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Rashid Zaman
Edith Cowan University


Nader Atawnah
Edith Cowan University

Muhammad Haseeb

Muhammad Nadeem

Saadia Irfan

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Does corporate eco-innovation affect stock price crash risk?

Rashid Zaman^{a,*}, Nader Atawnah^a, Muhammad Haseeb^b, Muhammad Nadeem^c, Saadia Irfan^d

^a School of Business and Law, Edith Cowan University, 270 Joondalup Drive, Joondalup, 6027, Australia

^b Department of Finance and Banking, University of Malaya, 50603, Kuala Lumpur, Malaysia

^c Otago Business School, University of Otago, New Zealand

^d NUST Business School, National University of Sciences and Technology, Pakistan

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ABSTRACT

We examine the effect of corporate environmental innovation (hereafter eco-innovation) on stock price crash risk and document a significant negative association. Utilising a large sample of publicly listed U.S. firms for the period 2003 to 2017, we find that an increase in eco-innovation from the 25th to the 75th percentile is associated with 17.62% reduction in stock price crash risk. This outcome remains robust to a variety of sensitivity tests and after accounting for potential endogeneity concerns. Eco-innovative firms attract more institutional investors and equity analyst following and disclose more information leading to lower stock price crash risk. Additional tests reveal that the negative effect of eco-innovation is contingent on the political leadership's ideology and environmental sensitivity. Our paper contributes to the ongoing discourse on the costs and benefits of eco-innovation, documenting the value-enhancing perspective of eco-innovation.

1. Introduction

We examine whether environmental innovation (hereafter eco-innovation) has any impact on stock price crash risk.¹ Our study is motivated by fairly recent catastrophic environmental incidents, such as the 2010 B P Deepwater Horizon oil spill in the Gulf of Mexico, and the 2015 Volkswagen emissions scandal that triggered extensive media coverage and negative reaction from investors (Jain & Zaman, 2020).² These criticisms, along with recent legislative/regulatory developments and much more focus on socially responsible investment (SRI) and protecting the environment, have forced companies' management to consider environment-focused innovation as an effective strategy to gain a competitive advantage (Cheng, Yang, & Sheu, 2014; Metcalf, Mackelprang, & Galbreth, 2016; Xue, Zhang, & Li, 2020; Zaman, Jain, et al., 2020). Indeed, prior studies show that eco-innovation enhances firms' financial performance (Przychodzen & Przychodzen, 2015; Song, Zhao, & Zeng, 2017), generates higher stock return (Szutowski, 2020), mitigate financial constraints (Zhang, Xing, & Wang, 2020), reduces information asymmetry (Fondevila, Moneva, & Scarpellini, 2019; Vieira & Radonjić, 2020) and results in flexible credit terms (Liao, 2020). Since eco-innovation reduces information asymmetry, it is entirely possible that eco-innovative businesses are not at great risk of a price crash that can arise due to bad news hoarding. Our paper

* Corresponding author.

E-mail addresses: r.zaman@ecu.edu.au, rashidzamanantoli@gmail.com (R. Zaman).

¹ Eco-innovation is defined as: "the production, assimilation or exploitation of a product, product process, service or management or business method that is novel to the organisation and which results, through its lifecycle, in a reduction of environmental risk, pollution and other negative impacts of resources use compared to relevant alternatives" (Kemp & Pearson, 2008, p. 7).

² For example, a week after the announcement of the Volkswagen (VW) scandal, the price of VW stock crashed by 50% (Jain & Zaman, 2020).

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addresses this fundamental question by examining whether eco-innovative firms are more or less likely to suffer a stock price crash.

Stock price crash risk captures the likelihood of sudden but infrequent large price decreases, and it arises when managers hide bad news beyond some triggering threshold and sudden release of the information causes a significant drop in stock price (Zhu, 2016). Understanding what causes stock market crashes is imperative for investment and risk management decisions, and has received considerable attention from multiple stakeholders, including investors and legislators (Habib, Hasan, & Jiang, 2018). At the market level, such risk cannot be mitigated through diversification of investment portfolio (Kim, Li, & Li, 2014), and thus explains a significant fraction of the equity premium (Barro, 2006; Gabaix, 2012). Similarly, even at the organisational level, stock price crash risk is considered to be a key determinant of expected return (Conrad, Dittmar, & Ghysels, 2013; Yan, 2011). Stock price crash risk also predicts option prices, which are incremental to stock return volatility (Pan, 2002). These important economic implications associated with stock price crash risk call for a deeper understanding of its determinants.

Many published studies seeking to determine the stock price crash risk base their analysis on agency theoretical framework as suggested by Jin and Myers (2006). In their seminal paper, Jin and Myers argued that the presence of information asymmetries between management and stockholders leads to stock price crash. Recent empirical studies have also shown that corporate tax avoidance (Kim, Li, & Zhang, 2011b), earnings management (Zhu, 2016), opaque financial reporting (C. Kim, Wang, & Zhang, 2019; Kim & Zhang, 2014), and senior management characteristics such as CEO incentive plans (Kim, Li, & Zhang, 2011a), CEO age (Andreou, Louca, & Petrou, 2017), CEO overconfidence (Kim, Wang, & Zhang, 2016) and CEO power (Al Mamun, Balachandran, & Duong, 2020) increase the risk of stock price crash. Conversely, monitoring mechanisms such as the Securities Exchange Commission (SEC) and board of directors (Cao, Sun, & Yuan, 2019; Kubick & Lockhart, 2016), industry specialist auditors (Robin & Zhang, 2015), social trust (Cao, Xia, & Chan, 2016), institutional ownership (Callen & Fang, 2013), analyst coverage (Kim, Lu, et al., 2019), financial statement readability (Kim, Wang, et al., 2019) and county-level religiosity (Callen & Fang, 2015) reduce stock price crash risk. Our study complements these studies by examining important yet unexplored determinants of stock price crash risk, i.e. eco-innovation. Considering the growing number of environmental anomalies and carbon footprints, what remains is for a thorough and urgent examination of whether and how eco-innovation affects stock crash risk.

We anticipate that eco-innovative firms exposed to less stock crash risk for two main reasons. First, eco-innovative firms lead to more institutional investors and analyst's coverage.³ Recently, the world witnessed a significant surge in responsible investing (often termed as a green investment).⁴ Such a precedented growth in socially responsible investment (SRI) means an increased number of investors particularly institutional investors and equity analyst under the clientele effect are directed to eco-friendly companies (i.e. eco-innovative firms). The presence of such a large number of institutional shareholders and equity analyst reduces the ability of a firm to hoard bad news and increase its information transparency – this could in turn reduce stock price crash risk.⁵ Second, recent studies show that eco-innovative firms disclose more information about their activities and exhibit less information asymmetry (Fondevila et al., 2019; García-Sánchez, Raimo, & Vitolla, 2021; Radu & Francoeur, 2017; Vieira & Radonjić, 2020). The implication of these studies is that eco-innovative firms are more transparent and less likely to withhold bad news, leading to lower stock price crash risk.

We test our conjecture using a large sample of US-listed companies for the period 2003–2017.⁶ We capture the firm's eco-innovation using eco-innovation score from Thomson Reuters Eikon database. Following Chen, Hong, and Stein (2001) and Kim et al. (2011b), we use negative skewness (*NSKEW*) and down-to-up volatility (*DUVOL*) as two measures of stock price crash risk. Our original results reveal a negative association between eco-innovation and stock price crash risk. Our results hold after controlling for a large set of firm-level accounting, and the inclusion of industry and year fixed effects. Furthermore, these results are not only statistically significant but also economically meaningful. We find that an increase in eco-innovation from the 25th to the 75th percentile is associated with a 17.62% reduction in stock price crash risk.

These findings remain consistent following the application of a large number of robustness tests, including: (i) alternative measure of eco-innovation, i.e. industry adjusted eco-innovation; (ii) alternative specifications such as Fama Macbeth and change on change analysis; and (iii) excluding the Global Financial Crisis (GFC) period. We employ four additional tests to overcome endogeneity concerns. First, we employ the instrumental variable approach using ISO Certificate and Policy Emission as instruments. Second, we use the Heckman Selection Model that addresses sample selection induced endogeneity biases. Third, we utilise the two-step Generalized Method of Moments (GMM) approach which accounts for reverse causality and dynamic endogeneity. Fourth, we conduct a Propensity Score Matching (PSM) analysis to address the selection bias arising from: firstly, firm-related characteristics; and secondly, bias related to functional misspecification (Rosenbaum & Rubin, 1983). In all four tests, which more formally address

³ Barber and Odean (2008) show that retail investor buy stock based on attention such as stocks with extreme one-day returns. In contrast, institutional investors invest significant resources and time to search stock using more sophisticated computer aid programs. Hence, eco-innovation being a long-term phenomenon will lead to more institutional ownership (IO) especially monitoring IO.

⁴ For instance, the number of investment companies adopting the UN-backed Principles for Responsible Investment (PRI) when they were first launched in 2006 has grown (i.e. 63 companies with 6.5 trillion USD in *Asset Under Management* to 1715 investment companies with 81.7 trillion USD AUM by 2018). For details see http://www.gsi-alliance.org/wp-content/uploads/2019/03/GSIR_Review2018.3.28.pdf.

⁵ One might assume that since eco-innovation is a kind of innovation, the propriety cost might limit eco-innovative companies' disclosure ability. However, very recently, Ben-Nasr et al. (2021) have tested such a conjecture by examining the association between general innovation (captured through number of patents) and stock price crash risk. Their findings negate such an assumption and suggest that companies' innovation activities send a high-quality signal and reduce propriety information costs, which lowers information asymmetry and enhances disclosure. Throughout our analysis, we control for patent innovation measured as the natural logarithm of number of patents (i.e. $\ln(1 + \text{Patent})$) to ensure that our results are not driven by a firm's relative innovation activities.

⁶ We begin our sample in 2003 due to the availability of eco-innovations data.

endogeneity concerns, we find consistent results with our baseline findings.

Having established a negative association between eco-innovation and stock price crash risk, we empirically tested our underlying assumption that institutional investors and equity analyst under the clientele effect of SRI are directed to eco-innovative firms and their presence limits information asymmetry, which in turn curtails the stock price crash risk. Specifically, we use a two-step process. Firstly, we applied *t*-test and PSM matching technique to test whether there is any heterogeneity in institutional shareholding and equity analyst among eco-innovative and non-eco-innovative firms. Our findings indicate a large presence of institutional shareholders and equity analyst for eco-innovative firms compared to non-eco-innovative firms. Secondly, we use a sub-sampled approach and re-run our baseline model for two subsamples: firms with higher information asymmetry (financial opacity, financial statements comparability and quoted spread higher than cross-sectional median) versus firms with lower information asymmetry (financial opacity, financial statements comparability and quoted spread lower than the cross-sectional median). We find evidence suggesting that the negative association between eco-innovation and stock price crash risk is more pronounced for the firm characterised by high level of information asymmetry.

