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“It can’t rain all the time.” The effects of heavy rains on European firms financing

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Abstract

Purpose – This paper aims to investigate how recurrent heavy rain events affect the financial conditions and productivity of European small and medium-sized enterprises (SMEs). It also examines whether nati onal green policy environments can enhance SMEs’ financial resilience.

Design/methodology/approach – The authors combine meteorological data from the European Severe Weather Database with firm-level financial data for the 2016–2022 period. The analysis focuses on 40,000 unlisted, independent SMEs (186,156 firm-year observations). The authors estimate baseline ordinary least squares regressions and conduct extensive robustness checks using alternative econometric approaches, estimators and subsamples.

Findings – The results show that heavy rainfall significantly reduces SMEs’ cash flow and productivity while increasing their leverage. The impact on liquidity is less clear, with coefficients varying across specifications. When rainfall events cause damage, injuries or fatalities, negative effects intensify. Green policy indicators play a mitigating role by improving SMEs’ financial conditions. However, green policies are associated with short-term productivity losses, suggesting transitional compliance costs.

Practical implications – The major policy implication of the study is the need to improve green measures to mitigate adverse climate change effects.

Originality/value – The paper contributes to climate finance research by shifting the focus from temperature anomalies and catastrophic events to recurrent heavy rainfall, and from large firms to unlisted European SMEs. It also provides novel evidence of institutional environments, showing how green policies shape financial resilience but may entail short-term efficiency trade-offs.

Keywords Corporate governance, Capital structure, Corporate finance, Environmental social and governance

Paper type Research paper

1. Introduction

In recent years, regulators and policymakers have paid increasing attention to the consequences of climate change in the economic system (Financial Stability Board [FSB], 2015). Environmental policy has recently been put at the center of European Union (EU) strategy (European Commission, 2019, 2020), and climate change has also become relevant in the agendas of international financial supervisors with unprecedented initiatives (Basel Committee on Banking Supervision, 2020; EBA, 2020; ECB, 2019; ECB, 2020; EIOPA,

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2019; Financial Stability Board [FSB], 2020; United Nations Framework Convention on Climate Change [UNFCCC], 2015).

There is mounting evidence that climate change strongly affects firms (Addoum, *et al.*, 2020; Krueger *et al.*, 2020; Hossain and Masum, 2022). Extreme weather events such as heavy rains can reduce soil quality and damage agricultural machinery (Skendžić *et al.*, 2021), alter tourism patterns (Dubois *et al.*, 2016), damage industrial assets (Zhang *et al.*, 2018), disrupt logistics and transport (Wu *et al.*, 2023) and reduce labor productivity (Koetse and Rietveld, 2009).

Unlike other shocks (e.g. technological or competitive), climate shocks create systemic effects that propagate from firms to the financial system (Sharma and Aragón-Correa, 2005; Chenet *et al.*, 2021). Banks and investors face losses through credit, liquidity and operational risk channels, yet they do not always price these risks adequately (Ehlers *et al.*, 2022). Financial constraints can then amplify shocks, limiting firms' recovery (Dunz *et al.*, 2023).

This paper analyses how heavy rain events affect the financial conditions and productivity of European small and medium-sized enterprises (SMEs), while also examining whether national green policy frameworks strengthen firms' financial resilience.

The present study makes a two-fold contribution to the literature on climate-related financial risks and green transition economics. While the effects of climate change on firm performance have received increasing scholarly attention, existing research has largely focused on either long-term temperature trends (Zhang *et al.*, 2018; Addoum *et al.*, 2020) or major catastrophic events such as hurricanes, floods and wildfires (Nguyen and Wilson, 2018). These approaches, though valuable, tend to overlook the growing prevalence of moderate yet recurrent meteorological phenomena, such as heavy rainfall, whose cumulative impact on business ecosystems remains poorly understood. This study addresses that gap by investigating the financial and operational consequences of subcatastrophic rain events, which are becoming a defining feature of the European climate landscape.

