with the propensity score matching (PSM) approach, as Chen, Hung, and Wang (2018) suggest. The PSM procedure involves a logistic regression in the first stage to estimate the likelihood of being a treatment firm. We include all control variables used in Equation (2) in the first-stage regression, as Shipman, Swanquist, and Whited (2017) suggested. Using the predicted propensity score from the first-stage regression, we match without replacement a firm-year observation with a *TREAT* set equal to 1 (a treatment observation) to another firm-year observation with a *TREAT* set equal to 0 (a control observation). We employ the caliper matching method and match within a caliper of 0.001, where the caliper is the difference in predicted probabilities between the treatment and control observations (Dehejia and Wahba 2002).

Panel A of Table 9 reports the covariate comparison between treatment and control samples before and after PSM matching. We find insignificant differences in covariates between treatment firms and their matched control counterparts following the use of PSM. Next, we estimate the DiD regression analysis. Panel B of Table 9 reports the regression results. The coefficient of $TREAT \times POST$ is positive and statistically significant, consistent with our main conjecture. This result corroborates the finding that firms with higher carbon risk experience a higher crash risk after introducing the exogenous event.[14]

To further validate the parallel trend assumption, we conduct a parallel trends test in the pre-treatment periods based on the method suggested by Bertrand and Mullainathan (2003). We replace *POST* with indicator variables that track the impact of the UKCDR before and after it became effective, using 2013 as the benchmark year. We then create four variables, PRE^{-4}, PRE^{-3}, PRE^{-2}, and PRE^{-1}, for the pre-period and four variables, $POST^{1}$, $POST^{2}$, $POST^{3}$, and $POST^{4}$, for the post-period. Next, we interact these eight timing variables with treatment firms *(TREAT)*. The pre-period variables, $TREAT \times PRE^{-4}$, $TREAT \times PRE^{-3}$, $TREAT \times PRE^{-2}$, and $TREAT \times PRE^{-1}$, allow us to assess whether any crash risk effect can be found before the introduction of the UKCDR. Panel B of Table 9 reports the regression results. We find that the coefficients on $TREAT \times PRE^{-4}$, $TREAT \times PRE^{-3}$, $TREAT \times PRE^{-2}$, and $TREAT \times BEFORE^{-1}$ are statistically insignificant. However, we find that $TREAT \times POST^{1}$, $TREAT \times POST^{2}$, $TREAT \times POST^{3}$, and $TREAT \times POST^{4}$ are positive and statistically significant. These results support the parallel trend assumption, suggesting that the increased crash risk for our treatment firms is observed after the UKCDR becomes effective. These findings support our prediction that carbon risks significantly increase crash risk.

4.4.4 | Evidence From Machine Learning

To provide more insights into the impact of carbon risk in predicting future crash risk, we apply an advanced supervised machine learning approach. Machine learning algorithms identify com-

TABLE 8 | Instrumental variable analysis.

	First-stage DV = $CRISK_t$ (1)	Second-stage DV = $NCSKEW_{t+1}$ (2)	First-stage DV = $CRISK_t$ (3)	Second-stage DV = $DUVOL_{t+1}$ (4)
CRISK_PREDICTED		0.045*		0.010*
		(2.580)		(1.730)
EMI_COUNTRY	0.224***		0.224***	
	(16.020)		(15.980)	
RENEW	−0.572***		−0.572***	
	(−11.230)		(−11.230)	
Intercept	3.322***	−0.393**	−1.577***	−0.094
	(6.260)	(−2.030)	(−2.990)	(−1.360)
Control variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	13,165	13,165	13,165	13,165
R-squared	0.589	0.043	0.589	0.046
Shea's partial R-squared	0.034		0.018	
Partial F-statistic	226.975***		48.727***	
Saran test statistic				
(Over-identification test)		1.752		
(p value = 0.186)		1.333		
(p value = 0.248)				