Our results indicate that eco-innovation alleviate the effects of information asymmetry as firms benefited more from eco-innovation when they have higher information asymmetry. In further tests, we examine whether the eco-innovation and stock price crash risk nexus are contingent on political leadership's ideology regarding environmental matters and the extent of firms' sensitivity to them. Our results show that the negative association between eco-innovation and stock price crash risk is more pronounced in President Obama's 2009–2017 tenure compared to President Bush's 2001–2008 tenure, as well as for environmentally sensitive firms.

Our paper is closely related to that of Ben-Nasr et al. (2021), who find a negative association between patent innovation and crash risk. However, our paper does differ in three important aspects. First, while Ben-Nasr et al. (2021) concentrate on the implications of the patented grants and citation, our focus is on eco-innovation. This includes R&D on environmental issues and reflects a company's capacity to reduce environmental costs and burdens for its customers. Second, in our empirical analysis, we control for patent innovation measured as natural logarithm of number of patents (i.e. $\ln(1 + \text{Patent})$) and examine any incremental effect that eco-innovation has on stock price crash risk. Our inferences are therefore not based on whether general corporate innovation is good for the firm but, instead, whether eco-innovation has positive implications for a firm beyond that of patent innovation. Third, we find that institutional investors and equity analyst under the clientele effect of SRI pay more attention to eco-innovative firms, and their presence limit information asymmetry which in turn lowers stock price crash risk. The underlying economic mechanism in our study is therefore distinct.

Our paper makes significant contributions to several strands of literature. First, our study adds to the growing literature on corporate innovativeness and its economic consequences. Prior studies focusing on consequences of firm innovativeness have examined the impact of patent innovation on stock return (Hirshleifer, Hsu, & Li, 2013), corporate stock price crash risk (Ben-Nasr et al., 2021), default risk (Hsu, Lee, Liu, & Zhang, 2015), and market risk premium (Hsu, 2009). However, none of these studies has captured the nuances associated with green innovation such as eco-innovation. We have provided an excursion of such literature by focusing on eco-innovation through a novel and yet unexplored measure of eco-innovation. To the best of our knowledge, this is the first study that not only captures nuances associated with the eco-innovation and stock price crash risk nexus. It also explores scenarios through which eco-innovation affects stock price crash risk.

Second, we contribute to growing literature factors predicting stock price crash risk. Recent theoretical and empirical research has identified a variety of firm and manager characteristics that are determinants of stock price crashes (see, Habib et al., 2018). We extend prior studies by identifying a new factor that mitigates future stock price crash risk. This paper provides nuanced evidence illustrating eco-innovation incremental ability in predicting future stock price crash risk, over and above other predictors including patent innovation identified by previous research.

Third, our study informs the regulatory debate about the effectiveness of eco-innovation and broadens our understanding of the implications of eco-innovation on financial markets in general and stock price crash risk in particular. In this way, we envision the eco-innovation and stock price crash risk relationship by empirically testing for political leadership ideology. For at least a decade, scholars have commented on the importance of executive values for corporate environmental performance (Chin, Hambrick, & Treviño, 2013; Woodward, Edwards, & Birkin, 2001) but the research on political leadership ideology has been exceedingly sparse. Our paper sheds new light on the interplay between eco-innovation and political leadership ideology by documenting that presidential views and policies shape the investor, regulator and managerial views on corporate environmental performance (i.e. eco-innovation in our case). Finally, our study has important implications for environmentalists and especially environmentally responsible investors who want to manage tail risk in their investment portfolio.

The remainder of the paper is structured as follows. Section 2 discusses the literature review. Section 3 presents the data and methodology, while Section 4 reports the empirical findings. Section 5 and Section 6 highlight possible channel and further analysis, respectively. Finally, Section 7 concludes the study.

2. Literature review

2.1. Eco-innovation

After the seminal work of Fussler and James (1996) who introduced eco-innovation as a business strategy to meet contemporary sustainability challenges, eco-innovation has started to receive growing academic attention from a variety of disciplines (Arena, Michelin, & Trojanowski, 2018; He, Miao, Wong, & Lee, 2018). However, the major of the eco-innovation research still focuses on the macro-level (i.e. country level) with more recent work being done on its implications at the corporate level (Arena et al., 2018; He et al., 2018). Corporate level eco-innovation research focuses on the identification of determinants or consequences of such innovation

on organisational outcome (He et al., 2018). Studies identifying the firm-level determinants of eco-innovation found that boardroom gender diversity (García-Sánchez, Raimo, & Vitolla, 2021; Nadeem, Bahadar, Gull, & Iqbal, 2020), ownership structure (García-Sánchez, Aibar-Guzmán, & Aibar-Guzmán, 2020), managerial environmental awareness (Peng & Liu, 2016), CEO hubris (Arena et al., 2018), organisational internal capabilities (Salim, Ab Rahman, & Abd Wahab, 2019), customer demand (Liao & Tsai, 2019), firms' proactive sustainability strategy (Tsai & Liao, 2017), better corporate social responsibility practices (Pan, Sinha, & Chen, 2021) and regulations (Doran & Ryan, 2012) influence corporate eco-innovation. However, compared with antecedents, the literature on the consequences of eco-innovation is limited.

In this way, prior studies indicate that companies' eco-innovation commitment improves business performance (Cheng et al., 2014; Hojnik & Ruzzier, 2017), generates higher stock return (Szutowski, 2020), enhances environmental performance (Fernando & Wah, 2017), results in greater transparency and disclosure (Fondevila et al., 2019; García-Sánchez, Raimo, et al., 2021; Radu & Francoeur, 2017; Vieira & Radonjić, 2020; García-Sánchez, Gallego-Álvarez, et al., 2021). However, despite there being eco-innovation implications particularly its relevance to SRI literature, not much has been published on understanding its implications for the capital market – the exception being the study by Szutowski (2020). Szutowski (2020) examines the effect of eco-innovation on stock return for European companies over three years (2016–2019). Their results indicate that a high degree of eco-innovation leads to a larger increase in stock return. Against this backdrop, our study aims to investigate whether and how firm eco-innovation affects stock price crash risk.

2.2. Theoretical framing and hypothesis development

Conceptually, stock price crash literature is based on the agency framework which focuses on the role of information asymmetry arising due to separation of ownership (i.e. principal) and control (i.e. agent) (Jensen & Meckling, 1976). Owners being outsiders rely on controlling agents (i.e. management) for information to make decisions (Fama & Jensen, 1983; Jensen & Meckling, 1976). Despite being required to provide owners with timely, fair and relevant information, the agents delay the disclosure of information (particularly if it is negative) for an extended period for strategic or non-strategic reasons (Jin & Myers, 2006). However, the managers can only retain this information for a specific time until it has to be released (Jin & Myers, 2006). Upon sudden release of such information, the market reacts negatively, and it causes a large dip in the company's stock price – often referred to as stock price crash.

Since stock price crash risk mainly arises due to firm-specific or managerial characteristics, owners cannot mitigate it through portfolio diversification (Kim et al., 2014). Therefore, a growing body of researchers has attempted to explore the factors that encourage/discourage manager to hoard information. In this manner, studies suggest that the stock price crash can arise from the nature of companies' activities and business operations (Habib et al., 2018). For instance, Ben-Nasr and Ghouma (2018) have examined the companies' excessive employee welfare activities and how this can shape stock price crash risk. Their finding indicates that generous employee welfare schemes promote managerial ability to hoard information for an extended period – increasing the stock price crash risk. Similarly, Kim et al. (2014) focused on the companies' CSR commitment and explored whether such commitment deters managers from hoarding negative information, or managers use such commitment intentionally to obfuscate what is really happening. In contrast to the information obfuscation hypothesis, their findings suggest that more socially responsible companies commit to a higher standard of transparency and thus engage less in information hoarding – leading to lower stock price crash risk. More recently, Ben-Nasr et al. (2021) have investigated the role of companies' general innovation activities on stock price crash risk. Their findings indicate that companies' innovation activities send high-quality signal and reduce propriety information cost, which reduce information asymmetry, enhance disclosure and eventually lead to lower crash risk. We extend such studies and examined the impact of innovation that focused on the generation of a positive effect of companies' operations/services on external environment, i.e. eco-innovation on stock price crash risk.

We argue that eco-innovative firms are susceptible to stock price crash risk for several reasons. Eco-innovative firms may be prone to a higher stock price crash risk because of inherent innovation characteristics that are embedded in eco-innovation.⁷ For instance, uncertainty, higher capital cost, delayed payback period and high failure-to-success ratio associated with innovation may generate more bad news for such firms, which is a key antecedent of stock price crash risk. Similarly, like any other innovation that aims to provide a competitive advantage to firms, the underlying proprietary information behind eco-innovation may reduce their disclosure ability and thereby increase the stock price crash risk probability. However, despite the aforementioned similarities, eco-innovation has many distinct features from general innovation which make such companies less susceptible to stock price crash risk.

First, unlike general innovation, eco-innovation is not much exploratory focused, i.e. radical changes in processes or generation of patent. Rather, it focuses on the incremental development of existing technology or processes/services to reduce corporate environmental externalities. Hence, compared to general innovation, the probability of hoarding information in an eco-innovative firm will be limited. As such the availability of more information for eco-innovation activities may send positive signals to the market and reduce the stock price crash risk. Against this backdrop, Vieira and Radonjić (2020), specifically investigated whether companies communicate eco-innovation activities. Their finding suggests that a large number of eco-innovative companies disclose information on different types of eco-innovation activities. Other studies have also highlighted the disclosure aspect of eco-innovative firms. For example, Fondevila et al. (2019) found eco-innovation is a key driver for disclosure among Spanish firms. Likewise, García-Sánchez, Raimo, et al. (2021) note there is a positive relationship between firms' eco-innovation activities and voluntary disclosure.

⁷ We are thankful to one of the anonymous reviewers for making us think in this direction.