Methodologically, the paper introduces a novel empirical setting by combining high-frequency meteorological data from the European Severe Weather Database (ESWD) (Dotzek *et al.*, 2009) with firm-level financial data from a large sample of European SMEs. The analysis focuses specifically on unlisted firms, which represent most of the European business structure but are often excluded from empirical studies due to data limitations. These firms are especially vulnerable to liquidity shocks and financial instability, as highlighted in prior research (Myers and Majluf, 1984; Abdulsaleh and Worthington, 2013), making them a crucial yet under-explored population for understanding climate-finance interactions.

Theoretically, the study builds upon the premise that climate events act as exogenous shocks to firm cash flow and productivity, particularly in the absence of hedging instruments, insurance mechanisms or flexible financial structures. The use of precipitation as the primary climate risk variable is justified by emerging scientific evidence highlighting precipitation variability as a more direct driver of soil moisture loss and ecological disruption than rising temperatures alone (Vargas Zeppetello *et al.*, 2024).

The study introduces a second original component: the examination of national green policy environments and their role in shaping SMEs' financial conditions. Specifically, this paper empirically tests whether the degree of green competitiveness and industrial carbon dependency can enhance SMEs' financial resilience. This approach offers a more nuanced understanding of climate-finance dynamics. The finding that green policy indicators correlate with improved financial conditions – yet potentially reduce productivity in the short term – adds complexity to existing theories of climate adaptation and transition risk (Bolton and Kacperczyk, 2021; Shi *et al.*, 2022). This suggests that green policies may serve a protective function in financial terms, even if they introduce transitional costs in terms of operational efficiency.

In summary, this study stands out by reframing the analysis of climate-related business risks around two core innovations: the focus on frequent, subcatastrophic rain events and the analyses of green policy environments.

The remainder of the paper is organized as follows. Section 2 illustrates the literature review and hypotheses. Section 3 deepens the measurement of climate risk and the data collection. Section 4 describes the empirical strategy we applied. Section 5 reports the results of our analyses and Section 6 restates the major conclusions and discusses the implications for regulators and for further research.

2. Literature review

The link between climate change and corporate finance has received increasing attention, yet significant gaps remain, particularly concerning the role of frequent weather shocks and the moderating influence of institutional green policies. Prior research can be organized into two main strands: (i) the consequences of climate shocks on firms' financing and productivity and (ii) the role of green policy and institutional frameworks in shaping resilience and financial and productivity outcomes. These streams provide the theoretical foundation for our hypotheses.

2.1 Climate change and firms' financial performance and productivity

A growing body of evidence shows that climate shocks affect firms' financing, profitability and access to capital. Investors demand higher risk premia for carbon-intensive companies (Bolton and Kacperczyk, 2021) and environmental risks influence both funding availability and research and development investments (Wang *et al.*, 2016). Weather events such as heavy rainfall can increase borrowing costs, reflecting creditors' concerns about default risks (Zhao *et al.*, 2024). In addition, operational disruptions – damaged infrastructure, transportation delays or reduced workforce availability – translate into significant productivity and financial losses (Koetse and Rietveld, 2009; Liu and Song, 2019; Wu *et al.*, 2023). These impacts can propagate to the banking sector, amplifying credit and liquidity risks (Chenet *et al.*, 2021; Dunz *et al.*, 2023).

SMEs are especially vulnerable. Compared to large firms, SMEs lack product diversification, geographic reach and easy access to equity markets. They rely heavily on short-term credit, operate with thinner liquidity buffers and are strongly embedded in local markets (Myers and Majluf, 1984; Berger and Udell, 1998; Cassar and Holmes, 2003; Fatoki and Asah, 2011; Abdulsaleh and Worthington, 2013). This territorial dependence makes them more exposed to localized climate events, such as floods or heavy rainfall, which can disrupt revenues, increase costs and tighten financing constraints (Dubois *et al.*, 2016; Skendžić *et al.*, 2021).