Note: This table presents the regression results of the two-stage least squares (2SLS) instrumental variables. Columns (1) and (3) show the first-stage regression results. Columns (2) and (4) show the second-stage regression results using *NCSKEW* and *DUVOL* as dependent variables, respectively. All coefficient values (robust t-statistics) are shown with standard errors clustered at the country level. We use the same controls as in Table 4. The superscripts ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

plex patterns in the data, select the best variables to explain an outcome variable, and identify optimal combinations of variables to produce accurate out-of-sample predictions (e.g., Bertomeu et al. 2019). Recent research shows that machine learning-based predictive modeling, which incorporates many explanatory variables, reduces out-of-sample prediction error and provides valuable information based on better prediction outcomes (e.g., Bertomeu et al. 2019; Jones 2017). Furthermore, machine learning algorithms can complement causal inferences (e.g., Mullainathan and Spiess 2017). Therefore, we employ the tree-based advanced machine learning model known as extreme gradient boosting. The critical feature of extreme gradient boosting is that it converts weak learners into strong learners.

For machine learning analysis, we use 12 variables from the primary regression model in Table 4, seven variables from prior studies (Kim, Li, and Li 2014; Wu and Lai 2020), 65 country-level variables following previous studies (Ben-Nasr and Ghouma 2018; Dhaliwal et al. 2012), and 23 industries. The country-level variables that we include in Equation (1) are the wealth of the country (*LNGDPC*), macroeconomic risk (*STD_GDPC*), the legal environment (*LEGAL*), and whether the firm is domiciled in a stakeholder-oriented country (*STAKE*), and the country-level global climate-change performance risk (*CCPI*), and environmental stringency (*ENV_STR*).[15] The boosting-based machine learning models do not produce any sign or coefficient for parameters. Instead, they make the percentage of variance explained by the parameters. We transform the percentage of variance explained by the machine learning model into a relative variable influence (*RVI*) score on a scale from 0 to 100, where we assign 100 to the most robust predictor, and the other variables are ranked relative to it. Table 10, Panel A shows that, of the 41 variables used in the model, *CRISK* is the fourth strongest indicator (*RVI* = 26.95) of the *NCSKEW* measure of crash risk. Furthermore, when we reestimate the gradient boosting model with the *DUVOL* measures of crash risk, it shows that *CRISK* is the third strongest indicator (*RVI* = 39.22) of crash risk (Panel B). Overall, the machine learning approach findings show that *CRISK* is a strong predictor of future stock price crash risks.

4.4.5 | Additional Robustness Tests

Much of our sample consists of firms headquartered in the United States. Therefore, Panel A of Table 11 shows our base estimation from Tables 4 and 5, which is estimated only for US firms. We find that our results remain unchanged.

TABLE 9 | Quasi-experimental analysis: Introduction of UK mandatory greenhouse gas (GHG) emissions disclosures.

Panel A: Mean-test of variables between treatment and control sample after PSM analysis

	Mean-difference after PSM matching using NCSKEW			Mean-difference after PSM matching using DUVOL		
	Treatment	**Control**	**Mean-test (*p* value)**	**Treatment**	**Control**	**Mean-test (*p* value)**
NCSKEW/DUVOL	0.052	0.023	0.297	0.018	0.024	0.512
SIZE	8.202	8.216	0.805	8.186	8.247	0.311
MB	3.164	3.232	0.670	3.184	3.394	0.210
LEV	0.255	0.257	0.788	0.254	0.258	0.653
ROA	0.057	0.055	0.522	0.058	0.061	0.288
DTURN	−0.006	−0.003	0.119	−0.006	−0.007	0.468
MEAN_RET	−0.034	−0.169	0.320	−0.020	−0.128	0.419
SD_RET	0.032	0.031	0.205	0.032	0.031	0.149
EM	0.037	0.035	0.460	0.037	0.036	0.859
IND_HERF	0.332	0.330	0.839	0.330	0.0335	0.621
FIRM_HERF	0.062	0.061	0.775	0.062	0.064	0.565

Panel B: Difference-in-differences (DiD) regression analysis with PSM-matched sample