Second, due to the nature of eco-innovation activities particularly their focus on lowering corporate environmental impact might lead such companies to more institutional shareholders and equity analyst following. The presence of large institutions to eco-innovative firms is highly plausible due to a significant upward spike in SRI that consider companies' environmental aspects. For example, most recently [Eccles and Klimenko \(2019\)](#) interviewed 70 executives from 43 global investing institutions. Their analysis suggests global investment institutions actively consider environmental footprints of investees who need to decide where to put their money. Similarly, the 2018 report by Global Sustainability Investment Alliance, has noted a 34% increase in SRI asset value (i.e. 30.7 trillion) in 2018 compared to 22.8 trillion in 2016.⁸ We believe the presence of such institutions makes it difficult for companies to hoard information and thus reduces stock price crash risk. Our inference is based on the documented literature that considers such institutions (i.e. shareholders and equity analyst) a major stakeholder influencing corporate strategies and managerial decisions ([Chang, Dasgupta, & Hilary, 2006](#); [McCahery, Sautner, & Starks, 2016](#)). Supporting this, [An and Zhang \(2013\)](#) suggest that institutional monitoring mitigates managerial bad information hoarding and decreases stock price crash risk. Likewise, [Kim, Lu, et al. \(2019\)](#) discovered a significant increase in a firm ex-ante expected stock price crash risk following an exogenous drop in analyst coverage. Based on the above discussion, we expect eco-innovative firms to be less prone to future stock price crash risk and posit the following hypothesis.

H1. Corporate eco-innovation is negatively associated with stock price crash risk

3. Data and descriptive statistics

3.1. The sample

We obtain data from several sources. Eco-innovation measure is estimated from the Thomson Reuters Eikon database. Stocks data are derived from the Centre for Research in Security Prices (CRSP) [database](#). Accounting data are from the COMPUSTAT database. Institutional ownership data are from the Thomson-Reuters Institutional Holdings database. Economic policy uncertainty is an index variable directly obtained from [Baker, Bloom, and Davis \(2016\)](#), while GDP is based on the World Bank's publicly available database. We exclude observations with missing accounting data. Our final sample consists of 6996 firm-year observations during the 2003–2017 period.

3.2. Stock price crash risk measures

We follow prior studies (e.g., [Chen et al., 2001](#); [Kim & Zhang, 2014](#); [Kim & Zhang, 2016](#)) and estimate our stock price crash risk measures: (i) negative skewness (*NSKEW*); and (ii) down-to-up volatility (*DUVOL*) based on the extended market model. We start by regressing weekly stock returns of each sample firm on the value-weighted market return and use two weeks lead and lag value-weighted market return as follows:

$$r_{i,w} = \alpha_s + \beta_1 r_{m,w-2} + \beta_2 r_{m,w-1} + \beta_3 r_{m,w} + \beta_4 r_{m,w+1} + \beta_5 r_{m,w+2} + \varepsilon_{i,w} \quad (1)$$

where ' $r_{i,w}$ ' is the stock return on firm i , at week w , and $r_{m,w}$ is the value-weighted market index of firm i at week w , and $\varepsilon_{i,w}$ is an error term. To account for non-synchronous trading we include lag and lead values of the value-weighted market in our estimation ([Dimson, 1979](#)). We then measured firm-specific weekly return for firm i at week " w " ($R_{i,w}$) as the natural log of one plus the residual return from Eq(1):

$$R_{i,w} = \log(1 + \varepsilon_{i,w}) \quad (2)$$

We base our first proxy on skewness to capture the asymmetry of the return distribution ([Zaman, Bahadar, et al., 2020](#)). To do so, we calculate the negative third moment of firm-specific weekly return $R_{i,w}$ for the individual sample year over the standard deviation of firm-specific weekly return raised to the third power as follows:

$$NSKEW_{s,T} = - \frac{(n(n-1)^{\frac{3}{2}} \sum R_{i,w}^3)}{((n-1)(n-2) (\sum R_{i,w}^2)^{3/2})} \quad (3)$$

We base our second proxy on down-to-up volatility (*DUVOL*) because the absence of the third moment avoids the over-influence of extreme week return ([Habib & Hasan, 2017](#)). We group the firm-specific weekly returns into two groups: 'down weeks' and 'up weeks'. The 'down weeks' represent below annual mean return while the 'up weeks' denote above annual mean return. We then calculate the standard deviation of the firm-specific returns for individual groups. Finally, we apply the natural logarithm to the ratio of standard deviation in the down weeks to standard deviation of up weeks to capture *DUVOL* as follows:

$$DUVOL_{i,T} = \log \frac{(n_{up} - 1) \sum_{down} R_{i,w}^2}{(n_{down} - 1) \sum_{up} R_{i,w}^2} \quad (4)$$

⁸ See http://www.gsi-alliance.org/wp-content/uploads/2019/03/GSIR_Review2018.3.28.pdf.

where ' n_{up} ' is the number of 'up weeks' and ' n_{down} ' is the number of 'down weeks'. A higher value of *NSKEW* and *DUVOL* reflects higher crash risk.

3.3. Eco-innovation measure

Prior studies have adopted Research and Development (R&D) to capture general innovation. However, we rely on Thomson Reuters Eikon eco-innovation score instead of R&D due to difficulty in obtaining environmental-related R&D expenses as it is not compulsory for a firm to disclose environmental processes improvement-related information. Eco-innovation score as documented in the Thomson Reuters database has been used in recent research (e.g. [Arena et al., 2018](#); [Nadeem et al., 2020](#); [Zaman, Jain, et al., 2020](#)). Thomson Reuters Eikon eco-innovation score reflects a company's capacity to reduce environmental costs and burdens for its customers, and thereby creating new market opportunities through new/improvement in existing environmental technologies and processes or eco-designed products or processes (Thomson Reuters Eikon). Thomson Reuters Eikon eco-innovation score is a weighted average industry adjusted composite score on a scale of 0–100 and encompasses twenty variables related to the organisational eco-product and eco-processes, where 100 reflects a high level of eco-innovation commitment (see supplementary file for details). Of note, we standardised the eco-innovation percentage score into fractions by dividing it with 100.

3.4. Control variables

We employ a set of control variables that are known to be determinants of stock price crash risk in the literature ([Habib et al., 2018](#)). First, the effect of eco-innovation on crash risk is influenced by the level of innovation activities ([Ben-Nasr et al., 2021](#)). For this reason, in our regression analysis, we control for innovation activities as captured by the $\ln Patent$.⁹ Second, previous studies find that firms with high crash risk in year t are likely to have high return skewness in year $t + 1$ ([Kim et al., 2016](#); [Kim & Zhang, 2014](#)). Therefore, we include *NSKEW_t* and *DTURN_t* in all regression analyses. Third, we include a set of variables that are related to company performance. Previous studies find highly profitable large-sized firms that perform better in the market may have a higher probability of meeting investors' negative reactions ([Chen et al., 2001](#); [Hutton, Marcus, & Tehranian, 2009](#); [Zaman, Bahadar, et al., 2020](#)). Accordingly, we control market performance (*MTB*), (*Firm size*), and firm profitability (*ROA*). Likewise, a firm with high debt-to-asset ratio has a greater propensity to experience a stock price crash ([Zaman, Bahadar, et al., 2020](#)). Consequently, we use firm leverage as a control variable (*Leverage*).

Recent anecdotal evidence suggests that heterogeneity among investors' beliefs and stock volatility influences stock price crash risk (e.g., [Chen et al., 2001](#); [Kim & Zhang, 2014](#); [Kim & Zhang, 2016](#)), allowing us to control for (*DTO*), which captures the difference between average monthly turnover at the end of year t and year $t-1$. We control for average weekly return (*Return*) and sigma which is measured as the standard deviation of firm-specific weekly returns of firm i for time t (*SIGMA*). We also added control for earnings quality using modified Jones model (*Discretionary accrual*), and managerial characteristics (*CEO duality*) that have recently been identified as determinants of stock price crash risk in recent scholarship ([Andreou, Antoniou, Horton, & Louca, 2016](#); [Yeung & Lento, 2018](#); [Zaman, Bahadar, et al., 2020](#)). It is also likely that stock price will fall at the announcement of a policy change and where policy uncertainty is evident because political and economic conditions cause market volatility ([Pastor & Veronesi, 2012](#); [Pástor & Veronesi, 2013](#)). Therefore, we control for economic policy uncertainty (*Economic policy uncertainty*) and gross domestic product ($\ln GDP$) ([Jin, Chen, & Yang, 2019](#); [Zaman, Bahadar, et al., 2020](#)). All variables are winsorised at the 1st and 99th percentiles. Detailed definitions of variables are presented in [Appendix 1](#).

3.5. Descriptive statistics and correlation matrix

[Table 1](#) presents the descriptive statistics of the sample. The mean values of crash-risk measures, *NSKEW*, and *DUVOL* are 0.257, and 0.102, respectively. These positive mean values indicate that, on average, the sample firms have more left-skewed firm-specific weekly returns and slightly more volatile firm-specific returns in down weeks than in up weeks. Eco-innovation measure, on average, has a mean of 0.506 and a standard deviation of 0.230. An average firm in our sample has 4 patents and a market-to-book ratio of 3.590. The summary statistics for the control variables resemble those reported in prior studies ([Kim et al., 2011a, 2011b](#), and [Callen & Fang, 2015](#)).

[Table 2](#) reports the results of the correlation matrix. The two crash risk measures *NSKEW* and *DUVOL* have a high correlation of 0.95, which is comparable to that reported elsewhere (e.g., [Chen et al., 2001](#); [Callen and Fang, 2015](#)). We find that Eco-Innovation measure is negatively and significantly correlated with both measures of stock price crash measures, namely negative conditional skewness (*NSKEW*) and down-to-up volatility (*DUVOL*). Such findings underpin and support our main hypothesis that eco-innovation of firms does reduce unpleasant events, such as stock price crash measures.

⁹ We are indebted to one of the anonymous referees for this suggestion.

Table 1
Descriptive statistics.

	N	Mean	Std.	P25	Median	P75
<i>Panel A: Dependent variables</i>						
<i>NSKEW</i>	6996	0.257	0.972	-0.270	0.135	0.641
<i>DUVOL</i>	6996	0.102	0.406	-0.154	0.079	0.337
<i>Panel B: Independent variables</i>						
<i>Eco-Innovation</i>	6996	0.506	0.230	0.337	0.471	0.675
<i>Panel C: Control Variables</i>						
<i>Ln Patent</i>	6996	1.639	2.035	0.000	0.693	3.178
<i>MTB</i>	6996	3.590	4.666	1.660	2.620	4.230
<i>Firm size</i>	6996	16.04	1.20	15.18	15.91	16.78
<i>Leverage</i>	6996	0.297	0.176	0.171	0.278	0.399
<i>ROA</i>	6996	0.068	0.069	0.036	0.064	0.102
<i>Sigma</i>	6996	3.517	1.747	2.339	3.030	4.109
<i>Return</i>	6996	-0.093	0.529	-0.361	-0.054	0.222
<i>DTO</i>	6996	0.000	0.002	-0.001	0.000	0.000
<i>Discretionary accrual</i>	6996	0.045	0.055	0.012	0.028	0.055
<i>CEO duality</i>	6996	0.720	0.449	0.000	1.000	1.000
<i>Economic policy uncertainty</i>	6996	120.5	31.28	93.05	111.45	143.95
<i>Ln GDP</i>	6996	0.765	0.569	0.611	0.863	1.049

This table presents descriptive statistics for the variables used in this study. The sample consists of 6996 firm-year observations during the 2003–2017 period. Detailed definitions of variables are provided in [Appendix 1](#).