From a financial theory perspective, exogenous shocks such as extreme weather can reduce internal funds, increase cash flow volatility and limit self-financing (Myers and Majluf, 1984). At the same time, lenders often respond by tightening credit conditions, perceiving climate-exposed firms as less creditworthy (Cotter and Najah, 2012; Ehlers *et al.*, 2022). The combined effect is particularly severe for SMEs, which face higher borrowing costs and limited opportunities to hedge against risk.

Based on this reasoning, we proposed the following:

H1. Heavy rainfall events negatively affect SMEs' financial conditions.

H2. Heavy rainfall events reduce SMEs' productivity.

Theoretically, these hypotheses are based on the pecking order framework (Myers and Majluf, 1984) and the financial growth cycle model (Berger and Udell, 1998). Both suggest that SMEs are structurally disadvantaged in financing markets, as they rely more heavily on debt and face higher information asymmetries with lenders. Extreme weather shocks further intensify these disadvantages: reduced liquidity lowers internal financing capacity, while heightened risk perceptions make external credit costlier or less accessible. This mechanism implies that climate shocks translate directly into deteriorating financial outcomes for firms.

2.2 Green policy, institutional context and climate resilience

A parallel research strand emphasizes the role of institutional frameworks and green policies in mitigating climate-related financial risks. International initiatives such as the European Green Deal (European Commission, 2019) and the Paris Agreement [United Nations Framework Convention on Climate Change (UNFCCC), 2015] underline the centrality of environmental governance. Financial intermediaries are increasingly integrating climate risk management into their strategies, although adoption remains uneven (Toma and Stefanelli, 2022).

An emerging line of research suggests that the institutional environment, especially in terms of environmental policies and green transition efforts, can mitigate the financial risks associated with climate shocks (Chenet *et al.*, 2021). Countries with advanced green policy frameworks may invest more in infrastructure resilience, provide better financial and regulatory support for affected firms and promote innovation and cleaner technologies that improve firms' long-term viability. Firms in countries with sophisticated green policies may benefit from institutional support, financial incentives and investor confidence, which can improve financial performance after a climate shock. However, productivity may suffer in the short term due to increased compliance costs, changes in input structures or the redirection of resources toward green compliance (Shi *et al.*, 2022).

Accordingly, we hypothesized:

H3. Stronger green policies and institutional frameworks are positively associated with SMEs' financial conditions.

H4. Stronger green policies and institutional frameworks are negatively associated with SMEs' productivity.

From a theoretical perspective, the resource-based view of a firm highlights the importance of adaptive capacity and institutional support in mitigating external risks (Sharma and Aragón-Correa, 2005). In economies where, green policies foster innovation and diversification, firms may be better equipped to absorb or offset the financial effects of climate shocks. Institutional theory also stresses that firms are embedded within broader regulatory and policy environments, that both constrain and enable their strategies. Winn *et al.* (2011) argued that climate change creates new institutional pressures that redefine competitive advantage and risk management. In contexts where governments adopt ambitious green agendas, financial intermediaries are incentivized to support firms investing in resilience, thereby moderating the negative impact of weather events on credit access and liquidity. Conversely, in economies with high carbon lock-ins, the absence of strong green frameworks exacerbates vulnerability and financing costs.

3. Measurement of climate risk and data collection

A significant body of research has sought to identify reliable measures of climate risk and to link them to financial outcomes. Traditionally, studies have relied on temperature shocks or gradual warming as proxies for climate change. For instance, Addoum *et al.* (2020) documented that unexpected temperature shocks reduce establishment-level sales in the USA, while Zhang *et al.* (2018) showed that temperature extremes can decrease productivity in Chinese manufacturing plants by distorting factor allocation. Similarly, Krueger *et al.* (2020) provide evidence that institutional investors are increasingly factoring climate risk – measured through long-term temperature projections – into their asset allocation decisions.