	Dependent variable = $NCSKEW_{t+1}$ (1)	Dependent variable = $DUVOL_{t+1}$ (2)
TREAT × POST	0.088**	0.034**
	(2.279)	(2.355)
POST	−0.061	−0.047*
	(−0.929)	(−1.966)
Intercept	−2.191***	−0.625***
	(−5.673)	(−4.375)
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	1710	1710
R-squared	0.299	0.302

Panel C: Parallel trend analysis with PSM-matched sample

	Dependent variable = $NCSKEW_{t+1}$ (1)	Dependent variable = $DUVOL_{t+1}$ (2)
$TREAT \times PRE^{-4}$	−0.013	0.000
	(−0.219)	(0.016)
$TREAT \times PRE^{-3}$	−0.125	−0.018
	(−1.630)	(−0.700)
$TREAT \times PRE^{-2}$	−0.023	−0.002
	(−0.372)	(−0.086)
$TREAT \times PRE^{-1}$	0.077	0.026
	(1.383)	(1.059)

(Continues)

Panel C: Parallel trend analysis with PSM-matched sample	Dependent variable = $NCSKEW_{t+1}$ (1)	Dependent variable = $DUVOL_{t+1}$ (2)
$TREAT \times POST^1$	0.414***	0.148***
	(4.077)	(4.045)
$TREAT \times POST^2$	0.416**	0.172***
	(2.443)	(2.779)
$TREAT \times POST^3$	0.309***	0.095***
	(3.391)	(4.100)
$TREAT \times POST^4$	0.187***	0.096***
	(2.918)	(4.007)
Intercept	−2.322***	−0.717***
	(−5.852)	(−5.031)
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	1710	1710
R-squared	0.333	0.345

Note: This table presents the regression results of the quasi-experimental analysis using the introduction of the UK mandatory GHG emissions disclosures. Panel A shows the *t*-test of significant differences in the means of variables between treatment and control samples after PSM analysis. Panel B shows a PSM-matched sample's difference-in-differences (DiD) regression analysis. Panel C shows the parallel trend analysis with a PSM-matched sample. All coefficient values (robust *t*-statistics) are shown with standard errors clustered at the country level. We use the same controls as in Table 4. The superscripts ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.
Abbreviations: DUVOL, down-to-up volatility; EM, earnings management; LEV, leverage; MB, market-to-book; PSM, propensity score matching.

Although we control for several firm- and country-level variables in Equation (1) that can potentially affect both carbon and crash risks and include industry and year-fixed effects in all our models, the findings may suffer from omitted variable bias. We run firm fixed effects regressions in Table 11 Panel B to mitigate this concern. The potential benefit of including firm fixed effects is removing the omitted time-invariant firm characteristics that could cause a spurious correlation between carbon and crash risks. In this specification, the coefficient of *CRISK* is positive, and the coefficient on *CRISK* × *HIGH_CDISC* is negative and statistically significant. These findings suggest that our findings do not suffer from time-invariant omitted variable bias.

In Panel C of Table 11, our analysis focuses on financial friction as a primary factor influencing decisions on disclosure and monitoring, echoing the perspective of Rampini and Viswanathan (2010). These decisions are integral to corporate risk management and are influenced by a firm's financial constraints. Similarly, Kim and Xu (2022) and Bartram, Hou, and Kim (2022) found that firms with fewer financial constraints hedge against climate-related risks better. We measure financial constraints using the KZ index (Kaplan and Zingales 1997). A higher KZ index value indicates greater financial constraints for a firm. We compute an indicator variable of *HIGH_FINCONS* that takes a value of one if the firm's KZ index value is greater than the country-industry-year adjusted median value of the KZ index and zero otherwise. Our findings indicate that financially constrained firms are crucial to the observed results. A notable positive correlation exists between carbon and crash risks in financially constrained firms. However, this correlation is not present in firms that are not financially constrained.

TABLE 10 | Machine learning results.

