ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
Master Thesis Business and Economics: Financial Economics

The relationship between green activity and stock price crash risk in European listed firms

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Date	October 30th, 2024

Abstract
This paper examines whether the relationship between green activity and stock price crash risk found for US firms in previous studies persists when using a sample of firms incorporated in Europe in the period 2002-2022. Green activity is captured by using six ESG-dummies that represent firms' environmental sustainability focussed activities. In addition to the baseline results, this paper introduces variable Non-Polluting Sectors that captures whether a firm is in a non-polluting sector or not, and conditional thereon extends its results. The paper finds mixed results on the relationship between specific green activities and stock price crash risk. The results found in the baseline results do not persist for the robustness check with an alternative proxy for crash risk. The paper makes suggestions for further research on this relationship based on the findings in this paper.

Contents

1. Introduction

In recent decades, a rise of public concerns about environmental and sustainable business has taken place (Nguyen et al., 2023). As a result of these public concerns, as well as heightened sustainability due diligence obligations (European Union, 2024), EU firms make an increasing effort to conduct more sustainable business and undertake and report green activity (Euronext, 2024). Alongside these developments, the increase in availability of Environmental, Social and Governance (ESG) data since 2002 in financial databases (LSEG, 2024) have allowed for research on the three ESG-factors and their economic consequences, resulting in a significant increase in studies on the effect of corporate sustainable activity on financial performance. Not only has research into the effect of ESG strategies on financial performance become more feasible and widespread; ESG research has also gained a growing interest from policy makers and financial intermediaries. Central Banks, for example, are increasingly paying attention to the importance of ESG strategies within risk management processes and how climate risks translate into financial risks (Fiordelisi et al., 2023). This paper includes research on the relationship between corporate sustainable activity with regards to the 'Environmental' factor, captured by 'green activity', and stock price crash risk.

Prior research using US firm data for the period 2002-2021 has investigated the relationship between green activity and stock price crash risk (Nguyen et al., 2023). This paper assesses whether the negative relationship between green activities and stock price crash risk found in Nguyen et al. (2023) also holds for a dataset of EU firms, using the same metrics for green activity: (1) climate risks and opportunities (*CCCRO*), (2) emission reduction target (*ERT*), (3) target energy efficiency (*TEE*), (4) renewable and clean energy products (*RCEP*), (5) renewable energy use (*REU*), and (6) green building (*GB*).

This paper makes two contributions. First, it adds to the growing literature on firms' ESG 'Environmental' factor and its economic consequences. Specifically, it extends the literature on the relationship between the 'Environmental' factor (captured by green activities) and stock price crash risk through the usage of EU firm data, which is distinct from prior studies that focus similar relationships for data from the US (Nguyen et al., 2023; Zaman et al., 2021) and China (Liu et al., 2022; Lou et al., 2023; Xie et al, 2023). Research into the relationship between environmental engagement (capturing a similar effect as green activity) and stock price crash risks exists for the EU banking industry (Fiordelisi, 2023), but not for EU-firms in general. Further justification towards research using data from different geographical contexts is found in prior research finding that the relationship between ESG disclosure and stock price crash risk significantly differ between the US, EU and Japan (Murata & Hamori, 2021).

Secondly, this paper adds to prior research using industry categorisation to further understand emergence of a relationship between green activity and stock price crash risk in different contexts (Fiordelisi, 2023). Where prior research included industry fixed effects in the models (Nguyen et al., 2023), the contribution is executed by including an additional variable (‘Non-polluting Sectors’; *NPS*) that captures whether the firm is operating in one of the sectors that can be classified as non-polluting according to a classification system used in Swart & Marrewijk (2011). Through this, it is investigated whether the emergence of a relationship between stock price crash risk and firms’ green activity is significantly different depending on whether a firm is operating in a Non-Polluting Sector, or not.

The method adopted in this research is in line with previous research on the relationship between green or sustainable corporate activity and stock price crash risk. This paper adopts a common proxy for stock price crash risk: negative conditional skewness of weekly stock returns (*NCSKEW*). The paper present baseline results using EU listed firm data, which is followed by the second contribution of results conditional on whether firms operate in a Non-Polluting Sector (*NPS*), or not. The baseline results are accompanied with an endogeneity test and the robustness of all results are tested using an alternative proxy for stock price crash risk, namely down-to-up volatility of weekly stock returns (*DUVOL*). Lastly the paper uses the sample data to further explore the relationship between green activity and *NPS*. The paper ends with a conclusion to the results, as well as a discussion, including the research limitations of this paper and suggestions for further research.

The baseline results of this paper do not find concluding evidence of a relationship between green activity a stock price crash risk; whenever it does find a significant relationship, it is not in line the theory suggesting stock price crash risk and green activity are negatively associated. When analysing the results of the regressions of green activity against stock price crash risk conditional on whether firms are operating in a Non-Polluting Sector or not, we find mixed results, namely: a significant positive relationship between stock price crash risk and green activity dummies *TEE* (energy efficiency target) and *RCEP* (renewable/clean energy products), and a significant negative relationship between stock price crash risk and *ERT* (emission reduction target) . The latter result is in line with the Hypothesis 1 that green activity is negatively associated with stock price crash risk, but not in line with Hypothesis 2 that firms in the *NPS*==0 subsample experiences a stronger negative relationship between green activity and stock price crash risk, as the relationship for ERT was only found for the *NPS*==1 sample. After performing the robustness check using an alternative proxy for stock price crash risk (*DUVOL*), the results found in the baseline results and *NPS*-depedent regression results found for independent variable *NCSKEW* do not persist, which decreases the generalizability of the results found in this paper.

The Theoretical Framework (Chapter 2) of this paper argues why further research on the relationship between green activity and stock price crash risk is relevant and will engage in more detail with the theoretical foundation underlying the relationship between green activity and stock price crash risk. Chapter 3 of this paper discusses the sample and methodology used in this paper. Chapter 4 presents the results, an endogeneity measure, and a robustness check using an alternative proxy for stock price crash risk. Chapter 5 (Section 4.5) explores the relationship between green activity and *NPS*, and whether a random- or fixed-effects is more suitable. The paper is concluded in Chapter 5, and Chapter 6 discusses the limitations of the paper as well as suggestions for further research.

2. Theoretical framework

2.1 Relevance of stock price crash risk research

The stock market turmoil in recent years indicates the significance of crash risk to investors; especially retail investors concentrating their investments in a small number of firms can face a highly detrimental effect on their personal wealth because of stock price crashes in their portfolio (Habib et al. (2018). A better understanding of what affects stock price crash risk is seen as a significant contribution towards protecting shareholder value (Habib et al., 2018). Since "crash risk captures higher moments of the stock distribution – that is extreme negative returns" it has "important implications for portfolio theories and for asset option pricing models. Investors expect higher returns for stocks with more negative skewness, implying that skewness is a priced risk factor" (Habib et al., 2018, p. 212)[1].

2.2 Corporate activity and stock price crash risk

Prior to research focus on the financial consequences of corporate environmental activity, such as green activity, research had been focussed on the economic consequences of corporate social responsibility (CSR), such as the link between corporate social responsibility and corporate financial performance (Kim et al., 2014; Nguyen et al., 2023[2]). This was followed by an emergence of research on the relationship between CSR activity and firm risk, such as stock price crash risk (Kim et al., 2014).

Stock price crash risk is different from stock performance and firm risk; it focusses on conditional skewness captures asymmetry in risk, which makes it important for investment decisions and risk management (Kim et al., 2014). The study of Kim et al. (2014) was built on prior research examining the relationship between CSR disclosure and financial reporting transparency. Managerial intransparency, i.e. the managerial tendency to withhold bad information from investors, had emerged in prior research as a "prominent predictor of stock price crash risk"; previous research furthermore confirms that "opaque financial reporting" is positively associated with firm-specific crash risk (Kim et al., 2024, p. 2). Moreover, Kim et al. (2014) mentions that

[1] For further reading: Habib et al. (2018) cites: Kim et al., 2014; Callen and Fang, 2015a; Kim and Zhang, 2015; Harvey and Siddique, 2000; Conrad et al., 2013.
[2] For further reading: Nguyen et al. (2023) cites (e.g. Roman et al., 1999; Margolis and Walsh, 2001; Jiao, 2010; Kim and Statman, 2012).

"firms that undertake socially responsible activities provide more financial disclosure"; a negative relationship between CSR reporting and stock price crash risk confirms the notion that CSR reporting increases transparency, which explains the negative relationship between undertaking CSR activities and stock price crash risk. On the other hand, CSR could also be used as a method to conceal corporate misbehaviour (Kim et al., 2014, p. 3). A positive relationship between CSR disclosure and stock price crash risk would reveal that the company uses CSR reporting as a tool to disguise bad news and divert shareholder scrutiny.

2.3 Green activity and stock price crash risk

Although existing literature finds decreased overall risk for high ESG firms (Fiordelisi et al., 2023; Gillan, Koch & Starks, 2021), the exact relationship between green activity and stock price crash risk is not sufficiently understood (Nguyen et al., 2023) and largely unexplored (Fiordelisi et al., 2023). The hypothesised relationship between green activity and price crash risk can be explained using two theories (Nguyen et al., 2023): 1. the information asymmetry theory (also referred to as 'signalling theory' in Fiordelisi et al., 2023), and 2. the risk management theory.

Stock price crash risk represents the "possibility that a firm's stock prices fall quickly and sharply", which may occur due to the hoarding of bad news by a firm's management and abruptly releasing it to the market. Firstly, firms engaging in green activity and more committed to environmentally friendly operations are assumed to be more transparent in disclosing information about their business activities. As green activity generally benefits a firm by adding long-term competitive edge and fulfilling sustainable needs of their investors, firms engaging in relatively much green activity have a larger incentive to signal their good imago and intentions of being a responsible and sustainable organisation that protects long-term stakeholder and shareholder value (Nguyen et al., 2023). A high level of transparency, caused by increased consistent and extensive reporting, lessens information asymmetry, which reduces stock price crash risk (Nguyen et al., 2023[3]).

Secondly, firms engaging in green activity should have a lower stock price crash risk as "they can better handle the physical and transition risks related to climate change" (Nguyen et al., 2023, p. 2). Green activity enables a firm to mitigate its future sensitivity to climate-related

[3] Nguyen et al. (2023) cites various literature to motivate this conclusion: Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2014; Habib et al., 2018.

disruptions and extreme climate events, as well as changes to environmental and climate policy (collectively can be referred to as 'climate market shocks'). As confirmed in Nguyen et al. (2023), previous research shows how green stocks react better to climate change policy events (Pham et al., 2023). Moreover, firms with stronger commitments to climate change activities are better at managing uncertainty of future cash flows related to such 'climate market shocks' (Nguyen et al., 2023)[4].