Other measures used in the literature include firm-level CO_2 emissions, as in Wang *et al.* (2016), while Agoraki *et al.* (2024) investigated the impact of climate change on the cost of capital, growth opportunities and new investment, relying on conference calls.

However, recent studies have questioned whether temperature alone the most appropriate proxy for climate change is. Vargas Zeppetello *et al.* (2024) demonstrated that precipitation variability explains a larger share of soil moisture trends and exerts stronger long-term ecological and economic effects than temperature shifts. This line of work has suggested that precipitation-related shocks, such as heavy rainfall, droughts or variability in seasonal patterns, may be more disruptive for firms, particularly in sectors reliant on land use, infrastructure and transportation. Wu *et al.* (2023) confirmed this intuition, showing that rainfall disrupts industrial activity by affecting logistics and labor availability. Our study has built on this perspective by adopting heavy rain events as exogenous, quantifiable shocks, extending the climate-finance literature into an area that remains under-explored.

Data on heavy rain events were collected from the ESWD available at Dotzek *et al.* (2009). The objective of the ESWD is to collect and provide detailed, quality-controlled information on severe convective storm events in Europe [1].

The ESWD defines heavy rain events as "rain falling in such large amounts that significant damage is caused, or no damage is known, but exceptionally high precipitation amounts have been observed within a period of at most 24 h [2]."

Data on heavy rain events are matched with a sample of companies that have their registered addresses in the same geographical area. From the Orbis Bureau van Dijk database, we selected firms headquartered in the 27 EU countries covered by the ESWD. To focus on SMEs, we exclude large firms, listed companies and corporate groups. We also exclude start-ups, whose financing follows different dynamics, often driven by venture capital and early-stage investment cycles (Dimov and De Clercq, 2006; Janeway *et al.*, 2021) and firms in the financial and extractive sectors, which have distinct governance and financing structures (Mehran and Mollineaux, 2012). This ensures a sample of independent, unlisted SMEs that are most exposed to liquidity shocks and have limited access to equity markets.

A crucial methodological step concerns the alignment of rainfall data with firm-level financial data. Heavy rain events recorded in the ESWD were originally reported at the daily level and geolocated to specific municipalities or smaller localities. To ensure comparability with the annual accounting data from Orbis, we aggregated rainfall events at the annual frequency. This allowed us to construct yearly measures of rainfall intensity (number of events, cumulative amount and duration) that are consistent with firms' yearly financial statements.

Aggregation was performed at the nomenclature of territorial units for statistics, level 2 (NUTS2) regional level [3] where rainfall data were matched to the registered locations of firms. This step was done partially manually by searching for each location indicated in the ESWD's corresponding NUTS2 region. This spatial unit represents an appropriate compromise between granularity and data availability: it captures localized heterogeneity in exposure to weather events while avoiding excessive fragmentation that would reduce the reliability of regional aggregates. Similar approaches have been used in recent climate-finance studies that rely on regional identifiers to link weather shocks with economic or financial outcomes (e.g. Zhao *et al.*, 2024).

This procedure ensures consistency in both time (annual aggregation to match balance sheet frequency) and space (NUTS2 as a standard regional unit for European analyses), while reducing the risks of measurement errors. By focusing on firms with a single registered location, we further minimize mismatches between event exposure and firm-level financial data.

We obtained a data set of 26,851 heavy rain events in the 2016–2022 period in 27 EU countries matched with a sample of 49,809 companies distributed in 225 NUTS2 regions for seven years, for a total sample of 186,156 firm-year observations.

There was extensive damage to homes, roads, bridges or land in 50.4% of the events. Unfortunately, 36% of the heavy rain events resulted in serious consequences for people in the areas; these events involved 737 people, of whom 187 were injured and 545 were killed.