4. Empirical results

4.1. Baseline regression results

To examine the effect of eco-innovation on stock price crash, we estimate the following regression model:

$$StockPriceCrash_{it+1} = \beta_0 + \beta_1 ECO - Innovation_{it} + \beta_2 Controls_{it} + \varphi_i + \phi_t + \varepsilon_{i,t}, \quad (5)$$

where i and t refer to industry and year, respectively. The dependent variable is the negative conditional skewness (*NSKEW*) or down-to-up volatility (*DUVOL*). The main independent variable of interest is eco-innovation (*Eco-Innovation*). Control variables consist of the natural logarithm of number of patents (*Ln Patent*), lag value of crash risk (*NSKEW_t* and *DTURN_t*), market-to-book ratio (*MTB*), firm size (*Size*), leverage ratio (*Leverage*), Return on assets ratio (*ROA*), standard deviation of firm-specific weekly returns (*SIGMA*), stock return (*Return*), detrended share turnover (*DTO*), absolute discretionary accruals (*Discretionary accrual*), CEO duality (*CEO duality*), policy uncertainty index (*Economic Policy Uncertainty*), and the natural logarithm of gross domestic product per capita (*Ln GDP*). Detailed definitions of variables are presented in [Appendix 1](#). In all regressions, we include industry and year fixed effects and report t -statistics with robust standard errors clustered at the firm level. Our results are reported in [Table 3](#).

[Table 3](#) presents the results of regressing stock price crash risk measures on eco-innovation proxy. Columns (1) and (4) include all control variables except the natural logarithm of number of patents (*Ln Patent*), whereas in columns (2) and (5) we include (*Ln Patent*) as the conventional innovation proxy. Including (*Ln Patent*) allows us to examine whether the effect that eco-innovation has on stock price crash holds, even after controlling for each firm's relative innovation activities. We find that *Eco-Innovation*, across all the models, is negatively and statistically related to stock price crash risk measures. Specifically, the coefficient estimates on *Eco-Innovation* are negative and significant at the level of 5% in columns (1)–(2), where we relate the negative conditional skewness (*NSKEW*) to eco-innovation measure. The coefficient estimates on *Eco-Innovation* are also negative and significant at the 5% level in columns (4) and at the 10% level in columns (5), where we test down-to-up volatility (*DUVOL*) with eco-innovation proxy. In columns (3) and (6), we include firm- and year-fixed effects in our regressions. Year fixed effects help us account for common macroeconomic shocks, whereas firm fixed effects account for all time-invariant firm-level characteristics which might be associated with both the level of eco-innovation score and stock price crash risk. The specification that includes firm fixed effects is more robust as it overcomes simple endogeneity concerns stemming from omitted variables bias. The results remain consistent with our main findings, indicating that our findings are not sensitive to the inclusion of firm-fixed effects.

The results are not only statistically significant but also economically significant. For example, the coefficient estimate reported for *Eco-Innovation* in column (2), which is the most robust model specification using *NSKEW* as a proxy for crash risk (includes all firm-level controls, as well as industry and year fixed effects), is -0.134 . This coefficient estimate suggests that moving from the 25th percentile of *Eco-Innovation* (0.337 from [Table 1](#)) to the 75th percentile (0.675 from [Table 1](#)) is associated with a decline in stock crash risk of 0.0453 (-0.134×0.338), which represents 17.62% of the cross-sectional mean of *NSKEW*. Similarly, the coefficient for *Eco-*

Table 2
Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) <i>NSKEW</i>	1.000														
(2) <i>DUVOL</i>	0.954***	1.000													
(3) <i>Eco-Innovation</i>	-0.025**	-0.020**	1.000												
(4) <i>Ln Patent</i>	-0.032***	-0.044***	0.216***	1.000											
(5) <i>MTB</i>	0.016	0.013	0.031***	0.116***	1.000										
(6) <i>Firm size</i>	-0.032***	-0.024**	0.225***	0.406***	0.192***	1.000									
(7) <i>Leverage</i>	0.007	0.012	-0.044***	-0.195***	-0.016	-0.121***	1.000								
(8) <i>ROA</i>	0.008	0.010	-0.005	0.090***	0.168***	0.246***	-0.157***	1.000							
(9) <i>Sigma</i>	0.043***	0.041***	-0.102***	-0.106***	-0.091***	-0.396***	0.062***	-0.282***	1.000						
(10) <i>Return</i>	-0.011	0.012	0.001	0.041***	0.147***	0.203***	-0.086***	0.178***	-0.279***	1.000					
(11) <i>DTO</i>	0.011	0.010	0.015	-0.009	-0.020*	-0.022*	0.092***	-0.043***	-0.014	-0.089***	1.000				
(12) <i>Discretionary accrual</i>	0.002	-0.005	-0.048***	0.052***	0.041***	-0.012	-0.044***	-0.090***	0.196***	-0.035***	-0.021*	1.000			
(13) <i>CEO duality</i>	-0.036***	-0.031***	0.009	0.050***	0.017	0.148***	-0.076***	0.068***	-0.065***	0.029**	-0.015	-0.012	1.000		
(14) <i>Economic policy uncertainty</i>	-0.023*	-0.021*	-0.016	-0.021*	-0.093***	-0.146***	0.000	-0.033***	0.129***	0.011	-0.065***	0.012	-0.031***	1.000	
(15) <i>Ln GDP</i>	0.015	0.016	0.006	0.018	0.014	0.038***	-0.010	0.060***	-0.090***	-0.060***	0.086***	-0.076***	0.018	-0.300***	1.000

Note: This table shows pairwise correlation matrix between proxies of stock price crash risk (*NSKEW* & *DUVOL*) and *Eco-Innovation*, market-to-book ratio, firm size, leverage, ROA, Sigma, Returns, detrended share turnover, discretionary accruals, CEO duality, economic policy uncertainty and gross domestic product. ***, **, and * show significance at the 1%, 5% and 10% level, respectively.

Table 3
Eco-innovations and stock price crash risk.

	NSKEW _{t+1}			DUVOL _{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Eco-Innovation</i>	-0.145** (-2.55)	-0.134** (-2.31)	-0.178** (-2.32)	-0.048** (-1.98)	-0.042* (-1.71)	-0.067** (-2.05)
<i>Ln Patent</i>		-0.020 (-1.58)	-0.033 (-1.23)		-0.011** (-2.09)	-0.012 (-1.10)
<i>NSKEW_t</i>	-0.015 (-0.83)	-0.015 (-0.83)	-0.095*** (-5.11)			
<i>DUVOL_t</i>				-0.006 (-0.37)	-0.006 (-0.39)	-0.078*** (-4.85)
<i>MTB</i>	0.005 (1.54)	0.005 (1.52)	0.004 (1.00)	0.002 (1.51)	0.002 (1.48)	0.001 (0.81)
<i>Firm size</i>	0.028* (1.73)	0.042** (2.32)	0.379*** (8.15)	0.013* (1.90)	0.020*** (2.63)	0.168*** (9.04)
<i>Leverage</i>	-0.048 (-0.51)	-0.045 (-0.48)	-0.172 (-1.02)	-0.031 (-0.80)	-0.029 (-0.76)	-0.068 (-0.94)
<i>ROA</i>	0.262 (1.23)	0.232 (1.09)	-0.010 (-0.03)	0.151* (1.65)	0.135 (1.48)	0.081 (0.63)
<i>Sigma</i>	0.017 (1.48)	0.017 (1.50)	0.004 (0.24)	0.010** (2.18)	0.010** (2.22)	0.004 (0.70)
<i>Return</i>	0.026 (1.01)	0.021 (0.83)	-0.075*** (-2.69)	0.034*** (3.10)	0.031*** (2.86)	-0.011 (-0.90)
<i>DTO</i>	1.707 (0.26)	1.951 (0.29)	1.122 (0.16)	0.253 (0.09)	0.382 (0.14)	0.244 (0.08)
<i>Discretionary accrual</i>	-0.081 (-0.31)	-0.079 (-0.30)	-0.260 (-0.90)	-0.041 (-0.38)	-0.040 (-0.38)	-0.117 (-1.00)
<i>CEO duality</i>	-0.074** (-2.57)	-0.073** (-2.53)	-0.060 (-1.19)	-0.027** (-2.20)	-0.026** (-2.16)	-0.021 (-0.98)
<i>EPU</i>	0.088 (1.25)	0.087 (1.26)	0.014 (0.19)	0.039 (1.36)	0.038 (1.37)	0.007 (0.26)
<i>Ln GDP</i>	0.159 (1.03)	0.129 (0.83)	-0.048 (-0.30)	0.062 (0.98)	0.046 (0.72)	-0.025 (-0.38)
Industry & Year FE	YES	YES	NO	YES	YES	NO
Firm & Year FE	NO	NO	YES	NO	NO	YES
Observations	6996	6996	6996	6996	6996	6996
Adjusted R ²	0.036	0.037	0.168	0.038	0.039	0.168

This table reports regression results on the relation eco-innovations and stock price crash risk. Detailed definitions of variables are provided in [Appendix 1](#). All regressions control for the industry and year fixed effects. Standard errors clustered at the firm and year and *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Innovation in column (4), is -0.042 . This coefficient estimate suggests that an increase in *Eco-Innovation* from the 25th percentile to the 75th percentile of its distribution is associated with a reduction in stock crash risk of approximately 13.92% relative to the sample mean. The baseline results reported in [Table 2](#) are therefore not only statistically significant but also economically meaningful.¹⁰

4.2. Robustness tests

In this subsection, we retest our predictions and provide supporting evidence that eco-innovation reduces stock price crash risk. We provide evidence that our main results remain consistent when we use an alternative independent measure, include different specifications, such as Fama–MacBeth (1973), regress the change in our crash risk measures on eco-innovation measure, and controlling for the Global Financial Crisis (GFC). We include the same set of control variables as in the baseline results reported in [Table 3](#), include industry and year fixed effects where applicable, and correct standard errors for clustering at the firm level. For brevity the table only reports the coefficients on the variables of interest.

Panel A of [Table 4](#) reports the results using an alternative independent measure. Specifically, we construct an industry adjusted eco-innovation score, which captures the relative eco-innovation activities of a firm relative to industry peers. Specifically, for each industry and year, we calculate the average eco-innovation score and deduct this average score from the firm-level eco-innovation score for a particular year (*Industry adj. Eco-Innovation*). The results reveal that our results stay qualitatively unchanged when we use the alternative measure.