The contribution of this paper is to expand research on the relation between green activity and stock price crash risk, specifically through the usage of EU data, and by adding a sector classification system that groups firms in our dataset into 'Non-Polluting Sector' (*NPS*) and 'Polluting Sector' firms. Since stock price crash risk is a relative metric, i.e. it measures the crash risk within a specific sample to a benchmark that best suits the sample (MSCI Europe index in this paper), the same hypothesis (H1) as in Nguyen et al. (2023) with regards to the baseline relationship between green activity and stock price crash risk will be tested.

In relation to the second contribution, prior research finds that a stock crash has more severe consequences in for example the banking industry, due to a potential chain-reaction (Fiordelisi et al., 2023). Other research finds that both within and outside the banking industry, crash risk has been associated with opaque assets, such as those without a universally accepted valuation standard (Wu & Lai, 2020). This comes back to the information asymmetry theory underlying the relationship between CSR/green activity and stock price crash risk; firms with low CSR/green activity report less frequently and are therefore less transparent, which increases information asymmetry and the opportunity for bad news-hoarding behaviours, resulting in a higher stock price crash risk (Nguyen et al., 2023). It does, however, not mean that a higher green activity reporting rate in specific industries automatically brings about transparency in green activity reporting behaviour. A vicious cycle can be identified where the emergence of green activity is accompanied with greenwashing (Fiordelisi et al., 2023), which may happen due to the lack of legal requirement to publish ESG statements or a lacking need to verify that such statements are true (Ramus & Montiel (2005).

Hypothesis 2 on a difference in the effect of green activities on stock price crash risk in *NPS*/non-*NPS* industries could be explained the level of information asymmetry for the group of

[4] Nguyen et al. (2023) builds this argument on: Pham et al., 2023; Orlitzky and Benjamin, 2001; Oikonomou et al., 2012; Lemma et al., 2021.

industries that are predominantly included in the *NPS*==1-sample, as such asymmetry follows from aforementioned literature as a ‘driving force’ for a stronger effect between green activity and stock price crash risk. However, the Non-Polluting Sectors (*NPS*) dummy variable used in this paper (see Section 3.3.4) is set to one for a diverse group of industries; as such, Hypothesis 2 cannot be intuitively derived from the level of information asymmetry in a specific industry.

Prior research has, on the other hand, established that polluting companies are generally documented as more information asymmetric (Martinez-Ferrero et al., 2015). Moreover, two recent papers from 2024 have found that green bond issuance and stock price crash risk have a more pronounced negative relationship in polluting industries (Zhang et al., 2024; Ge et al., 2024). Although the conditions for an industry to be labelled ‘polluting’ versus ‘non-polluting’ in this paper does not perfectly align with the Martinez-Ferrero et al. (2014), Zhang et al. (2024) and Ge et al. (2024), these findings are used to formulate Hypothesis 2. Based on the ‘information asymmetry theory’ underlying the relationship between green activity and stock price crash risk, as well as the aforementioned findings on the relationship between green bond issuance (which can be seen as a form of green activity) and stock price crash risk, this paper hypothesises that the suppressive effect of green activity on stock price crash risk is stronger for polluting sector (NPS==0), than for non-polluting sectors (NPS==1).

2.4 Hypotheses

The Theoretical Framework leads to the formulation of the following hypotheses:

H1: Green activity is negatively associated with stock price crash risk when using EU firm data.

H2: Operating in a polluting industry (non-*NPS*; NPS==0) intensifies the negative relationship between green activity and stock price crash risk.

3. Data and methodology

3.1 Data selection

The data used in this paper consists of Equity data from Eikon Datastream. The sample consists of European listed firms (i.e. incorporated in Europe in 2024) from the top 5 European exchanges in terms of market capitalisation in 2024 (Statista, 2024)[5], that were active during the period 2002-2022. This period is chosen based on the availability of ESG data in Eikon Datastream; ESG data is generally available as of 2002 (LSEG), and for the year 2023 many firms' ESG data had not yet been updated in Eikon Datastream at the data collection date. The composition per exchange in the original dataset is presented in Table 3.1.

Table 3.1

Composition original data sample

Name of exchange	Number of firms
Deutsche Boerse AG	738
London Stock Exchange (LSE)	397
OMX (Nasdaq Nordic) Exchange Copenhagen	88
Swiss Six	154
Euronext	491
Euronext Lisbon	29
Euronext Paris	339
Euronext Amsterdam	55
Euronext Brussels	68

This table shows the composition of the original data sample as number of firms per exchange.

Based on the above data selection, the original dataset consisted of 1864 firms in total. After cleaning the data, 373 firms are left in the dataset. The following criteria for cleaning are applied:

1. Firms cannot have missing data for <u>all</u> firm-years for:
    a. Necessary fundamentals[6],
    b. Any of the 'green activity' ESG variables used[7],
    c. Stock return data necessary for constructing *NCSKEW*.

[5] All Euronext exchanges available in Eikon Datastream (Lisbon, Paris, Amsterdam, Brussels) are included—these are also the Euronext exchanges that are part of the Euronext exchange during the entire period 2002-2022.
[6] The fundamentals necessary for constructing control variables.
[7] See Section 3.3 on the handling of missing ESG data for specific firm-years when constructing the dummy variables.

2. Firms with data missing for any of the above variables solely for specific firm-years, but not missing all observations for a specific variable, are included in the sample; the specific firm-year then contains no observation.

3.2 Datasets

The selected data is comprised out of four datasets:

- A dataset including weekly stock returns data, as well as the MSCI Europe index returns, used for constructing the variable *NCSKEW* (and robustness check *DUVOL*) per firm *j* per year, which are used as proxies for stock price crash risk, following prior literature (Nguyen et al., 2023; Kim et al., 2014).
- A dataset of six ESG variables representing firms' green activity. The same six green activity dummies are used based on previous literature on the relationship between green activity and crash risk, to compare the results for this European-focused research to the results found for US-data (Nguyen et al., 2023).
- A set of control variables that potentially impact stock price crash risk in our regression models are incorporated.
- A self-constructed sector dummy variable per firm, Non-Polluting Sectors (*NPS*). This variable adds an extra layer of contextual information about the firms in the sample. For the construction of *NPS*, 4-digit SIC1 codes are collected from Eikon Datastream and combined with a list of 4-digit SIC1 codes of Non-Polluting Sectors, as presented in (Swart & Marrewijk, 2011).

A more detailed description of the variable construction follows in the next section.

3.3 Construction of variables

The below section will touch more specifically upon the construction of the following variables: *NCSKEW* as a measure for Stock Price Crash Risk (3.3.1); the six 'green activity' dummies (3.3.2); control variables (3.3.3); the Non-Polluting Sectors dummy '*NPS*' (3.3.4). All variables and their meaning are presented in Table 3.3 below. The descriptive statistics for the constructed variables are reported in Table 3.4.

Table 3.3
Variable descriptions.

Variable names	**Description**
Price crash risk variable	
NSKEW	Negative conditional skewness of weekly stock returns.
DUVOL	Down-to-up volatility of weekly stock returns.
Green variables	
CCCRO	Climates change commercial risks opportunities: A dummy variable that takes the value of one if the company is aware that climate change can represent commercial risks and/or opportunities in the respective year, and zero otherwise.
ERT	Emission reduction target: A dummy variable that takes the value of one if the company has set an emission reduction target in the respective year, and zero otherwise.
TEE	Target energy efficiency: A dummy variable that takes the value of one if the company sets targets or objectives to be achieved on energy efficiency in the respective year, and zero otherwise.
RCEP	Renewable/clean energy products: A dummy variable that takes the value of one if the company develops products or technologies for the use in clean/renewable energy (such as wind, solar, hydro and geo-thermal and biomass power) in the respective year, and zero otherwise.
REU	Renewable energy use: A dummy variable that takes the value of one if the company makes use of renewable energy in the respective year, and zero otherwise.
GB	Green buildings: A dummy variable that takes the value of one if the company reports about environmentally friendly or green sites or offices in the respective year, and zero otherwise.
Control variables	
DTURN	Average monthly share turnover over the current fiscal year minus the average monthly share turnover over the previous fiscal year.
RET	Average firm-specific weekly return over the fiscal year, multiplied by 100.
SIZE	Natural logarithm of the market value of equity.
SIGMA	Standard deviation of firm-specific weekly returns over the fiscal year.
LEV	Ratio of total liabilities to total assets.
ROA	Net income divided by total assets.
Non-Polluting Sectors	
NPS	A dummy variable that takes the value of one if the company operates in one of the ‘Non-Polluting Sectors’, and zero otherwise.

3.3.1 Stock Price Crash Risk measures: NCSKEW and DUVOL

This paper uses two measures of firm-specific stock price crash risk, following Nguyen et al. (2023): negative conditional skewness of firm-specific returns over the fiscal year (*NCSKEW*) and down-to-up volatility of weekly stock returns (*DUVOL*). Using firm-specific returns ensures the risk measures capture firm-specific factors rather than broad market movements (Kim et al., 2014). An important difference between the two measures is that DUVOL does not involve third moments and is therefore lesser influenced by extreme weekly returns (Kim et al., 2014).

The construction of the first measure of firm-specific stock price crash risk, negative conditional skewness of firm-specific returns over the fiscal year (*NCSKEW*), follows from Equation 1 and Equation 2.

Firstly, Equation 1 estimates the expanded market model regression:

$$Ri,\tau = \alpha_i + B_{1i}R_{mkt,\tau-2} + B_{1i}R_{mkt,\tau-1} + B_{1i}R_{mkt,\tau} + B_{1i}R_{mkt,\tau+1} + B_{1i}R_{mkt,\tau+2} + \varepsilon_{i,\tau}\,, \qquad (1)$$

where Ri,τ is firm i stock returns in week τ. $R_{mkt,\tau}$ is the MSCI Europe Index in week τ. The obtained residual $\varepsilon_{i,\tau}$ are used to compute the weekly return as $W_{i,\tau} = \ln{(1 + \varepsilon_{i,\tau})}$.

The residuals of Equation 1 are then converted to $W_{i,\tau}$, by taking the natural logarithm of 1 plus the residual from the Equation. $W_{i,\tau}$, is used as an input for Equation 2, whereby *NCSKEW* is constructed. This method of constructing *NCSKEW* is in line with prior research (Nguyen et al., 2023)[8].