Table 1 shows the distribution of heavy rain events over the analysis period. It can be seen in the table that heavy rain events have become more frequent as time has passed. The year with heavier rain events was 2022 with 6,118 events corresponding to 22.78% of all events, followed by 2021 with 5,253 events (19.56%) and 2018 with 3,499 events (13.03%). The year with the lowest number of events was 2017, with 2,155 events. This growing trend highlights the increasing frequency of such meteorological phenomena, reinforcing the importance of examining their economic impact over time and confirming the relevance of using recent data for analysis.

Table 2 reveals a marked geographic concentration of heavy rain events, with Germany and Poland alone accounting for nearly 46% of the total. Italy, France and Austria also reported significant numbers. These figures reflect heterogeneous exposure to climate-related risks across European regions, underscoring the importance of analyzing firm-level financial vulnerability in a geographically disaggregated framework.

The number of firm-year observations (Table 3) is relatively stable across the years, with a slight increase in 2019, which reflects improved data availability for that year. The balanced distribution across the seven-year period enhances the reliability of the econometric analysis and reduces the likelihood of temporal bias in the estimation of climate-related financial effects.

Table 4 shows the number of firm-year observations by country. The data set shows a strong concentration of observations in Italy, which accounts for almost 50% of the total sample. This unbalanced distribution is acknowledged as a limitation, although it also reflects real-world differences in data availability and SME density across Europe. The country with the second-greatest number of firms represented is Spain with 48,653 observations (26.14%), followed by Sweden (14,716 observations, 7.91%), Portugal (10,913 observations, 5,86%), Bulgaria (8,168 observations, 4.39%), Greece (5,325 observations, 2.86%) and Slovenia (2,916 observations, 1.57%). Each of the remaining countries had fewer than 1,500 observations corresponding to less than 1% of the total.

Table 5 describes the distribution among the industries for the sample firms. These firms were mostly concentrated in a few sectors: the first seven industries included around 72% of the total observations. Precisely, the industry with the greatest number of observations is construction with 33,287 observations (17.88% of total), followed by wholesale trade (31,692 observations corresponding to 17.02%), business services (17,814 observations,

Table 1. Heavy rain events by year

Year	No. of heavy rain events	Freq. (%)
2016	3,395	12.64
2017	2,155	8.03
2018	3,242	12.07
2019	3,499	13.03
2020	3,189	11.88
2021	5,253	19.56
2022	6,118	22.78
Total	*26,851*	*100*

Source(s): Authors' own work

Table 2. Heavy rain events by country

Country	No. of heavy rain events	Freq. (%)
Austria	1,711	6.37
Belgium	795	2.96
Bulgaria	196	0.73
Croatia	409	1.52
Czech Republic	1,164	4.34
Denmark	112	0.42
Estonia	55	0.20
Finland	32	0.12
France	2,696	10.04
Germany	6,191	23.06
Greece	375	1.40
Hungary	205	0.76
Ireland	40	0.15
Italy	2,900	10.80
Latvia	35	0.13
Lithuania	26	0.10
Luxembourg	73	0.27
Malta	30	0.11
Netherlands	550	2.05
Poland	6,093	22.69
Portugal	134	0.50
Republic of Cyprus	65	0.24
Romania	518	1.93
Slovakia	467	1.74
Slovenia	402	1.50
Spain	1,515	5.64
Sweden	62	0.23
Total	*26,851*	*100*

Source(s): Authors' own work

9.57%), retail trade (14,498 observations, 8.00%), metallurgy and metal products (13,455 observations, 7.23%), transportation, customs services and storage (12,115 observations, 6.51%) and travel, entertainment and hospitality (10,752 observations, 5.78%). Each of the remaining industries included less than 5% of the total.