Panel A: Relative variable importance and NCSKEW

Variable	% of Variance Explained	Relative Variable Importance (RVI) Score
STAKE	24.648	100.00
FIRM_HERF	20.034	81.28
INSTOWN	10.041	40.74
CRISK	**6.643**	**26.95**
SIZE	5.118	20.77
LNGDPC	4.200	17.04
ENV_STR	4.079	16.55
NCSKEW	2.929	11.88
SD_RET	2.606	10.57
CCPI	2.199	8.92
ROA	2.105	8.54
STD_GDPC	1.961	7.96
LEGAL	1.958	7.94
RDINT	1.492	6.05
MB	1.385	5.62
INTANG	1.348	5.47
CSR_PERF	1.164	4.72
IND_HERF	0.848	3.44
CGOV_PERF	0.811	3.29
DTURN	0.766	3.11
LEV	0.652	2.65
MEAN_RET	0.646	2.62
EM	0.590	2.40
CETR	0.497	2.01
ANALYST	0.487	1.98
PHARMA_IND	0.116	0.47
MFG_METAL_IND	0.109	0.44
MFG_INSTRUMENT_IND	0.092	0.37
EXTRACTIVE_IND	0.071	0.29
TEXTILE_IND	0.058	0.24
UTILITIES_IND	0.056	0.23
RETAIL_REST_IND	0.052	0.21
TRANSPORT_IND	0.051	0.21
COMPUTER_IND	0.046	0.19
FOOD_IND	0.044	0.18
SERVICE_IND	0.020	0.08
RETAIL_WHOLESALE_IND	0.017	0.07
RETAIL_MISC_IND	0.016	0.06
INSURANCE_IND	0.014	0.06
FINANCIAL_IND	0.012	0.05
MFG_RUBBER_IND	0.010	0.04

(Continues)

TABLE 10 | (Continued)

Panel B: Relative variable importance and DUVOL

Variable	% of Variance Explained	Relative Variable Importance (RVI) Score
STAKE	28.000	100.00
FIRM_HERF	21.114	75.41
CRISK	**10.982**	**39.22**
INSTOWN	10.596	37.84
LNGDPC	5.058	18.07
ENV_STR	4.226	15.09
SD_RET	3.531	12.61
SIZE	3.286	11.73
STD_GDPC	2.345	8.37
ROA	2.029	7.25
LEGAL	1.542	5.51
CCPI	1.206	4.31
MB	1.104	3.94
CSR_PERF	0.787	2.81
DUVOL	0.627	2.24
EM	0.395	1.41
LEV	0.340	1.21
INTANG	0.336	1.20
IND_HERF	0.303	1.08
CGOV_PERF	0.290	1.04
MEAN_RET	0.277	0.99
RDINT	0.259	0.93
RETAIL_REST_IND	0.259	0.92
DTURN	0.252	0.90
ANALYST	0.179	0.64
CETR	0.162	0.58
MFG_INSTRUMENT_IND	0.160	0.57
UTILITIES_IND	0.140	0.50
TEXTILE_IND	0.062	0.22
CHEMICAL_IND	0.052	0.18
FOOD_IND	0.023	0.08
SERVICE_IND	0.022	0.08
MFG_METAL_IND	0.020	0.07
EXTRACTIVE_IND	0.019	0.07
RETAIL_WHOLESALE_IND	0.017	0.06

Note: For machine learning analysis, we use 12 variables from the primary regression model in Table 4, seven (7) variables from prior studies (Kim, Li, and Li 2014; Wu and Lai 2020), five (5) country-level variables following previous studies (Ben-Nasr and Ghouma 2018; Dhaliwal et al. 2012), and 23 industries. The boosting-based machine learning models do not produce any sign or coefficient for parameters; instead, they make the percentage of variances explained by the parameters. We transform the percentage of variance explained by the machine learning model into a relative variable influence (RVI) score on a scale from 0 to 100, where we assign 100 to the strongest predictor, and the other variables are ranked relative to it. Panels A and B show the relative variable importance (RVI) scores for NCSKEW and DUVOL, respectively, which indicate the overall predictive influence of independent variables on future stock price risk.

Abbreviation: DUVOL, down-to-up volatility.

TABLE 11 | Carbon risk and crash risk—additional robustness tests.