NCSKEW (for each firm *i* in year *t*) is then computed using Equation 2, in which the negative of the third moment of firm-specific weekly returns for each year is taken, and normalised by the standard deviation of firm-specific weekly returns raised to the third power (Kim et al., 2014):

$$NCSKEW_{i,t} = -\left(\frac{\left[n(n-1)^{\frac{3}{2}}\sum W_{i,r}^{3}\right]}{\left[(n-1)(n-2)\left(\sum W_{i,r}^{3}\right)^{3/2}\right]}\right), \qquad (2)$$

where $W_{i,\tau}$ is the firm-specific weekly return as defined above, *n* is the number of weekly returns during year *t*.

[8] Justification for this methodology is found, via Nguyen et al. (2023), in: Kim et al., 2014; Wen et al., 2019; Zaman et al., 2021; Zuo et al., 2022.

The second measure of firm-specific stock price crash risk, used as a robustness check in this paper, is down-to-up volatility of weekly stock returns (*DUVOL*). *DUVOL* is commonly used as an alternative proxy to NCSKEW, when measuring stock price crash risk (Nguyen et al., 2023[9]). For the construction of DUVOL, for each firm *i* over a fiscal-year period *t*, firm-specific weekly returns are separated into a "down" and "up" group: a weekly return is labelled "down"("up") when the returns are below(above) the annual mean. DUVOL is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks (Kim et al., 2014), and estimated using Equation 3:

$$DUVOLi,t \ = \ln\left\{\frac{[(n,u-1)\ \sum_{down} W2\ i,\tau\ ]}{[(n,d-1)\ \sum_{up} W2\ i,\tau\ \ ]}\right\}, \tag{3}$$

where *n,u*(*n,d*) are the number of weeks that returns are higher(lower) than the annual average returns.

3.3.2 The six 'green activity' dummies

Five out of the six green activity ESG dummies could be extracted from Eikon Datastream in a binary form (Yes/No/NA). *ERT* had to be transformed from a percentage to a dummy; whenever there was an emission reduction target percentage given in the data, the dummy equals 1, otherwise 0.

For the cleaning of ESG data, another method is used than applied for missing fundamentals and returns data (the usual and applied treatment in such a case is leaving the datapoint out of regressions ("." in STATA). Whenever a company does not report on an ESG variable, the dummy value for that firm-year is set to 0. This assumption of a zero-value 'green activity' dummy in the case of no observation is in line with the method used in Nguyen at al. (2023), when we assume that their ESG data also had gaps (due to the very nature of ESG data), but their count of firm-year observations for the ESG dummy variables is equal to the maximum firm-year observations, i.e. descriptive statistics present a ESG observation for every firm-year. Although differently applied, this is in line with the method used in Kim et al. (2014), where the writers constructed a CSR score based on various MSCI ESG scores for companies. The writers

[9] Justification for this methodology is found, through Nguyen et al. (2023) and Kim et al. (2014), in: Deng et al., 2018; Ma et al., 2020; Zaman et al., 2021; Zuo et al., 2022.

then also managed to create a CSR_score variable for all firm-year observations. The method in this paper, in conclusion, entails that non-action for a specific green activity by the firm is assumed when a firm did not report the undertaking of a green activity in that firm-year.

3.3.3 Control variables

Control variables *DTURN, RET, SIZE, SIGMA, LEV, ROA* from previous research on this topic for firms (Nguyen et al., 2023; Kim et al., 2014; Kim et al. 2011; Chen et al. 2017) are constructed with weekly stock returns data and yearly fundamentals data. As mentioned in previously stated literature, the above-stated control variables have been included because they had previously been shown to affect future stock price crash risk. *DTURN* captures the change in trading volume, which is a proxy for the intensity in differences of opinion among investors—a predictor of stock price crash risk (Kim et al., 2014). Past returns, captured by *RET*, holds predictive power of stock price crash risk because of a 'bubble buildup' as indicated by high past returns, followed by a stark stock price drop (Kim et al., 2014). *SIGMA*, capturing stock volatility, since volatile stocks are more likely to be crash prone (Kim et al., 2014). *SIZE*, capturing the size of firms, is also included due to its predictive power on price crash risk. *LEV* and *ROA* are included as additional firm-specific control variables in previous studies (Kim et al., 2014; Nguyen et al., 2023).

3.3.4 The Non-Polluting Sectors dummy (NPS)

The variable '*NPS*' is a dummy variable that takes the value of one if the company operates in one of the 'Non-Polluting Sectors', and zero otherwise.

The industries in Table 3.3.4, presented by their general industry names and 4-digit SIC-1 codes, are classified as 'Non-Polluting' based on research (Swart & Marrewijk, 2011) that used the Industrial Pollution Projection System (IPPS) to order industries based on their Carbon Monoxide (CO) pollution intensity.[10] The paper groups industries into four sectors: 'Agriculture and Mining', 'Construction and Services, 'Non-Pollution Intensive Manufacturing' and 'Pollution Intensive Manufacturing'. The first three sectors ('Agriculture and Mining', 'Construction and Services', and 'Non-Pollution Intensive Manufacturing') are then grouped together and called

[10] Pollution intensity is defined as the ratio of kilograms of Carbon Monoxide Emission over the value of output, from the Industrial Pollution Projection System (Swart en Marrewijk, 2011, p. 7).

'Non-polluting Sectors' (*NPS*). All 4-digit SIC-1 codes comprising 'Non-Pollluting Sectors' are listed per category in Table 3.3.4. The dummy variable Non-Polluting Sectors (*NPS*) captures whether a firm's main operations (based on SIC-1 codes) are in a Non-Polluting Sector (dummy=1) or not (dummy=0).

NPS is constructed with a 'static industry assumption': the 4-digit SIC-1 codes are extracted from Eikon Datastream in July 2024 and firms are assumed to have their main operations (SIC1) in this sector (4-digit) during the entire sample period (2002-2022).

TABLE 3.3.4

Variable construction – Non-Polluting Sectors

4-digit SIC industry codes	Industry names
	Agriculture and Mining
SIC 0100-0299	
SIC 0700-1499	
	Construction and Services
SIC 1500-1799	
SIC 4000-6599	
SIC 6700-6799	
SIC 7000-7099	
SIC 7200-7399	
SIC 7500-7699	
SIC 7800-8499	
SIC 8600-8999	
SIC 9100-9799	
SIC 9900-9999	
	Zero pollution intensive manufacturing sectors
SIC 2021, 2045, 2053, 2068, 2097, 2098, 2241, 2252, 2254, 2273, 2311, 2323, 2325, 2326, 2329, 2331, 2335, 2337, 2342, 2353, 2361, 2369, 2371, 2381, 2384, 2385, 2386, 2387, 2389, 2391, 2393, 2394, 2395, 2397, 2399, 2411, 2448, 2449, 2451, 2452, 2514, 2591, 2656, 2657, 2673, 2674, 2675, 2676, 2677, 2678, 2741, 2761, 2796, 2835, 2836, 3052, 3061, 3082, 3083, 3084, 3085, 3086, 3087, 3088, 3131, 3142, 3143, 3144, 3149, 3151, 3171, 3172, 3199, 3262, 3263, 3363, 3364 3365, 3366, 3412, 3425, 3442, 3448, 3451, 3466, 3491, 3492, 3498, 3533, 3534, 3536, 3537, 3543, 3545, 3546, 3547, 3548, 3549, 3552, 3553, 3556, 3565, 3571, 3572, 3575, 3577, 3578, 3581, 3586, 3593, 3594, 3596, 3613, 3625, 3635, 3644, 3645, 3646, 3652, 3663, 3669, 3671, 3676, 3677, 3678, 3695, 3716, 3799, 3812, 3821, 3824, 3826, 3827, 3829, 3841, 3843, 3844, 3845, 3873, 3915, 3942, 3944, 3953, 3955, 3961, 3965.	

3.4 Descriptive Statistics

The data is winsorised at the 1% and 99 percentiles to remove outliers in the sample, in accordance with the method for winsorisation presented in similar research with US-data by Nguyen et al. (2023). Only control variable *DTURN* is winsorised further at the 10% and the 90% percentile due to the persistence of extreme outliers on both sides of the distribution. The summary statistics for the variables in this paper are shown in Table 3.4. For example, the proxies for stock price crash risk, *NCSKEW* and *DUVOL*, have means of 0.0002 and –0.138. For the green activity variables, the mean value of green activity dummy *CCCRO* is 0.489 which indicates that 48.9% of the firms are aware of commercial risks or opportunities caused by climate change for the business' conduct, business model and are aware they can develop products and services that align with such new risks and opportunities. Moreover, 19.6% of firms have an energy reduction target (*ERT*); 36.4% of firms have set a target for energy efficiency (*TEE*); 16.3% of firms produce renewable and/or clean energy products (*RCEP*); 53.9% of firms use renewable energy in their operations (*REU*); 25.4% of firms in the sample use environmentally friendly sites and/or offices for their operations (*GB*). For the Non-Polluting Sectors dummy (*NPS*), 64.9% of the firms in the sample are classified as having their operations in a non-polluting sector.

Table 3.4

Descriptive statistics.

Variables	Observations	Mean	SD	25th	50th	75th
NCSKEW	7,833	0.0002	.0027	-.00135	.00019	.00168
DUVOL	7,817	-0.138	0.727	-0.550	-0.111	0.337
CCCRO	7,833	0.489	0.499	0.000	0.000	1.000
ERT	7,833	0.196	0.397	0.000	0.000	0.000
TEE	7,833	0.364	0.481	0.000	1.000	1.000
RCEP	7,833	0.163	0.370	0.000	0.000	0.000
REU	7,833	0.539	0.499	0.000	1.000	1.000
GB	7,833	0.254	0.435	0.000	0.000	1.000
SIGMA	7,833	0.045	0.022	0.030	0.039	0.054
DTURN	7,351	-.154	6.059	-0.220	0.000	0.217
RET	7,833	0.236	0.670	-0.105	0.272	0.634
SIZE	7,811	8.199	1.740	6.988	8.290	9.464
LEV	7,800	0.619	0.194	0.498	0.614	0.750
ROA	7,800	0.038	0.060	0.009	-0.035	0.063
NPS	7,833	0.649	0.477	0.000	1.000	1.000

This table reports the descriptive statistics of the variables in the sample used in this paper.

4. Results

4.1 Baseline results

Using Model (1), which includes firm- and year-fixed effects, the effect of green activity on stock price crash risk is estimated:

$$NCSKEW_{i,t} = \alpha_0 + \beta_1 GREEN_{i,t-1} + \sum \gamma_k\, Control_{i,t-1} + \omega_t + \varepsilon_{i,t}\,, \qquad (1)$$

where $NCSKEW_{i,t}$ is the stock price crash risk for firm *i* in year *t*; $GREEN_{i,t-1}$ is the green activity measured by six variables (i.e. *CCRO*, *ERT*, *EET*, *RCEP*, *REU*, and *GB*); $Control_{i,t-1}$ includes *DTURN, RET, SIZE, SIGMA, LEV, ROA*. ω_t are year-fixed effects; and $\varepsilon_{i,t}$ is the error term.