Panel B of [Table 4](#) shows the relationship between eco-innovation and stock price crash risk measures using Fama–MacBeth (1973)

¹⁰ The mean of NSKEW (DUVOL) in our full sample period is 0.257 (0.102). The coefficient of eco-innovation is equal to -0.134 (-0.042). The standard deviation of eco-innovation is 0.230. A one-standard-deviation increase in eco-innovation is associated with a 12% (11%) decrease in NSKEW ($(-0.134 * 0.230)/0.257 = 0.12$) (DUVOL ($((-0.042 * 0.257)/0.102 = 0.11)$).

Table 4
Eco-innovations and stock price crash risk – robustness tests.

Panel A: Alternative independent variable		
	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)
<i>Industry adj. Eco-Innovation</i>	-0.158** (-2.32)	-0.052* (-1.80)
<i>Ln Patent</i>	-0.020 (-1.58)	-0.011** (-2.08)
All controls	YES	YES
Industry & Year FE	YES	YES
Observations	6996	6996
Adjusted R ²	0.037	0.039
Panel B: Fama–Macbeth (1973) regression results		
	(1)	(2)
<i>Eco-Innovation</i>	-0.106** (-2.76)	-0.023* (-1.69)
<i>Ln Patent</i>	-0.003 (-0.56)	-0.004 (-1.32)
All controls	YES	YES
Year FE	YES	YES
Observations	6996	6996
R ²	0.112	0.116
Panel C: Change of stock price crash		
	$\Delta NSKEW_{t+1}$	$\Delta DUVOL_{t+1}$
	(1)	(2)
Δ <i>Eco-Innovation</i>	-0.194*** (-3.05)	-0.065** (-2.42)
Δ <i>Ln Patent</i>	-0.024* (-1.85)	-0.012** (-2.21)
Δ All controls	YES	YES
Industry & Year FE	YES	YES
Observations	6279	6279
Adjusted R ²	0.069	0.069
Panel D: Excluding Global Financial Crisis (GFC)		
	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)
<i>Eco-Innovation</i>	-0.182*** (-2.69)	-0.057** (-2.02)
<i>Ln Patent</i>	-0.008 (-0.57)	-0.005 (-0.98)
All controls	YES	YES
Industry & Year FE	YES	YES
Observations	5678	5678
Adjusted R ²	0.023	0.023

This table presents the results of additional robustness tests for the baseline results reported in Table 3. For brevity, the coefficients of the control variables are not tabulated - only the coefficient estimates of the variables of interest. Detailed definitions of variables are provided in Appendix 1. Standard errors clustered at the firm and year and *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

two-stage regression to further support our results with respect to different estimation methods. We manage to find consistent results across all the models, strongly suggesting that our findings are not sensitive to employing the Fama-MacBeth (1973) method.

In Panel C of Table 4, we present results from using change analysis by converting our main dependent variables, namely the negative conditional skewness (*NSKEW*) and down-to-up volatility (*DUVOL*) into year-on-year change variables. The analysis overcomes endogeneity problems compared with testing level variables. The results reveal consistent findings across all the models. These results imply that the negative relationship between eco-innovation and stock price crash risk is not sensitive to model specification.

In Panel D of Table 4, we exclude Global Financial Crisis (GFC) because prior studies have reported a shift in investors' opinions during the GFC period due to the increase in the level of risk (Bhagat, Brickley, & Coles, 1994; Köster & Pelster, 2017). There might be a probability that the GFC may affect the eco-innovation and stock price crash nexus. Therefore, we follow Jain and Zaman (2020) and excluded 2007–2009 from our sample and re-estimated equation (5). The relationship between *Eco-Innovation* and crash risk remains consistent after dropping the GFC years.

Overall, the results presented in Tables 3 and 4 suggest that a negative and robust relationship exists between eco-innovation score and stock price crash risk measures. These results collectively are consistent with the notion that eco-innovation reduces business risk

Table 5
Eco-innovations and stock price crash risk – identifications.

Panel A: Instrumental Variable Approach				
	NSKEW _{t+1}		DUVOL _{t+1}	
	1st-stage	2nd-stage	1st-stage	2nd-stage
	(1)	(2)	(3)	(4)
<i>Predicted Eco-Innovation</i>		-0.508** (-2.25)		-0.177** (-1.97)
<i>ISO Certificate</i>	0.039*** (4.84)		0.039*** (4.84)	
<i>Policy Emission</i>	0.059*** (8.71)		0.059*** (8.72)	
<i>Ln Patent</i>	0.014*** (3.73)	-0.002 (-0.29)	0.014*** (3.73)	-0.004 (-1.27)
All controls	YES	YES	YES	YES
Industry & Year FE	YES	YES	YES	YES
Observations	6996	6996	6996	6996
R ²	0.060	0.009	0.060	0.014
F-statistics (P-value)	0.000		0.000	
<i>Instrument Validity Tests for IV regression</i>				
(i) F-test for excluded instrument in first stage				
Sanderson-Windmeijer F- test	198.95		198.95	
(ii) Under-identification test				
Anderson canon. Corr. LM statistic	377.97		377.97	
(iii) Weak identification test				
Cragg-Donald Wald F statistic	198.95		198.95	
Stock-Yogo weak ID test				
10% max IV size	19.93		19.93	
15% max IV size	11.59		11.59	
20% max IV size	8.75		8.75	
25% max IV size	7.25		7.25	
(iv) Over-identification test				
Sargan statistic (P-value)	0.402		0.402	
Panel B: Heckman Selection Model				
	NSKEW _{t+1}		DUVOL _{t+1}	
	(1)	(2)	(1)	(2)
<i>Eco-Innovation</i>	-0.141** (-2.41)		-0.044* (-1.77)	
<i>Ln Patent</i>	-0.019 (-1.49)		-0.010** (-2.02)	
<i>Inverse Mills Ratio</i>	-0.001 (-0.01)		0.010 (0.43)	
All controls	YES		YES	
Industry & Year FE	YES		YES	
Observations	6996		6996	
Adjusted R ²	0.030		0.032	
F-statistics (P-value)	0.000		0.000	
Panel C: Generalized Method of Moments (GMM) results				
	NSKEW _{t+1}		DUVOL _{t+1}	
	(1)	(2)	(1)	(2)
<i>Eco-Innovation</i>	-0.178** (-2.32)		-0.067** (-2.05)	
<i>Ln Patent</i>	-0.033 (-1.23)		-0.012 (-1.10)	
All controls	YES		YES	
Observations	6996		6996	
Number of Groups	717		717	
Number of Instruments	65		65	
F-statistics	0.000		0.000	
Hansen J test (P-value)	0.420		0.324	
Diff in Hansen J (P-value)	0.419		0.301	
AR (1) test (P-value)	0.000		0.053	
AR (2)/AR (3) test (P-value)	0.607		0.770	

This table presents the results of eco-innovations and stock price crash risk and control variables using a 2SLS, Heckman selection and system GMM approach. The dependent variables in the second stage are NSKEW and DUVOL, respectively. The dependent variable in the first stage regressions is eco-innovation score. The instrumental variables are ISO Certificate and Policy Emission test. For brevity, the coefficients of the control variables are not tabulated - only the coefficient estimates of the variables of interest. Detailed definitions of variables are provided in Appendix 1. All regressions control for industry and year fixed effects. Standard errors are corrected for clustering at the firm level and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

and improves firms' transparency, which in turns reduces stock price crash risk.

4.3. Endogeneity

Our results indicate so far that eco-innovation decreases stock price crash risk. However, it is possible that both eco-innovation and stock price crash risk are related because of omitted variables. Moreover, omitted variables that are time-varying or not firm-specific violates our results by causing the error term to be correlated with eco-innovation. In this section, we address potential endogeneity concerns using: (i) instrumental variable approach (IV), (ii) Heckman Selection Model, (iii) Generalized Method of Moments (GMM), and (iv) propensity score matching (PSM) analysis.

4.3.1. Instrumental variable approach (IV)

In this subsection, we employ the instrumental variable approach (IV) to provide a further solution to the endogeneity problems using ISO Certificate and Policy Emission as our instrumental variable.¹¹ Companies' eco-innovation performance often depends on written policies and procedures (i.e., *Emission policy*). These policies and procedures assist companies to effectively integrate their eco-innovation activities in business operations (Menguc & Ozanne, 2005). Likewise, a third-party certificate (i.e., *ISO Certificate*) for its processes and systems may enhance companies' commitment to eco-innovation (Menguc & Ozanne, 2005). As such, ISO Certificate and Policy Emission are more related to eco-innovation activities and have no direct relationship to stock price crash risk. We use both

Table 6
Eco-innovations and stock price crash risk – PSM analysis.

Panel A: Comparison of Treatment and Control Firms						
Dependent Variables	N	Treated	N	Control	Differences	t-statistics
<i>NSKEW</i> _{t+1}	635	0.222	635	0.369	-0.147	-2.08**
<i>DUVOL</i> _{t+1}	635	0.096	635	0.152	-0.056	-1.97**
<i>Ln Patent</i>	635	1.202	635	1.284	-0.082	-0.73
<i>NSKEW</i> _t	635	0.242	635	0.271	-0.030	-0.45
<i>DUVOL</i> _t	635	0.112	635	0.109	0.003	0.11
<i>MTB</i>	635	3.587	635	3.544	0.043	0.13
<i>Firm size</i>	635	15.755	635	15.752	0.003	0.04
<i>Leverage</i>	635	0.301	635	0.308	-0.007	-0.56
<i>ROA</i>	635	0.067	635	0.072	-0.005	-0.98
<i>Sigma</i>	635	3.479	635	3.463	0.016	0.09
<i>Return</i>	635	-0.123	635	-0.117	-0.005	-0.13
<i>DTO</i>	635	0.001	635	0.001	0.000	-1.60
<i>Discretionary accrual</i>	635	0.049	635	0.044	0.004	0.74
<i>CEO duality</i>	635	0.720	635	0.720	0.000	0.00
<i>Economic policy uncertainty</i>	635	124.970	635	127.800	-2.830	-1.37
<i>Ln GDP</i>	635	0.712	635	0.730	-0.018	-0.51

Panel B: Eco-innovation and stock price crash, PSM regression		
	<i>NSKEW</i> _{t+1}	<i>DUVOL</i> _{t+1}
	(1)	(2)
<i>Eco-innovation</i>	-0.312*** (-2.73)	-0.124*** (-2.59)
<i>Ln Patent</i>	-0.027 (-0.88)	-0.016 (-1.27)
All controls	YES	YES
Industry & Year FE	YES	YES
Observations	1270	1270
Adjusted R ²	0.048	0.050

This table presents the baseline results for the impact of eco-innovation on stock price crash risk, using PSM. The dependent variables are NSKEW and DUVOL in year t + 1 and the main independent variable is Eco-innovation in year t. For brevity, the coefficients of the control variables are not tabulated in Panel B - only the coefficient estimates of the variables of interest. All regressions control for industry and year fixed effects. Standard errors clustered at the firm and year and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

¹¹ In our baseline results, we included country-level variables such as GDP, economic policy uncertainty, and industry and year fixed effect.

instruments as exogenous variations to eco-innovation. ISO Certificate is a dichotomous variable that takes the value of 1 if an organisation has ISO14000 or EMAS certification, and zero otherwise. Emission policy is a dichotomous variable that takes the value of 1 if an organisation has a dedicated emission policy, and zero otherwise. Both instrumental variables are calculated based on Thomson Reuters Eikon dataset to capture firms' green or pro-environment initiatives. We present the results in Panel An of Table 5. In all regressions, we include industry and year fixed effects and report *t*-statistics with robust standard errors clustered at the firm level.