Panel A: US firms only				
	DV = $NCSKEW_{t+1}$		**DV =** $DUVOL_{t+1}$	
	(1)	**(2)**	**(3)**	**(4)**
CRISK	0.038***	0.051***	0.013***	0.020***
	(4.306)	(5.004)	(4.652)	(5.777)
CRISK × HIGH_CDISC		−0.024***		−0.011***
		(−3.370)		(−4.510)
HIGH_CDISC		0.067		0.069**
		(0.677)		(2.061)
Intercept	−0.401***	−0.576***	−0.098*	−0.180***
	(−2.712)	(−3.441)	(−1.861)	(−3.063)
Firm controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	3268	3268	3268	3268
R-squared	0.058	0.089	0.068	0.096

Panel B: Firm fixed effects analysis				
	DV = $NCSKEW_{t+1}$		**DV =** $DUVOL_{t+1}$	
	(1)	**(2)**	**(3)**	**(4)**
CRISK	0.021***	0.038***	0.006*	0.012***
	(2.801)	(4.166)	(1.948)	(3.054)
CRISK × HIGH_CDISC		−0.027***		−0.009***
		(−4.476)		(−3.702)
CCDS		0.108		0.049
		(1.334)		(1.643)
Intercept	−1.110***	−1.191***	−0.348***	−0.381***
	(−4.748)	(−5.456)	(−4.643)	(−5.050)
Firm controls	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Observations	13,165	13,165	13,165	13,165
R-squared	0.228	0.246	0.238	0.252

Panel C: Financial constraints		
	DV = $NCSKEW_{t+1}$	**DV =** $DUVOL_{t+1}$
	(1)	**(2)**
CRISK	−0.006	−0.001
	(−1.015)	(−0.519)
CRISK × HIGH_FINCONS	0.034***	0.011***
	(4.293)	(4.189)

(Continues)

Panel C: Financial constraints		
	DV = $NCSKEW_{t+1}$	**DV = $DUVOL_{t+1}$**
	(1)	**(2)**
Intercept	0.055	0.021
	(0.529)	(0.640)
Firm controls	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Observations	13,165	13,165
R-squared	0.164	0.147

Note: This table presents robustness analysis results. Panel A shows the effects of carbon risks on firm-level stock price crash risk and the moderating role of firm-level carbon disclosure quality in this association using only United States (US) firms. Panel B presents regression results, including firm-fixed effects. Panel C divides the firms into whether they are financially constrained or not using the KZ index (Kaplan and Zingales 1997). *HIGH_FINCONS* equals one if the firm's KZ index value exceeds the country-industry-year adjusted median value of the KZ index and zero otherwise. Columns (1) and (2) use *NCSKEW* as a dependent variable. Columns (3) and (4) use *DUVOL* as a dependent variable. All coefficient values (robust t-statistics) are shown with standard errors clustered at the country level. The superscripts ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.
Abbreviation: CCDS, carbon disclosure score.

5 | Conclusion

This article uses an international sample of firms to examine the relationship between carbon risk and future stock price crash risk and the moderating role of the quality of carbon disclosures in this relationship. Our analysis reveals that firms facing higher carbon risks tend to have an increased risk of future stock price crashes. This phenomenon is attributed to the overvaluation of carbon-intensive stocks, which stems from the underestimation of carbon risks and the growth in information asymmetry between firms and investors. This asymmetry is exacerbated by the complex and profound uncertainties associated with carbon risks. As carbon disclosure quality is conducive to reducing pricing uncertainties and information asymmetry, we find that it attenuates the likelihood of crashes accrued to carbon risk.

Further, we find that the positive association between carbon risk and stock price crash risk is attenuated by internal (e.g., corporate governance) and external monitoring (e.g., institutional investors and financial analysts). Additionally, the positive association between carbon risk and stock price crash risk is less pronounced for firms linking climate-related issues with incentive contracts and for firms domiciled in countries with stakeholder-oriented business cultures, stronger climate change performance, or greater financial transparency. Our findings are robust using quasi-experimental analysis based on the introduction of the UKCDR.