The results of the baseline regression are presented in Table 4.1 and includes the regression results for all six green activity dummies separately (coefficient of the green activity presented at the top of the table is found under 'GREEN'). The regression results show a positive relationship between the green activity *RCEP* (the production of clean/renewable products) and *NCSKEW* at the 10% significance level. The coefficient of this effect is 0.0002, meaning that the stock price crash risk of a firm (captured by *NCSKEW*) increases with 0.0002 when a firm produces clean or renewable energy products. This finding is inconsistent with Hypothesis 1 that green activity decreases stock price crash risk in firms.

In relation to the control variables, statistically significant coefficients are found for *SIGMA*, *RET*, *SIZE* and *ROA* at the 10% and above for all regressions in Table 4.1, which validates the selection of most control variables, which were selected in line with prior research. It is discovered that firms with a higher RET and *SIZE* are more susceptible to price crash, which is in line with theory stating that *RET* controls for 'bubble buildup' and that firms with a larger *SIZE* are more susceptible to price crash (see Section 3.3.3). The negative significant coefficient for SIGMA is not in line with theory stating that more volatile stocks are more prone to stock price crash risk (see Section 3.3.3)

Table 4.1

Baseline results of Model 1.

Dep. Var.	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW
Green variable	CCCRO	ERT	TEE	RCEP	REU	GB
NCSKEWt-1	-0.0697***	-0.0694***	-0.0698***	-0.0694***	-0.0693***	-0.0694***
	(0.0158)	(0.0159)	(0.0159)	(0.0159)	(0.0159)	(0.0159)
GREEN	0.000125	-0.000212	0.000142	0.0002*	-5.48e-05	0.000104
	(0.000112)	(0.000146)	(9.40e-05)	(0.000124)	(0.000112)	(0.000124)
SIGMA	-0.00742**	-0.00749***	-0.00748***	-0.00725**	-0.00727**	-0.00732**
	(0.00287)	(0.00287)	(0.00286)	(0.00286)	(0.00285)	(0.00286)
DTURN	-4.86e-07	-1.55e-07	-3.89e-07	-4.51e-07	-2.67e-07	-3.87e-07
	(4.74e-06)	(4.75e-06)	(4.75e-06)	(4.74e-06)	(4.75e-06)	(4.75e-06)
RET	0.000250***	0.000251***	0.000250***	0.000252***	0.000250***	0.000249***
	(8.60e-05)	(8.60e-05)	(8.60e-05)	(8.62e-05)	(8.60e-05)	(8.60e-05)
SIZE	0.000825***	0.000821***	0.000823***	0.000831***	0.000832***	0.000825***
	(8.36e-05)	(8.38e-05)	(8.40e-05)	(8.38e-05)	(8.39e-05)	(8.35e-05)
LEV	0.000271	0.000252	0.000295	0.000299	0.000279	0.000266
	(0.000612)	(0.000612)	(0.000613)	(0.000614)	(0.000613)	(0.000611)
ROA	-0.00202**	-0.00204**	-0.00201**	-0.00200**	-0.00203**	-0.00201**
	(0.000941)	(0.000942)	(0.000943)	(0.000944)	(0.000941)	(0.000942)
Constant	-0.00622***	-0.00618***	-0.00623***	-0.00629***	0.00628***	-0.00623***
	(0.000898)	(0.000899)	(0.000900)	(0.000901)	(-0.000898)	(0.000897)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,972	6,972	6,972	6,972	6,972	6,972
Number of firms	373	373	373	373	373	373
R-squared	0.062	0.062	0.062	0.062	0.061	0.06

This table reports the results from the baseline regression model (Model 1) to test the effect of green activity on stock price crash risk. The fixed effects model takes the form $NCSKEW_{i,t} = \alpha_0 + \beta_1 GREEN_{i,t-1} + \sum \gamma_k \, Control_{i,t-1} + \omega_t + \varepsilon_{i,t}$ where $NCSKEW_{i,t}$ is the stock price crash risk for firm i in year t; $GREEN_{i,t-1}$is the green activity measured by six variables (i.e. *CCRO, ERT, EET, RCEP, REU*, and *GB*); $Control_{i,t-1}$ includes *DTURN, RET, SIZE, SIGMA, LEV, ROA*. ω_t are year-fixed effects and $\varepsilon_{i,t}$ is the error term. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses.

4.2 Baseline results dependent on Non-Polluting Sector

As fixed effects Model 1 omits time-invariant dummy variable *NPS*[11], this paper alternatively explores the effect of *NPS* on the relationship between stock price crash risk and green activity by splitting the sample into two groups: *NPS* and non-*NPS*. Model 1 is regressed using the two different '*NPS* samples' separately, i.e. conditional on whether a firm is in a Non-Polluting Sector or not (*NPS*==1 or *NPS*==0, respectively).

The regression results show that more significant relationships are found between the green activities and *NCSKEW* in the NPS==1 sample (Table 4.2.1) as compared to the complete sample

[11] See Section 3.3.4.

(Table 4.1). Additional to the significant positive relationship between *RCEP* and *NCSKEW* at the 5% significant level, which is consistent with the baseline results, Table 4.2.1 also shows a significant relationship between *NCSKEW* and *ERT* (emissions reduction target) and *NCSKEW* and *TEE* (target for energy efficiency) at the 10% and 5% levels respectively. Additional to the positive significant relationship between *RCEP* and *NCSKEW*, it is found in the *NPS*-sample that setting a target of energy efficiency (*TEE*) is also significantly positively associated with stock price crash risk. On the other hand, setting an emission reduction target (*ERT*) is significantly negatively associated with stock price crash risk. The coefficients of *TEE* and *RCEP* are both 0.0003, meaning that stock price crash risk increases with 0.0003 in both scenarios: a firm sets a target on energy efficiency, or a firm produces clean or renewable energy products. The coefficient of *ERT* is –0.0004, which means that stock price crash risk decreases with 0.0004 when a firm sets an emissions reductions target. Only the finding of the significant negative relationship between *ERT* and *NCSKEW* in Table 4.2.1 (*NPS*==1) is in line with Hypothesis 1 that green activity reduces stock price crash risk.

No significant relationships between the green activity dummies and *NCSKEW* are found for the *NPS*==0 sample (Table 4.2.2), which is not in line with Hypothesis 2 that negative relationships observed in the baseline results are more pronounced for the *NPS*==0 sample than for the *NPS*==1 sample. The significant negative relationship found between *ERT* and *NCSKEW* for the *NPS*==1 sample did not persist for the *NPS*==0 sample; although the originally found negative effect is in line with Hypothesis 1, it rejects Hypothesis 2 that this effect would be more pronounced for the *NPS*==0 sample. The significant positive coefficients we find for *TEE* and *RCEP* in the *NPS*==1 sample are not in line with Hypothesis 1 since Hypothesis 1 prescribes a negative significant effect. *RCEP* shows an increase in the significant positive relationship by a difference of 0.0001, while a new significant positive relationship for dummy variable *TEE* is found. These results are to an extent in line with Hypothesis 2 that prescribes a weaker negative effect for the *NPS*==1 sample, as it is found that the *NPS*==1 sample has a stronger positive larger positive relationship between green activity and stock price crash risk compared to the whole sample.

As for the control variables, compared to the baseline regression results, the same control variables (*SIGMA*, *RET*, *SIZE*, and *ROA* only for the NPS==0 sample) show a significant relationship with *NCSKEW* at the 10% level and above. Again, the findings of the positive significant relationship between *NCSKEW* and *RET* and *SIZE* are in line with theory that states that stocks of larger firms, as well as more volatile stocks, are more prone to crash risk (Section 3.3.3).

Table 4.2.1

Regression results for Model 1, where *NPS* == 1

Dep. Var.	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW
Green variable	CCCRO	ERT	TEE	RCEP	REU	GB
NCSKEWt-1	-0.0782***	-0.0781***	-0.0787***	-0.0779***	-0.0775***	-0.0779***
	(0.0198)	(0.0199)	(0.0200)	(0.0199)	(0.0198)	(0.0199)
GREEN	0.0002	-0.0004*	0.0003**	0.0003*	-1.95e-05	0.0002
	(0.000149)	(0.000182)	(0.000115)	(0.000161)	(0.000145)	(0.000153)
SIGMA	-0.00612*	-0.00618*	-0.00621*	-0.00606*	-0.00594*	-0.00604*
	(0.00355)	(0.00353)	(0.00354)	(0.00354)	(0.00353)	(0.00353)
DTURN	-2.80e-07	1.92e-07	-3.09e-07	-5.12e-07	-1.25e-07	-2.69e-07
	(5.48e-06)	(5.48e-06)	(5.49e-06)	(5.47e-06)	(5.50e-06)	(5.48e-06)
RET	0.000280***	0.000279***	0.000281***	0.000284***	0.000282***	0.000278***
	(0.000106)	(0.000106)	(0.000106)	(0.000107)	(0.000107)	(0.000107)
SIZE	0.000826***	0.000819***	0.000825***	0.000836***	0.000831***	0.000825***
	(0.000108)	(0.000108)	(0.000109)	(0.000109)	(0.000109)	(0.000107)
LEV	0.000467	0.000401	0.000529	0.000507	0.000458	0.000450
	(0.000803)	(0.000804)	(0.000808)	(0.000805)	(0.000805)	(0.000801)
ROA	-0.000714	-0.000752	-0.000734	-0.000704	-0.000733	-0.000694
	(0.00115)	(0.00115)	(0.00116)	(0.00115)	(0.00115)	(0.00115)
Constant	-0.00666***	-0.00656***	-0.00670***	-0.00676***	-0.00670***	-0.00664***
	(0.00116)	(0.00116)	(0.00117)	(0.00117)	(0.00117)	(0.00116)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,508	4,508	4,508	4,508	4,508	4,508
Number of firms	242	242	242	242	242	242
R-squared	0.063	0.063	0.063	0.063	0.063	0.063

This table reports the results from the baseline regression model (Model 1) to test the effect of green activity on stock price crash risk, conditional on NPS==1. The fixed effects model takes the form $NCSKEW_{i,t} = \alpha_0 + \beta_1 GREEN_{i,t-1} + \sum \gamma_k \, Control_{i,t-1} + \omega_t + \varepsilon_{i,t}$ where $NCSKEW_{i,t}$ is the stock price crash risk for firm *i* in year *t*; $GREEN_{i,t-1}$is the green activity measured by six variables (i.e. *CCRO, ERT, EET, RCEP, REU,* and *GB*); $Control_{i,t-1}$ includes *DTURN, RET, SIZE, SIGMA, LEV, ROA.* ω_t are year-fixed effects and $\varepsilon_{i,t}$ is the error term. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses.