We present the first-stage regression results using *Eco-Innovation* as the dependent variable and the instruments as the main independent variable in columns (1) and (3). The coefficient estimates on *ISO Certificate* and *Policy Emission* across all first-stage regressions are positive and significant at the 1% level, suggesting that our IVs are positively associated with eco-innovation. Since the *P*-value of *F*-test, i.e. 0.000 of the first-stage regressions is significant at the 1% level, we can reject the null hypothesis that these instruments are weak (Larcker & Rusticus, 2010). Therefore, the coefficient estimates and their corresponding *t*-statistics in the second stage are likely to be unbiased and inferences based on them are reasonably valid. Results for the under-identification test (Anderson canon test) are significant (i.e. 377.97), rejecting the null hypothesis of under-identification. Similarly, linked to the strengths of the instrument, the value of Cragg-Donald Wald *F*-statistics (i.e. 198.95) is higher than stock-Yogo critical values (max 19.93 at 10%), confirming the instrument is strong. Finally, the insignificant value of Sargant test ($p = 0.402$) infers that our instrument is not over-identified. Taken together, these tests indicate the selected instrument is correctly identified, strong and valid.

We then present the second-stage regression results in columns (2) and (4). The coefficient estimates on the instrumented values of *Predicted Eco-Innovation* are negative and statistically significant at the 5% level across both columns. The IV regression results are consistent with our baseline findings and further support our predictions that eco-innovation improves the firm's information environment, hence reducing stock price crash risk.

4.3.2. Heckman Selection Model and GMM approach

We acknowledge the issue of incidental truncation in our sample section as we examine the connection between eco-innovation and stock price crash risk only for the firm with the eco-innovation score. Such a non-random sample selection may raise the omitted variable bias and induce endogeneity (Certo, Busenbark, Woo, & Semadeni, 2016). To minimise such bias and to correct sample-induced endogeneity, Heckman suggests a two-step process (Heckman, 1977). We applied the Heckman selection estimation following the process mentioned in Certo et al. (2016). We first use a probit model predicting the determinants of eco-innovation and create a selection parameter, i.e. the Inverse Mills Ratio (IMR) following equation (6)¹²:

$$\text{Eco-innovation}_{it} = \beta_0 + \beta_1 w_{it} + \varepsilon_{it}, \quad (6)$$

In equation (6), the variable eco-innovation takes the value of 1 if the firm follows eco-innovation activities, otherwise 0. w represents a vector variable that determines the likelihood of the firm entering the sample and ε_{it} represents the errors that are independent and identically distributed with a mean of 0. In the second stage, we incorporate the Inverse Mills Ratio (IMR) in the traditional model, i.e. equation (5) in our case. Our second stage results reported in Panel B of Table 5 remain qualitatively consistent across both stock crash risk measures.

We also adopted a two-step GMM approach which makes it possible to exploit the dynamic nature of relationships using internal instruments to produce consistent and unbiased results (Roodman, 2006). The approach also accounts for reverse causality and dynamic endogeneity while eliminating any potential unobserved firm-specific effects that might otherwise influence both our main dependent and independent variables (Flannery & Hankins, 2013; Wintoki, Linck, & Netter, 2012; Zaman, Bahadar, et al., 2020). We first follow Arellano and Bond (1991) and conducted instrument validity tests. In particular, the significant value of AR (1) $p < 0.05$ in Panel C of Table 5 confirms the suitability of lags to control the model dynamicity, whereas AR (2) fails to reject the possibility of no serial correlation in second difference. The insignificant *p*-value ($p > 0.10$) of Hansen J test and Difference in Hansen J test in columns (1) and (2), confirms the validity of our instruments. Overall, the results documented in Panel C of Table 5 are consistently negative and statistically meaningful, confirming that our main findings are less prone to the endogeneity issue.

4.3.3. Propensity score matching (PSM)

In this section, we adopted the PSM approach to address selection bias due to company-related characteristics and functional misspecification (Rosenbaum & Rubin, 1983). We apply propensity score matching to compare firm stock crash risk between a group of firms that have a high eco-innovation score (a treatment group) a group of firms that have a low eco-innovation score (a control group). In our analysis, we define a high (low) eco-innovation score as firms whose eco-innovation score is above (below) the top cross-sectional median of eco-innovation score. We choose the nearest neighbour with replacement to ensure that both groups are comparable, and no significant differences are detected between them. We report our results in Table 6.

Panel A of Table 6 reports univariate mean comparisons between treatment and control firms' characteristics using the same control variables included in Table 3. We also report the corresponding *t*-statistics for firms' characteristics control variables used. We start with estimating the propensity score regression in which we regress a dummy variable that equals one if a firm has an eco-innovation score above the cross-sectional median, and zero if otherwise and include all the control variables used in Table 3. We then use the propensity scores and choose the nearest neighbour with replacement. The comparison results indicate that no statistically significant differences exist in firms' characteristics. Moreover, the negative conditional skewness (*NSKEW*) and down-to-up volatility

¹² See supplementary file for the first stage results, i.e. equation (6).

Table 7
Eco-innovations and stock price crash risk- information asymmetry channel.

Panel A: Comparison between eco-innovative firms and non-eco-innovative firms using t-test				
Variables	Eco-innovative firms	Non-eco-innovative firms	Diff	t-statistics
<i>Institutional Ownership (IO)</i>	0.439	0.387	0.052***	9.12
<i>Monitoring IO</i>	0.024	0.020	0.004***	2.95
<i>Analyst following</i>	2.537	2.383	0.154***	5.85
Panel B: Comparison between eco-innovative firms and non-eco-innovative firms using PSM				
<i>Institutional Ownership (IO)</i>	0.427	0.389	0.038***	2.88
<i>Monitoring IO</i>	0.026	0.019	0.007***	2.67
<i>Analyst following</i>	2.416	2.391	0.025**	1.97
<i>Ln Patent</i>	1.288	1.296	-0.008	-0.09
<i>MTB</i>	3.482	3.569	-0.087	-0.36
<i>Firm size</i>	15.906	15.875	0.031	0.57
<i>Leverage</i>	0.299	0.307	-0.008	-0.88
<i>ROA</i>	0.065	0.065	0.000	-0.01
<i>Sigma</i>	3.727	3.727	0.000	0.01
<i>Return</i>	-0.105	-0.098	-0.007	-0.24
<i>DTO</i>	0.000	0.000	0.000	-0.44
<i>Discretionary accrual</i>	0.048	0.053	-0.005	-1.39
<i>CEO duality</i>	0.697	0.710	-0.013	-0.56
Panel C: PSM Regression				
	<i>Institutional Ownership (IO) t + 1</i> (1)	<i>Monitoring IO t + 1</i> (2)	<i>Analyst following t + 1</i> (3)	
<i>Eco-innovation</i>	0.470 *** (2.79)	0.027*** (2.82)	1.856** (2.06)	
<i>All controls</i>	YES	YES	YES	
<i>Industry & Year FE</i>	YES	YES	YES	
<i>Observations</i>	1041	1041	1041	
<i>Adjusted R2</i>	0.567	0.221	0.300	

This table reports the mean difference in institutional shareholding (*Institutional Ownership*, *Monitoring IO*) and equity analyst (*Analyst following*) among eco-innovative and non-eco-innovative firms. Detailed definitions of variables are provided in [Appendix 1](#). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

(*DUVOL*) are significant at the 5% level between both groups, respectively. Overall, the univariate comparisons suggest that the matching process has successfully removed observable differences between these two groups except those related to eco-innovation. This confirms that the difference in stock price crash risk is affected by the level of eco-innovation.

In Panel B of [Table 6](#), we run post-match PSM regression to make sure that our results are consistent after removing all observable differences between treatment and control groups. We run the same regression reported in [Table 3](#) in which we include all control variables and industry and year fixed effects. Our results remain consistently unchanged across all the models. More specifically, the coefficient estimates on the negative conditional skewness (*NSKEW*) and down-to-up volatility (*DUVOL*) are negative and statistically significant at the 1% level. Subsequently, we obtain qualitatively similar results to our baseline results in [Table 3](#).

5. Possible channel

In this section, we empirically tested our underlying assumption that institutional investors and equity analyst follow eco-innovative firms and the presence of these institutions limit information asymmetry which in turn lowers stock price crash. To test such an assumption, we followed a two-step process. Firstly, we examine whether there exists any difference in institutional shareholders and equity analyst following between eco-innovative and non-eco-innovative firms. Secondly, we test the anticipated information asymmetry channel in eco-innovation and stock price crash nexus.

5.1. Institutional shareholders and equity analyst heterogeneity

In the analysis presented in this section, we examine the mean difference in institutional shareholding and equity analyst among eco-innovative and non-eco-innovative firms. We use the *t*-test to capture the mean difference in institutional shareholding and equity analyst among two sample groups (i.e. eco-innovative and non-eco-innovative).¹³ We created an indicator variable to capture the difference between eco-innovation and non-eco-innovative firms. The indicator variable takes the value 'one' if the company eco-innovation score is greater than zero, and zero if the company eco-innovation score is zero. In addition, we followed the similar process mentioned in section 4.3.3 and applied PSM to compare institutional shareholding and equity analyst following, specifically between a group of firms that have undertaken eco-innovation activities (a treatment group) and a group of firms that do not take eco-

¹³ Of note, we use two measure of institutional ownership, i.e. *Institutional Ownership (IO)* and *Monitoring IO*.

Table 8
Eco-innovations and stock price crash risk- information asymmetry channel.