Our study is the first to offer international evidence on the impact of a firm's carbon risk on its future stock price crash risk. Our study provides several practical implications. As investors regard crash risk as a first-order concern, an understanding of crash risk informs investment decisions and risk management. Our study urges investors to be cautious about carbon risk. It also calls for financial markets and regulators to increase oversights of high-carbon risk firms and develop relevant policies to both improve the informational environment and reduce pricing uncertainties for such firms.

Data Availability Statement

We have used data from World scope, DataStream, Refinitiv ESG, CDP, World bank and other sources. Restrictions apply to the availability of these data, which were used under license for this study.

Endnotes

[1] There is no standard definition and measurement of carbon risk (Wang et al., 2022; Wang, 2023). Other studies have adopted either a narrower or broader definition of carbon risk. For instance, Nguyen and Phan (2020) refer to carbon risk as a firm's financial vulnerability when transitioning from a fossil fuel-based to a lower-carbon economy. Ehlers et al. (2022) define carbon risk as the potential economic impact attributable to more stringent carbon emissions policies. Trinks et al. (2022) view carbon risk as regulatory and market risks incurred by carbon-intensive firms when transitioning from a high to low-carbon production system. Wang (2023) holistically defines carbon risk as negative impacts induced by carbon emissions. Our study focuses on the aspects of carbon risk that are most pertinent to stock price crash risk. This includes the uncertainties and potential financial impacts of a firm's carbon footprint (proxied by emissions) and climate change policies (proxied by climate change disclosure performance).

[2] Financial impacts include increased regulation, taxation, greater clean-up and compliance costs, and reputational damage (Eccles et al., 2011). Noncompliance costs refer to costs like cap-and-trade programs where firms need to buy carbon emission allowances in the market place when they are noncompliant.

[3] Researchers refer to carbon disclosures (e.g., Bui et al., 2020) as either climate change disclosures (e.g., Daradkeh et al., 2023), greenhouse gas (GHG) disclosures (e.g., Liao et al., 2015; Tauringana & Chithambo, 2015), or the transparency of GHG disclosures (e.g., Peters & Romi, 2014). In this study, we refer to climate change disclosures to the Carbon

Disclosure Project as carbon disclosures following the methodology in Bose et al. (2023).

[4] Previous research indicates that information asymmetry, stemming from agency conflicts where managers hoard bad news, is a key factor leading to stock price crashes (Bleck & Liu, 2007; Hong et al., 2017; Jin & Myers, 2006). These conflicts arise as managers, driven by self-interest, make suboptimal decisions with firm resources to benefit personally (Jensen & Meckling, 1976). To maintain their positions and maximize their compensation, they often conceal negative information from the public, leading to stock overvaluation (Ball, 2009; Benmelech et al., 2010; Kothari et al., 2009). Eventually, when they can no longer hide this information, the sudden release of accumulated negative news causes a sharp decline in the firm's stock price (Hutton et al., 2009; Jin & Myers, 2006). Supporting this, various studies have linked characteristics of agency conflict, such as financial reporting opacity (Hutton et al., 2009; Kim & Zhang, 2014), earnings smoothing (Chen et al., 2017; Khurana et al., 2018), CEO power (Al Mamun et al., 2020), and the design of executive compensation (Jia, 2018; Kim et al., 2011), to an increased risk of stock price crashes. Relatedly, using China as the empirical setting, Ren et al. (2023) find that carbon price uncertainty motivates managerial bad news hoarding, which increases stock price crash risk.

[5] CDP is a not-for-profit charity that maintains the global disclosure system used for managing environmental impacts. Each year, CDP collects data from firms through issuance of a questionnaire.

[6] Our sample period starts from 2006 because the climate change disclosures data from CDP are only available from this year forward. Due to our lead–lag analysis approach, the stock price crash risk data covers the period from 2007–2022, whereas independent variables apply to the period from 2006–2021.

[7] Results using carbon emissions scaled by revenue are quantitatively and qualitatively similar.

[8] We acknowledge that although carbon emissions provide a tangible measure of a firm's environmental impact, they may not fully capture the broader spectrum of carbon risk management practices, including strategic responses to climate change challenges.