Table 4.2.2

Regression results for Model 1, where *NPS* == 0

Dep. Var.	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW
Green variable	CCCRO	ERT	TEE	RCEP	REU	GB
NCSKEWt-1	-0.0522*	-0.0527*	-0.0523*	-0.0520*	-0.0523*	-0.0526*
	(0.0269)	(0.0270)	(0.0268)	(0.0270)	(0.0268)	(0.0268)
GREEN	4.31e-05	0.000147	-5.14e-05	6.37e-05	-0.000123	-0.000255
	(0.000153)	(0.000257)	(0.000159)	(0.000190)	(0.000175)	(0.000210)
SIGMA	-0.00881*	-0.00858*	-0.00870*	-0.00868*	-0.00862*	-0.00893*
	(0.00468)	(0.00474)	(0.00470)	(0.00474)	(0.00467)	(0.00466)
DTURN	-7.28e-07	-7.95e-07	-6.96e-07	-5.83e-07	-5.16e-07	-7.63e-07
	(9.09e-06)	(9.11e-06)	(9.11e-06)	(9.10e-06)	(9.09e-06)	(9.11e-06)
RET	0.000274*	0.000270*	0.000274*	0.000274*	0.000272*	0.000280*
	(0.000150)	(0.000150)	(0.000150)	(0.000150)	(0.000149)	(0.000150)
SIZE	0.000910***	0.000919***	0.000916***	0.000911***	0.000921***	0.000924***
	(0.000122)	(0.000127)	(0.000123)	(0.000123)	(0.000122)	(0.000124)
LEV	-0.000138	-0.000132	-0.000120	-0.000133	-0.000122	-9.73e-05
	(0.000822)	(0.000822)	(0.000828)	(0.000824)	(0.000824)	(0.000829)
ROA	-0.00467***	-0.00465***	-0.00468***	-0.00466***	-0.00469***	-0.00469***
	(0.00149)	(0.00149)	(0.00149)	(0.00150)	(0.00149)	(0.00150)
Constant	-0.00614***	-0.00622***	-0.00619***	-0.00616***	-0.00622***	-0.00626***
	(0.00131)	(0.00134)	(0.00132)	(0.00131)	(0.00130)	(0.00132)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,464	2,464	2,464	2,464	2,464	2,464
Number of firms	131	131	131	131	131	131
R-squared	0.077	0.077	0.077	0.077	0.078	0.078

This table reports the results from the baseline regression model (Model 1) to test the effect of green activity on stock price crash risk, conditional on NPS==0. The fixed effects model takes the form $NCSKEW_{i,t} = \alpha_0 + \beta_1 GREEN_{i,t-1} + \sum \gamma_k Control_{i,t-1} + \omega_t + \varepsilon_{i,t}$ where $NCSKEW_{i,t}$ is the stock price crash risk for firm i in year t; $GREEN_{i,t-1}$is the green activity measured by six variables (i.e. *CCRO, ERT, EET, RCEP, REU*, and *GB*); $Control_{i,t-1}$ includes *DTURN, RET, SIZE, SIGMA, LEV, ROA.* ω_t are year-fixed effects and $\varepsilon_{i,t}$ is the error term. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses.

4.3 Endogeneity baseline results

Any evidence on the effect of green activity on stock price crash risk based on Model 1 could be sensitive to endogeneity due to: (1) potential serial correlation of *NCKSEW* (Kim et al., 2014), and (2) reverse causality between *NCSKEW* and green activity (Nguyen et al., 2023). Based on prior research, the models in this paper consider such endogeneity by including a lagged version of the independent variable *NCSKEW* in the regressions.

When comparing the regression results of a version of Model 1 where the lagged independent variable is included as a control (Table 4.1 presenting the baseline results and including a lag of independent variable *NCSKEW*) versus the regression results of Model 3 where this control is left out (Table 4.3), it is clear that the lagged independent variable is significantly correlated with the independent variable *NCSKEW* in Table 4.1 and that the results in Table 4.3 therefore miss an essential control variable. This finding further confirms the previously constituted importance of including the lagged independent variable as a means of controlling for endogeneity, also in the sample of this paper.

Table 4.3

Model 1 regression results without endogeneity control via lagged independent variable

Dep. Var.	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW	NCSKEW
Green variable	CCCRO	ERT	TEE	RCEP	REU	GB
GREEN	0.000115	-0.000210	0.000134	0.000213*	-5.60e-05	0.000101
	(0.000109)	(0.000144)	(9.13e-05)	(0.000121)	(0.000109)	(0.000120)
SIGMA	-0.00753***	-0.00761***	-0.00759***	-0.00737***	-0.00739***	-0.00745***
	(0.00281)	(0.00282)	(0.00281)	(0.00281)	(0.00280)	(0.00281)
DTURN	-8.49e-07	-5.27e-07	-7.59e-07	-8.20e-07	-6.35e-07	-7.57e-07
	(4.73e-06)	(4.74e-06)	(4.74e-06)	(4.73e-06)	(4.74e-06)	(4.74e-06)
RET	0.000463***	0.000463***	0.000464***	0.000464***	0.000462***	0.000461***
	(7.08e-05)	(7.07e-05)	(7.07e-05)	(7.10e-05)	(7.08e-05)	(7.08e-05)
SIZE	0.000810***	0.000806***	0.000809***	0.000816***	0.000817***	0.000811***
	(8.17e-05)	(8.19e-05)	(8.21e-05)	(8.19e-05)	(8.19e-05)	(8.16e-05)
LEV	0.000287	0.000268	0.000310	0.000314	0.000294	0.000282
	(0.000597)	(0.000597)	(0.000598)	(0.000599)	(0.000598)	(0.000597)
ROA	-0.00208**	-0.00210**	-0.00207**	-0.00206**	-0.00209**	-0.00207**
	(0.000938)	(0.000938)	(0.000939)	(0.000940)	(0.000938)	(0.000938)
Constant	-0.00625***	-0.00620***	-0.00626***	-0.00631***	-0.00630***	-0.00625***
	(0.000888)	(0.000889)	(0.000890)	(0.000891)	(0.000888)	(0.000887)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,972	6,972	6,972	6,972	6,972	6,972
Number of firms	373	373	373	373	373	373
R-squared	0.059	0.059	0.059	0.059	0.058	0.059

This table reports the results from the baseline regression model (Model 3) to test the effect of green activity on stock price crash risk, when a lagged version of the independent variable (*NCSKEW*) is not included as a control variable to control for endogeneity. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses.

4.4 Robustness test: DUVOL

This section provides a robustness test (additional to the robust standard errors used in all versions of Model 1), namely: an alternative measure for stock price crash risk. The alternative proxy is down-to-up volatility of weekly stock returns (*DUVOL*), and its construction is included in Section 3.3 of this paper. This additional robustness test is used to confirm the persistency of previous results found on the relationship between green activity and stock price crash risk. This robustness check also automatically includes a control for endogeneity by including a lagged version of the independent variable (see Section 4.3).

The usage of *DUVOL* in Model 1, as well as the interpretation of the direction of its coefficients, are like *NCSKEW* in the sense that a higher *DUVOL* represents a higher crash risk (Nguyen et al., 2023; Kim et al., 2014). The descriptive statistics for *DUVOL* are included in Table 3.4. Table 4.4.1 shows the results of the robustness check of the baseline results of Model 1, using *DUVOL* and lagged *DUVOL* instead of *NCSKEW* and lagged *NCSKEW*. Table 4.4.2 and 4.4.3 show this robustness check of Model 1 where the sample is divided into *NPS*==1 (Table 4.4.2) and *NPS*==0 (Table 4.4.3).

For the robustness check on the baseline results (Table 4.4.1), a significant negative relationship is found between *NCSKEW* and green activity dummy *REU* (renewable energy use) at the 10% level, which effect is in line with Hypothesis 1. This relationship was however not found in the baseline results when using *NCSKEW* as an independent variable capturing crash risk. The coefficient of *REU* is –0.046, meaning that whenever a company uses renewable energy in their operations their *NCSKEW* decreases with 0.046. Moreover, we find significant relationships between *NCSKEW* and the control variables *SIGMA*, *DTURN*, *RET* and *SIZE* at the 10% significance level and above. The direction of the coefficients found for *RET* and *SIZE* are in line with theory (see Section 3.3.3); this effect was also found in the baseline results (Section 4.1).

For the regression results of the robustness check of Model 3 dependent on the status of NPS, no significant relationships are found between any of the green activity dummies and *DUVOL*. However, the significant relationships between *DUVOL* and the same control variables as was seen in the robustness check of the baseline results (*SIGMA*, *DTURN*, *RET* and *SIZE*) persist.

Due to the non-persistence (significant relationships found when using *NCSKEW* do not persist when using *DUVOL*) and inconsistency (not the same significant relationships found when using *NCSKEW* or *DUVOL* as independent variable) of the relationships found between green activity and stock price crash risk based on Model 1, the generalisability of the baseline results is limited. The non-persistence and inconsistency of the results across different proxies for stock price crash risk are further discussed in discussion Sections 6.1.2 and 6.1.3.