Panel A: Comparison between eco-innovative firms and non-eco-innovative firms using t-test				
Variables	Eco-innovative firms	Non-eco-innovative firms	Diff	t-statistics
Opacity	0.175	0.199	-0.024 ***	-4.56
Comparability	-0.309	-0.365	0.056 ***	3.40
Quoted Spread	0.070	0.085	-0.015 **	-2.22
Panel B: Comparison between eco-innovative firms and non-eco-innovative firms using PSM				
Opacity	0.179	0.207	-0.028**	-2.24
Comparability	-0.308	-0.356	0.048*	1.74
Quoted Spread	0.040	0.051	-0.011**	2.48
Ln Patent	1.288	1.296	-0.008	-0.09
MTB	3.482	3.569	-0.087	-0.36
Firm size	15.906	15.875	0.031	0.57
Leverage	0.299	0.307	-0.008	-0.88
ROA	0.065	0.065	0.000	-0.01
Sigma	3.727	3.727	0.000	0.01
Return	-0.105	-0.098	-0.007	-0.24
DTO	0.000	0.000	0.000	-0.44
Discretionary accrual	0.048	0.053	-0.005	-1.39
CEO duality	0.697	0.710	-0.013	-0.56
Panel C: PSM Regression				
	Opacity t_{+1}	Comparability t_{+1}	Quoted Spread t_{+1}	
	(1)	(2)	(3)	
Eco-innovation	-0.092 *** (-3.08)	0.016** (2.12)	-0.024** (-1.97)	
All controls	YES	YES	YES	
Industry & Year FE	YES	YES	YES	
Observations	1036	1036	1036	
Adjusted R ²	0.159	0.185	0.217	

This table reports the mean difference in financial opacity, financial statements comparability, and quoted spread for eco-innovative firms and non-eco-innovative. Detailed definitions of variables are provided in [Appendix 1](#). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

innovation (a control group). We choose the nearest neighbour with replacement to ensure that both groups are comparable, and no significant differences are detected between them.

The *t*-test results reported in Panel A of [Table 7](#) confirm the significant positive mean difference in institutional shareholding and equity analyst among eco-innovative and non-eco-innovative firms. These results provide initial support to our inference that institutional shareholding and equity analyst pay attention to eco-innovative firms. To rule out that this difference is not driven by any other firm-level covariates, we use PSM and the results reported in Panel B reveal that no statistically significant differences exist in firms' characteristics. Moreover, the institutional shareholding (i.e. *Institutional Ownership* (IO) and *Monitoring IO*) and analyst following are higher for the eco-innovative subsample compared to non-eco-innovation subsample. The mean difference between the two groups is significant at the 1% level. Overall, the univariate comparisons suggest that the matching process has successfully removed observable differences between these two groups except those related to institutional shareholding (i.e. *Institutional Ownership* (IO) and *Monitoring IO*) and analyst following. This confirms that the difference in institutional shareholding and equity analyst is merely due to firm eco-innovation activities.

In Panel C of [Table 7](#), we run post-match PSM regression to make sure that our results are consistent after removing all observable differences between treatment and control groups. Our results remain consistently unchanged across all the models. More specifically, the coefficient estimates on the institutional shareholding (*Institutional Ownership*, *Monitoring IO*) and equity analyst (*Analyst following*) are positive and statistically significant at the 1% level, except equity analyst that is at 5% level. These results suggest more eco-innovation is positively associated with the percentage of institutional ownership, monitoring IO and analyst following.

5.2. Information asymmetry

The reported results in above section support our conjecture that the eco-innovative firm enjoys a significantly greater following from institutional shareholding and equity analyst compared to non-eco-innovative firms. Against this backdrop, the prior literature suggests that the presence of such institutions (i.e. institutional shareholding and equity analyst) lower information asymmetry by limiting the managerial bad news hoarding behaviour ([Chang et al., 2006](#); [McCahery et al., 2016](#)). Therefore, invoking our documented result with such literature findings suggest that the eco-innovative firms will result in lower information asymmetry due to timely disclosure of bad news, which is a key antecedent of stock price crash risk. However, in order to provide empirical validity to our conjecture, we tested the anticipated information asymmetry channel in eco-innovation and stock price crash nexus using two steps. Firstly, similar to the process mentioned in section [5.1](#) we use a *t*-test and PSM to examine whether there exists heterogeneity in the

Table 9
Eco-innovations and stock price crash risk – information asymmetry channel.

Panel A: Conditioning on opacity				
	NSKEW _{t+1}		DUVOL _{t+1}	
	<u>High Opacity</u>	<u>Low Opacity</u>	<u>High Opacity</u>	<u>Low Opacity</u>
	(1)	(2)	(3)	(4)
<i>Eco-Innovation</i>	-0.234** (-2.20)	-0.074 (-0.81)	-0.092** (-1.99)	-0.028 (-0.67)
All controls	YES	YES	YES	YES
Industry & Year FE	YES	YES	YES	YES
Observations	2528	2528	2528	2528
Adjusted R ²	0.049	0.038	0.048	0.038
Panel B: Conditioning on financial statements comparability				
	NSKEW _{t+1}		DUVOL _{t+1}	
	<u>High Comparability</u>	<u>Low Comparability</u>	<u>High Comparability</u>	<u>Low Comparability</u>
	(1)	(2)	(3)	(4)
<i>Eco-Innovation</i>	-0.171 (-1.54)	-0.243* (-1.73)	-0.072 (-1.59)	-0.114* (-1.78)
All controls	YES	YES	YES	YES
Industry & Year FE	YES	YES	YES	YES
Observations	1525	1525	1525	1525
Adjusted R ²	0.127	0.149	0.174	0.162
Panel C: Conditioning on Quoted spread				
	NSKEW _{t+1}		DUVOL _{t+1}	
	<u>High Spread</u>	<u>Low Spread</u>	<u>High Spread</u>	<u>Low Spread</u>
	(1)	(2)	(3)	(4)
<i>Eco-Innovation</i>	-0.252** (-2.16)	-0.031 (-0.28)	-0.107** (-2.14)	-0.009 (-0.18)
All controls	YES	YES	YES	YES
Industry & Year FE	YES	YES	YES	YES
Observations	3498	3498	3498	3498
Adjusted R ²	0.245	0.219	0.246	0.220

This table reports regression results on whether the effect of eco-innovations on stock price crash risk is affected by the degree of information asymmetry. For brevity, the coefficients of the control variables are not tabulated - only the coefficient estimates of the variables of interest. Detailed definitions of variables are provided in [Appendix 1](#). Standard errors clustered at the firm and year and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

information asymmetry (captured using three proxies, i.e. financial opacity, financial statements comparability and quoted spread) between eco-innovative and non-eco-innovative firms. Panel A and B of [Table 8](#) presents the results for the *t*-test and PSM, respectively.

The *t*-test results reported in Panel A confirms the significant mean difference in all three proxies of information asymmetries, i.e. financial opacity, financial statements comparability and quoted spread among eco-innovative and non-eco-innovative firms. These results provide initial support to our inference that eco-innovation firms enjoy a lower information asymmetry compared with non-eco-innovative firms. To rule out that this difference is not driven by any other firm-level covariates, we use PSM and the results reported in Panel B indicate that no statistically significant differences exist in firms' characteristics except information asymmetry proxies. Overall, the univariate comparisons suggest that the matching process has successfully removed observable differences between these two groups except those related to information asymmetry (financial opacity, financial statements comparability and quoted spread). This confirms that the difference in information asymmetry (financial opacity, financial statements comparability and quoted spread) is merely due to firm eco-innovation activities. In Panel C of [Table 8](#), we run post-match PSM regression to make sure that our results are consistent after removing all observable differences between treatment and control groups. We find that eco-innovation leads to better lower information asymmetry.

Secondly, we use a sub-sampled approach and re-run our baseline model for two subsamples: firms with higher information asymmetry (financial opacity, financial statements comparability and quoted spread higher than cross-sectional median) versus firms with lower information asymmetry (financial opacity, financial statements comparability and quoted spread lower than the cross-sectional median). [Table 9](#) presents the sub-sampled results.

Panel A of [Table 9](#) shows the results of eco-innovation and stock price crash risk for *High Opacity* versus *Low Opacity* subsamples. The coefficient estimates on eco-innovation in columns (1) and (3) are stronger among firms with a higher level of financial opacity for both proxies of stock price crash risk compared to businesses with less financial opacity. These results indicate that eco-innovation alleviates the effects of information asymmetry as firms benefited more from eco-innovation when they have higher information asymmetry.

Panel B of [Table 9](#) presents the relationship between eco-innovation and stock price crash risk for firms with *High Comparability* versus firms with *Low Comparability*. The results reported in column (2) and column (4) suggest the coefficient estimate on *Eco-*

Table 10

Eco-innovations and stock price crash risk – interplay with political ideology and environmental sensitiveness.

Panel A: Conditioning on political leadership ideology				
	NSKEW _{t+1}		DUVOL _{t+1}	
	Democrat President	Republican President	Democrat President	Republican President
	(1)	(2)	(3)	(4)
<i>Eco-Innovation</i>	-0.159** (-2.34)	-0.051 (-1.30)	-0.049* (-1.78)	-0.009 (-1.13)
All controls	YES	YES	YES	YES
Industry & Year FE	YES	YES	YES	YES
Observations	5369	1627	5369	1627
Adjusted R ²	0.082	0.177	0.082	0.188
Panel B: Conditioning on environmental sensitiveness				
	NSKEW _{t+1}		DUVOL _{t+1}	
	Environmentally sensitive	Environmentally insensitive	Environmentally sensitive	Environmentally insensitive
	(1)	(2)	(3)	(4)
<i>Eco-Innovation</i>	-0.243* (-1.73)	-0.171 (-1.53)	-0.114* (-1.78)	-0.072 (-1.59)
All controls	YES	YES	YES	YES
Industry & Year FE	YES	YES	YES	YES
Observations	1525	1525	1525	1525
Adjusted R ²	0.149	0.127	0.162	0.174

This table reports regression results on whether the effect of eco-innovations on stock price crash risk is affected by political ideology and environmental sensitiveness. For brevity, the coefficients of the control variables are not tabulated - only the coefficient estimates of the variables of interest. Detailed definitions of variables are provided in [Appendix 1](#). Standard errors clustered at the firm and year and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Innovation is more negative compared to the *Low Comparability* sub-sample than the *High Comparability* group. Such outcomes imply that eco-innovation plays an important role in improving transparency of firms and subsequently reduces stock price crash risk.

Finally, Panel C reports the relationship between eco-innovation and stock price crash risk for quoted spread. The results reported in columns (1) and (2) indicate that the negative association between eco-innovation and stock price crash risk is more pronounced in the *High Quoted Spread* subsample compared with the *Low Quoted Spread* subsample. Taken together, the results presented in [Table 9](#) are consistent with our underlying intuition that eco-innovation promotes information transparency, which results in lower stock price crash risk.