[9] The standard deviation (unreported) of *CRISK* is 2.529. We compute 6.32% and 2.28% as $[(0.025 \times 2.529) \times 100]$ and $[(0.009 \times 2.529) \times 100]$.

[10] The standard deviation of *CRISK* is 2.529. We compute 10.37% and 3.54% as $[(0.041 \times 2.529) \times 100]$ and $[(0.014 \times 2.529) \times 100]$. Further, we compute 5.56% and 1.77% as $[(-0.022 \times 2.529) \times 100]$ and $[(-0.007 \times 2.529) \times 100]$.

[11] The corporate governance performance rated by Refinitiv ESG consists of three dimensions of corporate governance: management; shareholder and CSR strategy. The management score measures a firm's commitment and effectiveness adhering to best practices in corporate governance principles. The shareholders score measures a firm's effectiveness in terms of equal treatment of shareholders and the usage of anti-takeover devices. The CSR strategy score shows a firm's practices for communicating how economic (financial), social, and environmental dimensions are integrated into its day-to-day decision-making processes.

[12] In the CDP questionnaire, there are two questions related to climate change incentives. The first question is: "*Do you provide incentives for the management of climate-related issues, including the attainment of targets?*" The second question is: "*Provide further details on the incentives provided for the management of climate-related issues*," specifically the CEO, board, top executives, or other. We use the answers to these questions to create indicator variables for whether climate-related incentives are provided to the CEO.

[13] The dataset covers worldwide, offering national insights and detailed subnational TL2 level data (broad subnational regions) for OECD nations and Argentina, Brazil, China, India, Indonesia, and South Africa. It also encompasses diverse aggregate data categories, covering different economic and regional clusters, including the Euro area, European Union, Advanced economies, Emerging market economies, G7, G20, and OECD. It further includes specific regional aggregates such as OECD Europe, OECD Asia Oceania, OECD Americas, and the Latin America and Caribbean (LAC) region.

[14] To demonstrate the impact of UKCDR on our H2, we create an interaction term, $TREAT \times POST \times HIGH\_CDISC$, which captures the effects of the UKCDR on the moderating role of carbon disclosure quality on stock price crash risk. Although we do not present the regression results for brevity, the unreported findings indicate that the coefficient on $TREAT \times POST \times HIGH\_CDISC$ is negative and statistically significant (coefficient = −0.261 for *NCSKEW* and −0.056 for *DUVOL*, both significant at 1%).

[15] The indicator variable, country-level legal environment (*LEGAL*), has a value of one if the firm operates in a civil law country, and zero if the firm operates in a common law country. Firms in civil law countries are considered having a higher level of stakeholder orientation. *STAKE* is from Simnett et al. (2009).

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Appendix A: Definition of variables

Variable notations	Variable name	Explanation	Source
NCSKEW	Crash risk	The negative skewness of firm-specific weekly returns over the fiscal year	DataStream
DUVOL	Crash risk	The natural logarithm of the standard deviation of down-week to up-week firm-specific weekly returns	DataStream
CRISK	Carbon risk	The natural logarithm of the total carbon emissions measured in millions of CO_2-e	CDP
CCDS	Quality of carbon disclosures	The quality of carbon disclosures	CDP
HIGH_CDISC	Quality of carbon disclosures	An indicator variable that takes a value of 1 if the firm-level carbon disclosure quality is higher than the country-industry-year adjusted median and 0 otherwise	CDP
SIZE	Firm size	The natural logarithm of the total market capitalization at the beginning of each year	World scope
MB	Market to book	The ratio of market to book value of equity	World scope
LEV	Leverage	The ratio of total debt scaled by total assets	World scope
ROA	Profitability	The ratio of net income scaled by total assets	World scope
DTURN	Detrended turnover	The difference between the average monthly turnover at the end of the fiscal year and the average monthly turnover at the beginning of the fiscal year	DataStream
MEAN_RET	Average week return	The average of firm-specific weekly returns over a fiscal year	DataStream
SD_RET	Standard deviation of weekly return	The standard deviation of the weekly returns over a fiscal year	DataStream
EM	Earnings management	Earnings management is computed using the modified Jones model	World scope
IND_HERF	Industry competition	The industry Herfindahl-Hirschman index is calculated using two-digit SIC industry sales	World scope
IND_FIRM	Firm competition	The firm Herfindahl-Hirschman index is calculated using individual firm sales	World scope
INSTOWN	Institutional investors ownership	The percentage of institutional investor ownership. *HIGH_INSTOWN* takes a value of 1 if the firm-level institutional investor ownership is greater than the median of the country-year adjusted score and 0 otherwise	FactSet
ANALYST	Analysts' coverage	The total number of analysts covering a firm. *HIGH_ANALYST* takes a value of 1 if the firm-level analysts' coverage is greater than the median of the country-year-adjusted analysts' coverage and 0 otherwise	I/B/E/S
CGOV	Corporate governance performance	The corporate governance performance score. *HIGH_CGOV* takes a value of 1 if the firm-level corporate governance performance score is greater than the median of the country-year adjusted corporate governance performance score and 0 otherwise	Refinitiv ESG
CLIMATE_INCENTIVE	Firm-level climate incentives	An indicator variable that takes a value of 1 if the firm links its CEO's compensation with the climate targets and 0 otherwise	CDP
STAKE	Country-level stakeholder-orientation	An indicator variable that takes a value of 1 if the firm is domiciled in a code law country and 0 otherwise.	Ball et al.