Table 4.4.1

Robustness test baseline regression: *DUVOL* as independent variable

Dep. Var.	DUVOL	DUVOL	DUVOL	DUVOL	DUVOL	DUVOL
Green variable	CCCRO	ERT	TEE	RCEP	REU	GB
DUVOLt-1	-0.0401***	-0.0404***	-0.0401***	-0.0402***	-0.0402***	-0.0404***
	(0.0133)	(0.0134)	(0.0133)	(0.0133)	(0.0133)	(0.0134)
GREEN	-0.0288	-0.0410	-0.00742	-0.00169	-0.0458*	0.0294
	(0.0256)	(0.0349)	(0.0219)	(0.0311)	(0.0267)	(0.0295)
SIGMA	-2.536***	-2.604***	-2.555***	-2.566***	-2.538***	-2.576***
	(0.675)	(0.671)	(0.677)	(0.674)	(0.675)	(0.675)
DTURN	-0.00308***	-0.00307***	-0.00311***	-0.00311***	-0.00303***	-0.00312***
	(0.00112)	(0.00113)	(0.00112)	(0.00112)	(0.00112)	(0.00112)
RET	0.114***	0.114***	0.114***	0.114***	0.114***	0.114***
	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)	(0.0189)
SIZE	0.159***	0.157***	0.159***	0.158***	0.161***	0.157***
	(0.0185)	(0.0184)	(0.0186)	(0.0185)	(0.0186)	(0.0185)
LEV	0.0768	0.0721	0.0752	0.0762	0.0808	0.0743
	(0.105)	(0.106)	(0.106)	(0.106)	(0.105)	(0.105)
ROA	0.317	0.314	0.317	0.318	0.311	0.322
	(0.216)	(0.216)	(0.215)	(0.215)	(0.216)	(0.215)
Constant	-1.457***	-1.435***	-1.451***	-1.449***	-1.470***	-1.442***
	(0.177)	(0.176)	(0.177)	(0.176)	(0.177)	(0.177)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,959	6,959	6,959	6,959	6,959	6,959
Number of firms	373	373	373	373	373	373
R-squared	0.107	0.107	0.107	0.107	0.107	0.107

This table reports the regression results of the robustness check on the baseline results (Model 1, Section 4.1) to test the relationship found between green activity and stock price crash risk using *NCSKEW* as a proxy for crash risk. The fixed effects model takes the form $DUVOL_{i,t} = \alpha_0 + \beta_1 GREEN_{i,t-1} + \sum \gamma_k\, Control_{i,t-1} + \omega_t + \varepsilon_{i,t}$ where $DUVOL_{i,t}$ is the alternative proxy for stock price crash risk for firm i in year t; $GREEN_{i,t-1}$is the green activity measured by six variables (i.e. *CCRO, ERT, EET, RCEP, REU*, and *GB*); $Control_{i,t-1}$ includes *DTURN, RET, SIZE, SIGMA, LEV, ROA*. ω_t are year-fixed effects and $\varepsilon_{i,t}$ is the error term. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses.

Table 4.4.2

Robustness test Model 1: *DUVOL* as independent variable, where NPS==1

Dep. Var.	DUVOL	DUVOL	DUVOL	DUVOL	DUVOL	DUVOL
Green variable	CCCRO	ERT	TEE	RCEP	REU	GB
DUVOLt-1	-0.0445***	-0.0449***	-0.0451***	-0.0446***	-0.0446***	-0.0453***
	(0.0167)	(0.0167)	(0.0167)	(0.0167)	(0.0167)	(0.0168)
GREEN	-0.0413	-0.0520	0.0201	0.0321	-0.0300	0.0482
	(0.0321)	(0.0452)	(0.0277)	(0.0392)	(0.0359)	(0.0369)
SIGMA	-2.706***	-2.796***	-2.784***	-2.771***	-2.747***	-2.796***
	(0.779)	(0.773)	(0.785)	(0.781)	(0.779)	(0.780)
DTURN	-0.00251*	-0.00250*	-0.00256*	-0.00259*	-0.00249*	-0.00258*
	(0.00143)	(0.00143)	(0.00143)	(0.00142)	(0.00142)	(0.00143)
RET	0.114***	0.114***	0.114***	0.114***	0.114***	0.113***
	(0.0254)	(0.0253)	(0.0254)	(0.0254)	(0.0254)	(0.0254)
SIZE	0.176***	0.173***	0.174***	0.175***	0.176***	0.173***
	(0.0247)	(0.0247)	(0.0248)	(0.0248)	(0.0249)	(0.0248)
LEV	0.0333	0.0282	0.0425	0.0426	0.0399	0.0349
	(0.128)	(0.129)	(0.129)	(0.128)	(0.128)	(0.128)
ROA	0.327	0.328	0.331	0.334	0.327	0.342
	(0.252)	(0.252)	(0.251)	(0.251)	(0.252)	(0.251)
Constant	-1.501***	-1.474***	-1.495***	-1.502***	-1.505***	-1.481***
	(0.221)	(0.220)	(0.221)	(0.221)	(0.221)	(0.222)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,497	4,497	4,497	4,497	4,497	4,497
Number of firms	242	242	242	242	242	242
R-squared	0.116	0.116	0.116	0.116	0.116	0.116

This table reports the regression results of the robustness check on the baseline results (Model 1, Section 4.2.1) to test the relationship found between green activity and stock price crash risk using *NCSKEW* as a proxy for crash risk, conditional on NPS==1. The fixed effects model takes the form $DUVOL_{i,t} = \alpha_0 + \beta_1 GREEN_{i,t-1} + \sum \gamma_k\, Control_{i,t-1} + \omega_t + \varepsilon_{i,t}$ where $DUVOL_{i,t}$ is the alternative proxy for stock price crash risk for firm i in year t; $GREEN_{i,t-1}$is the green activity measured by six variables (i.e. *CCRO, ERT, EET, RCEP, REU,* and *GB*); $Control_{i,t-1}$ includes *DTURN, RET, SIZE, SIGMA, LEV, ROA*. ω_t are year-fixed effects and $\varepsilon_{i,t}$ is the error term. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses.

Table 4.4.3

Robustness test Model 1: *DUVOL* as independent variable, where NPS==0

Dep. Var.	DUVOL	DUVOL	DUVOL	DUVOL	DUVOL	DUVOL
Green variable	CCCRO	ERT	TEE	RCEP	REU	GB
DUVOLt-1	-0.0313	-0.0314	-0.0318	-0.0323	-0.0315	-0.0312
	(0.0221)	(0.0221)	(0.0221)	(0.0221)	(0.0221)	(0.0221)
GREEN	0.00225	-0.00951	-0.0577	-0.0770	-0.0565	-0.0231
	(0.0439)	(0.0545)	(0.0358)	(0.0519)	(0.0396)	(0.0441)
SIGMA	-2.175	-2.188	-2.082	-2.317*	-2.097	-2.187
	(1.339)	(1.326)	(1.336)	(1.348)	(1.339)	(1.338)
DTURN	-0.00417**	-0.00416**	-0.00420**	-0.00427**	-0.00410**	-0.00417**
	(0.00186)	(0.00186)	(0.00186)	(0.00186)	(0.00186)	(0.00186)
RET	0.114***	0.115***	0.115***	0.114***	0.114***	0.115***
	(0.0291)	(0.0291)	(0.0292)	(0.0291)	(0.0291)	(0.0291)
SIZE	0.138***	0.138***	0.143***	0.141***	0.143***	0.140***
	(0.0249)	(0.0242)	(0.0247)	(0.0245)	(0.0247)	(0.0245)
LEV	0.131	0.132	0.142	0.136	0.135	0.134
	(0.177)	(0.178)	(0.177)	(0.178)	(0.179)	(0.178)
ROA	0.309	0.308	0.297	0.301	0.298	0.308
	(0.394)	(0.394)	(0.394)	(0.390)	(0.392)	(0.394)
Constant	-1.424***	-1.421***	-1.461***	-1.434***	-1.453***	-1.434***
	(0.281)	(0.276)	(0.277)	(0.278)	(0.278)	(0.278)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,462	2,462	2,462	2,462	2,462	2,462
Number of firms	131	131	131	131	131	131
R-squared	0.103	0.103	0.103	0.103	0.103	0.103

This table reports the regression results of the robustness check on the baseline results (Model 1, Section 4.2.2) to test the relationship found between green activity and stock price crash risk using *NCSKEW* as a proxy for crash risk, conditional on NPS==0. The fixed effects model takes the form $DUVOL_{i,t} = \alpha_0 + \beta_1 GREEN_{i,t-1} + \sum \gamma_k \, Control_{i,t-1} + \omega_t + \varepsilon_{i,t}$ where $DUVOL_{i,t}$ is the alternative proxy for stock price crash risk for firm i in year t; $GREEN_{i,t-1}$is the green activity measured by six variables (i.e. *CCRO, ERT, EET, RCEP, REU,* and *GB*); $Control_{i,t-1}$ includes *DTURN, RET, SIZE, SIGMA, LEV, ROA*. ω_t are year-fixed effects and $\varepsilon_{i,t}$ is the error term. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses.

4.5 The relationship between NPS and green activity

The baseline results of this paper present the relationship between green activity and stock price crash risk. Additional to the baseline results (Section 4.1), the paper includes results for Model 1 conditional on whether firms are in one of the non-polluting sectors, or not (Section 4.2). To further understand the relationship between *NCSKEW* and green activity, this section elaborates on the possible relationship between *NPS* and green activity, i.e. whether operating in a Non-Polluting Sector (status of dummy *NPS*==1) could be a predictor of firms undertaking green activities.

Establishing the relationship between *NPS* and green activity is interesting since the nature of the ‘regular’ six green activity dummies and the *NPS* dummy is different, namely: *NPS* concerns which sector a firm is operating in and whether such a sector is classified as ‘non-polluting’, which is to a lesser extent in the scope of control of a firm, and; 'green activities' concern undertakings by firms that are to a larger extent inside the scope of their control (i.e. they either undertake a specific 'green activity' or not).

The relationship between *NPS* and green activity cannot be measured with a fixed effects model dependent on data used in this paper, however, since *NPS* is constructed under the assumption that it is equal for firm *i* in all its firm-years (referred to as 'static sector assumption').[12] When using a fixed effects model, the variable *NPS* is omitted due to collinearity. A random effects model with the following from (Model 2) could be a solution for this restriction:

$$GREEN_{i,j,t} = \alpha_0 + \beta_1 NPS_{i,j,t-1} + \sum \gamma_k \, GREEN_{i,j,t-1} + \sum \gamma_k \, Control_{i,j,t-1} + \delta_j + \omega_t + \varepsilon_{i,j,t} \,, \qquad (2)$$

where $GREEN_{i,j,t}$ is the dependent variable, a dummy variable measured by one of the six green activity dummies (*CCCRO, ERT, TEE, RCEP, REU* and *GB*); $GREEN_{i,j,t-1}$ are the green activity dummy variables used as control variables (excluding the green activity dummy that is used as dependent variable). $NPS_{i,j,t-1}$ is the dummy that captures whether the firm operates in a Non-Polluting Sector. $Control_{i,j,t-1}$ includes the 1-period lags of *DTURN, RET, SIZE, SIGMA, LEV* and *ROA*. δ_j is the random effect, ω_t is the time-fixed effects, $\varepsilon_{i,j,t}$ is the error term.

The regression results of Model 2 using the data sample in this paper is presented in Table 4.5.1. Significant relationships between the different green activity dependent variables and *NPS* are found for the green activities 'target energy efficiency' (*TEE*) and 'green buildings' (*GB*). Firstly, a negative significant correlation of -0.125 at the 1% significance level is found for the relationship between *TEE* and *NPS*, which means operating in a Non-Polluting Sector decreases the chance of a firm engaging in the green activity of setting an energy efficiency target. Secondly, a positive significant relationship with correlation coefficient 0.172 is found between *GB* and *NPS* at the 1% significance level, which means operating in a Non-Polluting Sector increases the chances of a firm reporting about environmentally friendly, or green, sites or offices.