Overall, our results reported in [Tables 7–9](#) confirm our conjecture that institutional investors and equity analyst are directed more to eco-innovative firms. The presence of these institutions limits information asymmetry which in turn lowers stock price crash.

6. Further tests

6.1. Does the eco-innovation and stock price crash nexus vary across political ideology?

We finish our empirical analysis with an examination of the interaction between eco-innovation and political leadership ideology. CNN business research illustrates that stock market performance is conditioned on presidency tenure in the U.S. ([Matt Egan, 2019](#)). For example, we have witnessed a stronger stock market performance (+64% for first 743 days) during Barack Obama's tenure as president, compared with (-16% for first 743 days) the tenure of George W. Bush ([Matt Egan, 2019](#)). This is because the heterogeneous nature of U.S. presidents' political ideologies drives changes in the country's federal government policies ([Gizzi, 2012](#); [Ozmy & Jarrell, 2015](#)) or their working operations.

In the United States, the Environment Protection Agency (EPA) is responsible for devising environmental protection policies and monitors corporate environmental compliance. As such the consistency in EPA operations has been questioned time and again by prominent media outlets such as *The Wall Street Journal* and CNN. Despite having a consistent set of regulations and policies across EPA operations, the Bush (Republican) and Obama (Democrat) governments had a very different philosophy on managing EPA ([Westmoreland, 2010](#)).

In this manner, studies have suggested that enforcement of environmental law relies on political pressure and influence ([Buttel & Flinn, 1978](#); [Holland, Hughes, & Knittel, 2009](#)). On one hand, the Bush-led EPA was considered ineffective and vigilantly protective of business interests at the expense of the environment ([Goldenberg, 2009](#)). In contrast, the Obama-led EPA was said to follow an extreme anti-industry agenda, where 'environmental violations' were better enforced ([Ozmy & Jarrell, 2015](#)). Additionally, the Obama government was more focused on a 'Green America' concept and enacted several policies and rules to deter environmental anomalies such as the incorporation of greenhouse gas (GHG) emissions standard under the Clean Air Act 2010 and the Clean Power Plan (CPP) to reduce CO₂ emissions from electricity generating sectors. We argue that heterogeneity in the U.S. presidents' policies affecting EPA has the potential to influence firms' adoption of eco-innovation technologies and policies. We expect the negative association between

eco-innovation stock price crash risk to be more pronounced in the Obama (Democratic) presidency (2009–2017) compared with the Bush (Republican) presidency (2003–2008). To test this conjecture, we perform subsample analysis by dividing our sample into *Democrat President* and *Republican President* subsamples. We report our results in Table 10.

The results in Panel A of Table 10 reveal that the eco-innovation stock price crash nexus is more pronounced for firms during the Obama (*Democrat President*) presidency compared with firms during the Bush (*Republican President*) presidency. In particular, the coefficient estimate on eco-innovation is only statistically significant amongst the *Democrat President* sub-sample. These results suggest that political leadership ideology matters for companies if they want to embrace an eco-innovation policy or business strategy.

6.2. Does the eco-innovation and stock price crash nexus vary across firms' environmental sensitiveness?

Prior studies have reported on industrial heterogeneity in stock market returns (Ali, Klasa, & Yeung, 2008; Hou & Robinson, 2006). Here, the literature suggests that companies operating in highly concentrated industries earn lower stock return compared to companies in less concentrated industries (Hou & Robinson, 2006). Similarly, this variation has also been observed in stock price crash studies. For example, Ben-Nasr et al. (2021) in their findings suggest that the patent innovation and stock price crash relationship is more pronounced in firms operating in innovation-intensive industries compared to non-innovation intensive firms. More recently, the findings of Zaman, Bahadar, and Mahmood (2020) indicate that corporate misconduct and stock price crash risk is more pronounced in environmentally sensitive industries compared to environmentally insensitive ones. They argued that since these firms (environmentally sensitive) drive value from the extraction of natural resources, the probability of litigation risk is higher in these firms compared with environmentally insensitive businesses.

Further, these companies face significantly increased environmental-related exposure and market scrutiny than environmental insensitive companies (Cho & Patten, 2007). Likewise, Clarkson, Li, and Richardson (2004) argued that companies operating in environmentally sensitive industries are more likely to have covert environmental liabilities due to future capital spending obligations of environmental compliance. Accordingly, we expect that the value enhancement of eco-innovation would be more relevant to offset the negative environmental externalities in environmentally sensitive industries and would result in lower crash risk. We followed the prior literature and categorised firms as environmentally sensitive (take the value of '1') if they operate in any of the following industries: oil and gas; forestry, pulp and paper; energy; chemicals and drugs; mining and resources and utilities, otherwise environmentally insensitive (take a value of '0') (Aerts, Cormier, & Magnan, 2006; Cho & Patten, 2007).

We use a sub-sampled approach and re-run our baseline model for two subsamples: firms operating in environmentally sensitive industries (*Environmentally sensitive*) versus firms in environmentally insensitive industries (*Environmentally insensitive*). Panel B of Table 10 presents the sub-sampled results. We find the significant negative association between eco-innovation stock price crash risk to be pronounced and significant in the *Environmentally sensitive* subsample compared with the *Environmentally insensitive* subsample. This indicates that eco-innovation helps mitigate negative externalities for environmentally sensitive firms arising due to the nature of their operations. This result also reveals that investors pay more attention to the eco-innovation of companies operating in environmentally sensitive industries and are more likely to use this information – leading to lower stock price crash.

7. Conclusion

Does eco-innovation affect stock price crash risk? Utilising a large sample of U.S. firms over the period 2003 to 2017, we find that eco-innovation is negatively and significantly related to stock price crash risk. The effect is economically significant, with an increase in *Eco-Innovation* from the 25th percentile to the 75th percentile being associated with a 17.62% reduction in stock price crash risk relative to the sample mean. Results are robust to a set of robustness tests and fixed effect. We conduct several additional tests to address endogeneity concerns and find consistent results. First, we use the two least squares (2LS) approach using ISO Certificate and Policy Emission as instruments. Second, we use the Heckman Selection Model. Third, we utilise the two-step GMM approach. Fourth, we conduct a Propensity Score Matching analysis (PSM). In all four tests our results are consistent with our baseline findings.

We further explored underlying channels through which eco-innovation affects stock price crash risk. We find evidence that eco-innovation has an impact on stock price crash through the presence of institutional investors and equity analyst which reduces managers' hoarding of bad news. In particular, we find a significant positive mean difference in institutional shareholding and equity analyst that prefer eco-innovative firms over non-eco-innovative firms. Similarly, eco-innovative firms exhibit less information asymmetry compared to non-eco-innovation firms. Furthermore, the negative effect of eco-innovation on stock price crash is more pronounced among firms with high financial opacity, low financial comparability, and high quoted spread. Our results suggest that a key channel through which eco-innovation reduces stock price crash is a general decline in informational asymmetry. In our final set of results, we demonstrate that the negative effect of eco-innovation is contingent on the political leadership's ideology and environmental sensitivity.

Our paper makes significant contributions to the literature in at least three ways. First, it contributes to our understanding of the consequences of corporate innovativeness (Ben-Nasr et al., 2021; Hirshleifer et al., 2013; Hsu, 2009; Hsu et al., 2015). We extend these studies by highlighting the perverse effects of green innovation such as eco-innovation in reducing stock price crash risk. Second, our paper extends the literature on the determinants of stock price crash risk (e.g., Habib et al., 2018). We extend prior studies by identifying that eco-innovation has an incremental ability to predict future firm-specific crash risk, over and above other predictors including patent innovation identified by previous research. Third and finally, this paper sheds new light on the interplay between eco-innovation and political leadership ideology.

Author biographies

Dr. Rashid Zaman and Dr. Nadar Atawnah are working as Lecturer in Accounting and Finance at School of Business and Law, Edith Cowan University, Australia. Muhammad Haseeb is a Ph.D. Candidate at the Department of Finance and Banking - University of Malaya. Dr Muhammad Nadeem is a Senior Lecturer at the Department of Accounting and Finance, Otago University New Zealand. Dr. Saadia Irfan is an Assistant Professor of Finance and Investment at NUST Business School- National University of Sciences and Technology, Pakistan.

Appendix 1: Definitions of Variables

Dependent Variables	
<i>NSKEW</i>	Negative conditional skewness is a ratio of the third moment of weekly returns for each firm-year to the standard deviation of weekly returns raised to the third power and multiply that ratio by -1 . See equation (3) for details.
<i>DUVOL</i>	Down-to-up volatility is the natural logarithm of the ratio of the standard deviation in the ‘down’ weeks to the standard deviation in the ‘up’ weeks. See equation (4) for details.
Independent Variables	
<i>Eco-Innovation</i>	
	Eco-innovation score takes values from 0 to 100 with the lowest values correspond to less eco-innovation activities in a firm (see supplementary file for detail).
<i>Ln Patent</i>	The natural logarithm of one plus the number of patents applied for in year t .
<i>MTB</i>	Market-to-book ratio.
<i>Firm Size</i>	Natural log of market value of equity.
<i>Leverage</i>	Leverage is the ratio of total debt to total assets.
<i>ROA</i>	Return on assets is the ratio of income before extraordinary items to total assets.
<i>Sigma</i>	The standard deviation of firm-specific weekly returns.
<i>Return</i>	Average of firm-specific weekly returns.
<i>DTO</i>	Detrended share turnover is calculated as the average monthly share turnover in year t minus the average monthly share turnover in $t - 1$.
<i>Discretionary accrual</i>	Absolute discretionary accruals value calculated as in McNichols (2002).
<i>CEO duality</i>	CEO duality is a dichotomous variable that takes the value of ‘1’ if the CEO is also Chairman of the board, ‘0’ otherwise.
<i>Economic Policy Uncertainty</i>	Policy uncertainty Index—measured as the natural logarithm of the arithmetic Baker et al., 2016 index in 12 months of the firm’s fiscal year
<i>Ln GDP</i>	The natural logarithm of gross domestic product (GDP) per capita growth.
<i>Institutional Ownership IO</i>	Percentage of institutional shareholding held by 13-F institutions calculated as yearly average of shares outstanding held by institutions divided by total number of shares outstanding.
<i>Monitoring IO</i>	Follow the methodology proposed by Fich, Harford, and Tran (2015), we define monitoring institutions as those whose holding value in the firm is in the top 10% of their portfolio. We then calculate the number of shares held by these monitoring institutions and divide it by total shares outstanding.
<i>Analyst Following</i>	Natural logarithm of the maximum number of analyst following the company during the year.

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Appendix A. Supplementary data

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