(Continues)

Variable notations	Variable name	Explanation	Source
CCPI	Country-level climate change performance score	The climate change performance score. A higher score indicates higher country-level climate change performance. *HIGH_CCPI* takes a value of 1 if the country-level climate change performance score is greater than the median and 0 otherwise	Germanwatch and Climate Action Network
HIGH_OPAQUE	Country-level financial opaqueness	An indicator variable that takes a value of 1 if the country-level financial opaqueness is greater than the median and 0 otherwise	Dhaliwal et al. (2012)
DIRTY_COUNTRY	Dirty countries or polluted countries	An indicator variable that takes a value of 1 if the country-level carbon risk is higher than the median of the country-year adjusted carbon emissions and 0 otherwise	OECD
HIGH_EVAL	Environmental culture	An indicator variable that takes a value of 1 if the country-level environmental culture score is higher than the median and 0 otherwise	WVS survey
HIGH_FINCONS	Financial Constraint	An indicator variable of HIGH_FINCONS takes a value of 1 if the firm's KZ index value (Kaplan and Zingales 1997) is greater than the country-industry-year adjusted median value of the KZ index and 0 otherwise	World scope
DIRTY_INDUSTRY	Dirty industries or carbon-sensitive industries	An indicator variable that takes a value of 1 if the firms operate in a carbon-sensitive industry and 0 otherwise	CDP
PROPDISC	Industry pressure to respond to the CDP questionnaire	The proportion of firms in an industry that respond to the CDP questionnaire to total firms in the industry at a country-year level	CDP
CDP_DISC_LAG	Firm response to the CDP questionnaire in the prior year	An indicator equal to 1 if the firm responded to the CDP questionnaire for the previous year and 0 otherwise	CDP
EMI_COUNTRY	Country-level carbon emissions	The natural logarithm of the country-level carbon emissions	OECD

(Continues)

Variable notations	Variable name	Explanation	Source
RENEW	Country-level renewable energy	The amount of renewable energy produced at the country level	Our World of data
LNGDPC	Gross domestic product	The natural logarithm of the gross domestic product per capita	World bank
STGDPC	Macroeconomic risk	The standard deviation of the growth in GDP per capita each year	World bank
LEGAL	Legal environment	An indicator variable that takes a value of 1 if the firm operates in a civil law country and 0 if the firm operates in a common law country	World bank
LNCRI	Climate risk	The natural logarithm of country-level climate risk. A higher score indicates lower risk	Germanwatch and Climate Action Network

Abbreviations: CCDS, carbon disclosure score; CCPI, climate-change performance risk; CDP, Carbon Disclosure Project; DUVOL, down-to-up volatility; EM, earnings management; LEV, leverage; MB, market-to-book.