[12] See Sections 3.3.4 and 4.2.

TABLE 4.5.1

Regression results of Model 2

Dep. Var.	CCCRO	ERT	TEE	RCEP	REU	GB
NPS	-0.0131	-0.0164	-0.125***	-0.0374	0.0278	0.172***
	(0.0205)	(0.0100)	(0.0250)	(0.0283)	(0.0219)	(0.0290)
CCCRO		0.209***	0.199***	0.0828***	0.336***	0.118***
		(0.0126)	(0.0134)	(0.0100)	(0.0109)	(0.0117)
ERT	0.173***		0.00959	0.0537***	0.149***	0.000928
	(0.00998)		(0.0116)	(0.00849)	(0.00971)	(0.00997)
TEE	0.154***	0.0134		0.00763	0.116***	0.0710***
	(0.0103)	(0.0110)		(0.00885)	(0.0101)	(0.0103)
RCEP	0.119***	0.0549***	0.0163		0.0743***	0.116***
	(0.0138)	(0.0126)	(0.0159)		(0.0135)	(0.0139)
REU	0.356***	0.193***	0.159***	0.0616***		0.103***
	(0.0116)	(0.0127)	(0.0139)	(0.0104)		(0.0121)
GB	0.111***	0.00651	0.0930***	0.0859***	0.102***	
	(0.0119)	(0.0115)	(0.0137)	(0.0102)	(0.0117)	
SIGMA	1.405***	-0.717***	0.756***	0.786***	0.00858	0.459**
	(0.220)	(0.240)	(0.252)	(0.185)	(0.214)	(0.217)
DTURN	0.00137**	-0.00215***	0.000122	-0.000200	0.00132**	0.000761
	(0.000621)	(0.000747)	(0.000705)	(0.000512)	(0.000600)	(0.000601)
RET	0.0158***	0.00685	-0.00663	-0.00562	-0.000933	0.0153***
	(0.00598)	(0.00705)	(0.00681)	(0.00502)	(0.00580)	(0.00586)
SIZE	0.0579***	-0.0162***	0.0452***	0.0189***	0.0846***	0.0483***
	(0.00507)	(0.00361)	(0.00598)	(0.00508)	(0.00507)	(0.00572)
LEV	0.0625*	-0.105***	-0.0394	-0.000381	0.0438	-0.0222
	(0.0369)	(0.0269)	(0.0430)	(0.0348)	(0.0369)	(0.0398)
ROA	-0.210**	-0.283***	-0.0124	0.0143	-0.151*	-0.241***
	(0.0875)	(0.0905)	(0.1000)	(0.0741)	(0.0852)	(0.0866)
Constant	-0.385***	0.223***	-0.132**	-0.102**	-0.444***	-0.403***
	(0.0487)	(0.0340)	(0.0578)	(0.0516)	(0.0496)	(0.0570)
Observations	6,972	6,972	6,972	6,972	6,972	6,972
Number of firms	373	373	373	373	373	373

This table reports the results Model 2 to test the relationship between NPS and green activity. The random effects regression model takes the form $GREEN_{i,j,t} = \alpha_0 + \beta_1 NPS_{i,t-1} + \sum \gamma_k \, GREEN_{i,t-1} + \sum \gamma_k \, Control_{i,t-1} + \delta_j + \omega_t + \varepsilon_{i,j,t}$ where $GREEN_{i,j,t}$ is the dependent variable, a dummy variable measured by one of the six green activity dummies (*CCCRO, ERT, TEE, RCEP, REU* and *GB*); $GREEN_{i,j,t-1}$ are the green activity dummy variables used as control variables (excluding the green activity dummy that is used as dependent variable). $NPS_{i,j,t-1}$ is a dummy that captures whether the firm operates in a Non-Polluting Sector. $Control_{i,j,t-1}$ includes the 1-period lags of *DTURN, RET, SIZE, SIGMA, LEV* and *ROA*. δ_j is the random effect, ω_t is the time-fixed effects, $\varepsilon_{i,j,t}$ is the error term. p<0.01, ** p<0.05, * p<0.1. Robust standard errors are shown in parentheses.

To check the statistical consistency of Model 2, and to determine whether a random effects or fixed effects estimates are more appropriate to use, a Hausman test is conducted with green variable *CCCRO* as dependent variable (column 1 of Table 4.5.1). The results of the Hausman test are presented in Table 4.5.2.

H_0: Difference in coefficients is not systematic (random effects estimators are more appropriate).
H_α: Difference in coefficients is systematic (fixed effects estimators are more appropriate).

TABLE 4.5.2

Hausman test results

Test summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	42	11	0.000
Cross-section random effects test comparisons			
Variable	Var (Diff.)	Fixed	Random
ERT	-0.0034652	0.1699014	0.1733666
TEE	-0.0064759	0.1477242	0.1542
RCEP	-0.002363	0.1165096	0.1188726
REU	0.0024804	0.3586199	0.3561395
GB	0.222715	0.1333511	0.1110796
SIGMA	-0.0297369	1.374931	1.404668
DTURN	0.0000116	0.0013828	0.0013713
RET	0.0006197	0.0164172	0.0157975
SIZE	0.0024825	0.0604279	0.0579453
LEV	-0.0480324	0.0145011	0.0625335
ROA	0.0238288	-0.185872	-0.2097107

This table reports the results of the Hausman test of non-systematic difference in coefficients when comparing a fixed- and random-effects model to establish the relationship between NPS and green activity. The model includes the results when performing the test using green activity 'CCCRO' as the dependent variable.

The p value of 0.000 shows that the Hausman test's null hypothesis (H_0) of non-systematic difference in coefficients (i.e. the random effects are uncorrelated with the independent variables) is rejected, and that coefficients are statistically significant. This means that alternative hypothesis (H_α) should be adopted and that a fixed effects model would be the suitable model to establish the relationship between green activity and *NPS*.

Although the 'static sector assumption' on which *NPS* is computed in this paper creates a barrier for creating a fixed effects model with dependent variable *NPS*, the findings from the Hausman test provide insights in the sense that for future research on this relationship, it would be beneficial to construct *NPS* in a dynamic way, i.e. without a static sector assumption, in order to be able to explore the relationship through a fixed effects model.

Additional to this restriction, the establishment of an explanatory between *NPS* and green activity the relationship between *NPS* and green activity should be accompanied with a consideration that that policy requirements that limit firms' scope of control to undertake specific 'green activities' are not considered in the assumption about the nature of *NPS* and *green activity*, at the beginning of this section. This increases the likelihood of endogeneity in Model 2 when no further research is done into the necessary control variables to be included to isolate the relationship of interest.

The random effects regression, unaccompanied by correct control variables as the establishing of this relationship is not the centre of gravity of this paper, has strong limitations and little foundation in prior research and theory. Further research, however, could put this at the centre of gravity to effectively investigate this relationship. Ideally, such research would not have the data limitation that the variable *NPS* in this paper suffers from, namely: the static sector assumption underlying its construction causing *NPS* to be time-invariant and unsuitable for a fixed effects regression. Preferably, future research uses time-variant 4-digit SIC codes to construct *NPS* to overcome the impossibility of including such a dummy in a fixed-effects regression due to collinearity with other firm fixed effects.

5. Conclusion

The baseline results of this paper (Table 4.1) show a positive significant relationship of coefficient 0.0002 between green activity 'renewable/clean energy products' (*RCEP*) and stock price crash risk at the 10% level, which is inconsistent with Hypothesis 1. When splitting the sample into Non-Polluting Sector firms (*NPS*==1) and others (*NPS*==0), more significant relationships between green activity and crash risk are found for the *NPS*==1 sample (Table 4.2.1) as compared to the baseline results of the whole sample (Table 4.1) or the *NPS*==0 sample (Table 4.2.2). For the *NPS*==1 sample: a negative significant relationship at the 10% level with coefficient -0.0004 is found between having an emission reduction target (*ERT)* and stock price crash risk; the positive significant relationship between *RCEP* and crash risk found in the baseline results is affirmed with a significant coefficient of 0.0003 at the 10% level; and additionally a positive significant relationship is found at the 5% level between green activity 'energy efficiency target' and crash risk with a coefficient of 0.0003.

The finding for *ERT* in the *NPS*==1 sample is in line with Hypothesis 1, prescribing a negative relationship between green activity and crash risk, but not in line with Hypothesis 2, because this negative effect was not found for the *NPS*==0 sample (or the whole sample in general), while it is hypothesised that any negative relationship between green activity and crash risk is stronger for the *NPS*==0 sample (or the whole sample) than the *NPS*==1 sample. The findings of positive significant correlation coefficients for *RCEP* and *TEE* conditional on *NPS*==1 are not in line with Hypothesis 1, but they are to an extent in line with Hypothesis 2 in the sense that a stronger positive (i.e. 'weaker negative') relationship is found in the *NPS*==1 sample as compared to the whole sample.

In the robustness test of this paper, using an alternative proxy for stock price crash risk (*DUVOL*), a negative significant relationship between green activity 'renewable energy use' (*REU*) and crash risk (*DUVOL*) is found for the baseline regression of Model 1. This relationship is consistent with Hypothesis 1, but not consistent with the results found in the baseline results using *NCSKEW*. The robustness test on the *NPS*-conditional versions of Model 1 do not return any significant relationships between green activity and *DUVOL*. This finding is inconsistent with Hypothesis 2 in the sense that the negative relationship between *REU* and *DUVOL* is expected to be intensified in the *NPS*==0 sample.

The non-persistence of significant relationships found across different proxies for stock price crash risk (*NCSKEW* and *DUVOL*), as well as the inconsistency of significant relationships between stock price crash risk and the green activities in different *NPS*-subsamples, lead to the conclusion that the generalisability of the results found in this paper are limited.

This inconsistency is not in line with the findings of Nguyen et al. (2023) for US-data in a similar timeframe when using fixed effects modelling, which finds significant negative relationships between all green activity dummies and stock price crash risk, while these results persist when changing from *NCSKEW* to *DUVOL* as a proxy for stock price crash risk.

The results of the paper are concluded with the Hausman test results that suggest the significant relationships between *NPS* and green activity found through a random effects model (Model 2 in Section 4.5) are not statistically consistent with the null hypothesis that the random effects errors of such a model are uncorrelated with the independent variable. To test the existence of such a relationship, a fixed effects model would be more suitable.

The Discussion of this paper (Chapter 6) further discusses the research limitations of this paper related to non-persistence and inconsistency of the results, as well as some suggestions for further research: the inclusion of green bond data as green activity measure and alternative modelling methods to establish a relationship between green activity and stock price crash risk.

6. Discussion

6.1 Research limitations

The research limitations discussed in this section are the exclusion of the book-to-market ratio as a control variable in Model 1 (Section 6.1.1), the seemingly divert sample means and standard deviations of the constructed measures for stock price crash risk *NCSKEW* and *DUVOL* (Section 6.1.2), and the limited generalizability of the baseline results due to inconsistency and non-persistence of the significant results found for the different measures of stock price crash risk (Section 6.1.3).

6.1.1 Book-to-market ratio

In previous literature, Book-to-market ratio (*BM*) (Nguyen et al. 2023), or Market-to-book ratio (Kim et al., 2014), is included for similar reasons as *RET*; *BM* is included to control for 'glamour stocks' (stocks with a low *BM*-ratio) since those are often associated with higher stock price crash risk (Kim et al. 2014). However, the book value of equity was not directly available for the sample in this paper. The alternative method of constructing book value of equity (e.g. *Total assets – Total liabilities*, which are available for all firms in the dataset) does not return a realistic mean *BM-ratio*. Due to uncertainty regarding the correctness of the computed *BM-ratio* values, and considering that a control variable capturing a similar effect (*RET*) is already included as a control variable[13]—*BM* is not included as a control in this paper to avoid it corrupting the research results. The rest of the fundamentals do not present this issue upon their construction; none of the other control variables are moreover based on the available data for firms' book value, which seems to have posed the underlying issue with constructing the *BM*-ratio.

6.1.2 DUVOL and NCSKEW

Three things are striking when looking at the summary statistics of *NCSKEW* and *DUVOL* in the sample (Table 3.4): (1) the sample mean for *NCSKEW* is positive and the sample mean for *DUVOL* is negative (2) the sample mean for *NCSKEW* and *DUVOL* are relatively low compared to research using the US and European context, and; (3) *NCSKEW* and *DUVOL* have a large standard deviation.

[13] See: Section 3.3.3 on the construction of control variables.

The fact that the sample means found in this paper for *NCSKEW* and *DUVOL* are 0.0002 and –0.138 respectively do not pose an issue; a varying sign for the mean across different stock price crash risk proxies in the same sample is also found in Kim et al. (2014), which finds sample means of 0.035 and –0.002 respectively. Although both *NCSKEW* and *DUVOL* capture stock price crash risk, they are not perfectly correlated (Chen et al., 2001). *NCSKEW* measures the skewness of a stock's return distributions and focusses on the likelihood of extreme negative returns; a positive mean for *NCSKEW* shows that the sample, on average does not show extreme negative skewness—the sample is either symmetrically distributed or skewed positively. *DUVOL* measures the volatility of returns when the market index has negative returns; a negative mean *DUVOL* indicates that on average, downside volatility is lower than upside volatility (Nguyen et al., 2023). Both can happen simultaneously for a sample that does not have a strong tendency for extreme negative returns (i.e. the sample is positively skewed) and that has a downside volatility that is stronger than upside volatility.

The sample means of *NCSKEW* and *DUVOL* in this paper are 0.0002 and –0.128; especially the sample mean of *NCSKEW* seems to be low. Research on similar relationships, e.g. research on the relationship between corporate social responsibility (Kim et al., 2014) or green activity (Nguyen et al., 2023) and stock price crash risk, find an *NCSKEW* and *DUVOL* sample mean of 0.035 and –0.002, and 0.135 and 0.131, respectively. It is important to note that these papers investigate a US-context for the period 1995-2009 and 2002-2021 respectively. For the European context, sample means of *NCSKEW* and *DUVOL* can be derived from Fiodelisi et al. (2023), finding a sample mean of 0.075 and 0.038 respectively for a dataset including European bank data from 22 countries for the period 2015-2021. Other recent research using data from publicly listed European firms from all European countries for the period 2001-2017 finds sample means of –0.093 and –0.052 respectively (Dong et al., 2024). Dong et al. (2024) finds, for the European context, that stock price crash risk is on average reduced for firms with centralised regulated information, and moreover finds that higher average stock price crash risk might be associated with countries with poor investor protection. Other research finds that stronger total fundamental strength, higher profitability and higher operating efficiency is associated with a lower stock price crash risk for Chinese firms (Meng et al., 2023). Research also suggests that regions with higher integrity have lower future stock price crash risk (Liu & Liu, 2024). These factors could all explain why the sample mean of *NCSKEW* and *DUVOL* in our dataset is lower than in Nguyen et al. (2023), which uses a similar timeframe, i.e. 2002-2021 as opposed to 2002-2022 in this paper.

Moreover, the standard deviations of *NCSKEW* and *DUVOL* in this paper is quite large compared to their means, when comparing it to Nguyen et al. (2023). For a European banking-industry context, Fiordelisi (2023) also found standard deviations for *NCSKEW* and *DUVOL* that were very large and commented on this, relating it to other research using European data that found similar summary statistics (Fiordelisi et al., 2023, p. 9). When comparing our sample means to European listed firm data for the period 2001-2017 (Dong et al, 2024), which finds standard deviations of 0.597 and 0.316 for the above-stated sample means for *NCSKEW* and *DUVOL*, the standard deviations of the independent variables of our sample (.003 and 0.727) are similar when relating the standard deviations to the variable means of *NCSKEW* and *DUVOL*.

To conclude, when comparing the sample means and standard deviation for *NCSKEW* and *DUVOL* in our sample to similar research using a dataset of European listed firms, our sample means seem to be more comparable to such European-based research than what Nguyen et al. (2023) finds for US data. This finding could mean than on average European firms experience less stock price crash risk, and that the variance within the sample is larger than for US firms.

6.1.3 Generalizability of baseline results

As explained in the Theoretical Framework, it should be hypothesised that firms in polluting industries (subsample *NPS*==0) experience a stronger negative effect of green activity on stock price crash risk than firms in non-polluting industries (*NPS*==1). It is therefore not in line with Hypothesis 2 that the results for the baseline results only show a significant correlation between the green activity variable *RCEP* and *NCSKEW*, and that the *NPS*==1 subsample shows significant results for the relationship between *NCSKEW* and three green activity variables (*ERT*, *TEE* and *RCEP*), but that the NPS==0 subsample does not show any significant relationships.

The found relationships for *RCEP*, *ERT* and *TEE* moreover do not persist when using *DUVOL* as a measure for stock price crash risk. Generally, similar research finds that a significant relationship found between CSR activity (Kim et al., 2014) or green activity (Nguyen et al., 2023) and *NCSKEW*, persists when performing a robustness check using *DUVOL* as an alternative different proxy for stock price crash risk. The non-persistence of the results in this paper could be a construction issue with *NCSKEW* or *DUVOL*, or be explained by the fact that *NCSKEW* and

DUVOL capture a different effect and are not perfectly the same proxies for stock price crash risk (see Section 6.1.2). The fact that the results found when regressing green activity and *NCSKEW* do not persist when regressing green activity and *DUVOL* call for a conservative interpretation of the research results due to limited generalizability.

6.2 Suggestions for further research

In this section, two suggestions for further researched are presented. Firstly, the usage of green corporate bond issuance is suggested as an extra green activity dummy (Section 6.2.1); the construction of this dummy has also been tested for the purpose of this paper, using European green bond data from Bloomberg. Secondly, alternative modelling of the relationship between green activity and stock price crash risk through dynamic GMM models is suggested (Section 6.2.2), motivated by previous research finding significant relationships using such models, while establishing no significant relationships through fixed effects modelling, as in this paper.

6.2.1 Green corporate bond issuance as a 'green activity' dummy

For the purpose writing this paper, it has been explored whether it was possible to construct an extra 'green activity' dummy (additional to the six 'green activity' dummies used in this paper) as a research contribution. This extra dummy would capture for every firm-year whether a firm had issued a green corporate bond. Prior research by Zhang et al. (2024) has established a significant negative relationship between green bond issuance and stock price crash risk for Chinese listed firms in the period 2014-2022 (using difference-in-difference methods). This effect has also been established in a September 2024 published paper by Ge et al. (2024) using data from China in the period 2012-2022 (using difference-in-difference methods).

To investigate this relationship for the firm sample used in this paper, the ISIN-codes of all 373 firms in the dataset were matched to a dataset consisting of green bond issuance data for European firms in the period 2002-2022, obtained from Bloomberg. The desired outcome would be a dummy variable 'Green bond issuance' (*BOND*) for every firm-year that takes the value of one if a firm has issued a corporate green bond in a specific year, and zero otherwise.

Unfortunately, no matches were obtained between the equity and bond dataset, i.e. none of the firms in the dataset of 373 firms used in this paper had issued a green bond in the period 2002-

2022. Moreover, it was found that the issuance of green bonds by European listed and non-listed firms in the period 2002-2022 followed the below trend (Table 6.2.1).

Table 6.2.1
Green bond issuances by European listed and unlisted firms in the period 2002-2022

Year	Number of green bonds
2007	1
2014	5
2015	13
2016	31
2017	50
2018	75
2019	190
2020	387
2021	683
2022	673

It follows from Table 6.2.1 that the issuance of green corporate bonds in the period 2007-2019 was quite unique. This makes it less likely that, even if there were matches between the equity data set used in this paper and the bond data, the dummy variable *BOND* would capture a significant effect due to limited variability for this dummy in the dataset (i.e. for most firm-years the dummy would take value 0).

In case of a persistence or future increase in green corporate bond issuance by European firms, the inclusion of dummy variable *BOND* would be an interesting method of measuring green activity and could be used by future research to further understand the relationship between firms' green activity and their stock price crash risk in European listed firms.

6.2.2 Alternative modelling

The limited findings of this paper could be due to the modelling used. For example, Murata & Hamori (2021) regress ESG disclosure against stock price crash risk for the European, US and Japanese context using two-way fixed effects model as well as dynamic GMM models, in which they find no significant correlations between ESG disclosure and crash risk using the two-way fixed effects models but do find significant relationships for the European and Japanese contexts when using a dynamic GMM model. Although the metric used in Murata & Hamori (2021) does not exactly overlap with the collection of proxies for green activity used in this paper, it shows how the choice of model may impact the relationship found between corporate green activities and stock price crash risk. Moreover, it shows that a fixed effects regression might not capture the effect as well as dynamic GMM models.

Considering this paper also uses fixed effects models that include firm- and year-fixed effects and likewise finds no results that persist between the *NCSKEW*- and *DUVOL*-variations, it could be tested whether dynamic GMM models return significant results using the sample used in this paper.

It is to be said that Nguyen et al. (2023) also used GMM models as a robustness check against their significant baseline results found through fixed effects models. The GMM-models in their research gave less consistent and significant results than the fixed effects models, which further supports the methodology used in this paper to establish a relationship between green activity and stock price crash risk through fixed effects models and to focus on other contributions.

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