Table 3. Companies by year

Year	Observations	Freq. (%)
2016	25,048	13.46
2017	26,076	14.01
2018	26,777	14.38
2019	27,493	14.77
2020	27,393	14.72
2021	27,323	14.68
2022	26,046	13.99
Total	*186,156*	*100*

Source(s): Authors' own work

Table 4. Companies by country

Country	Observations	Freq. (%)
Austria	16	0.01
Belgium	73	0.04
Bulgaria	8,168	4.39
France	602	0.32
Germany	88	0.05
Greece	5,325	2.86
Hungary	37	0.02
Italy	91,940	49.39
Poland	1,104	0.59
Portugal	10,913	5.86
Romania	128	0.07
Slovakia	1,477	0.79
Slovenia	2,916	1.57
Spain	48,653	26.14
Sweden	14,716	7.91
Total	*186,156*	*100*

Source(s): Authors' own work

4. Empirical strategy

4.1 Empirical strategy: heavy rainfall and small and medium-sized enterprises' financial conditions and productivity

We adopt ordinary least squares (OLS) regression as it offers clear, easily interpretable coefficient estimates for the relationship between rain events and financial indicators. This is especially important for policy relevance. Furthermore, OLS is widely used in the empirical climate-finance literature (e.g. Agoraki *et al.*, 2024; Zhao *et al.*, 2024), allowing comparison and replication. Specifically, we adopted the following OLS model:

$$Finance_{i,j,t} = \beta_0 + \beta_1 Rain_{j,t} + \beta_2 Control_{i,t} + Year\,F.E. + Country\,F.E. + Industry\,F.E. + \varepsilon_{i,t} \tag{1}$$

where:

$Finance_{i,j,t}$ = proxy for a company's financial conditions by company *i* in year *t* in region *j*;

Table 5. Company by industry

Industry	Observations	Freq. (%)
Agriculture, horticulture and livestock	7,915	4.25
Biotechnology and life sciences	133	0.07
Business services	17,814	9.57
Chemicals, pharmaceuticals, petroleum, rubber, etc.	3,646	1.96
Communications	383	0.21
Computer hardware	81	0.04
Computer software	2,373	1.27
Construction	33,287	17.88
Food and tobacco industry	5,400	2.90
Information services	61	0.03
Leather, stone, clay and glass products	2,326	1.25
Media and telecommunications	467	0.25
Metallurgy and metal products	13,455	7.23
Mining and quarrying	21	0.01
Other manufacturing	1,012	0.54
Production of industrial, electrical and electronic machinery	6,975	3.75
Public administration, education, health and social services	5,025	2.70
Publishing and printing	2,475	1.33
Retail trade	14,896	8.00
Textile and clothing industry	5,974	3.21
Transportation equipment manufacturing	748	0.40
Transportation, customs services and storage	12,115	6.51
Travel, entertainment and hospitality	10,752	5.78
Utility services	506	0.27
Waste management and treatment	765	0.41
Wholesale trade	31,692	17.02
Wood, furniture and furniture industry	5,859	3.15
Total	*186,156*	*100*

Source(s): Authors' own work

$\text{Rain}_{j,t}$ = index that accounts for heavy rain events in year t in region j; and
$\text{Controls}_{i,j,t}$ = vector of control variables for company i in year t in region j.

Specifically, our dependent variables are the cash flow ratio (cash flow), gearing ratio (Gear) and liquidity ratio (Liq). We then studied the effects of firm productivity with the same models with the productivity of company i in year t in region j as the dependent variables.

As a proxy for heavy rain events, we adopted measures of the extent of the event in the region in the year, such as the total number of heavy rain events (R_event), the total amount of heavy rain (R_amount) and the total length of heavy rain events (R_length).

We included as control variables the age of the company (Age) (Myers, 1984; Gregory *et al.*, 2005), the size of the company (Size) (Abdulsaleh and Worthington, 2013), the profitability of the company measured by the Return on Equity, the company revenues (Sales) (Fu *et al.*, 2002), the number of employees (Emp) (Abdulsaleh and Worthington, 2013), the long-term debt (Cassar and Holmes, 2003) and the interest coverage (Cassar and Holmes, 2003).

Finally, we added year, country and industry fixed effects. Appendix 1 lists the definitions and source for each variable analyzed.

To ensure that our baseline results are not driven by model choice, we complemented the OLS estimates with three alternative econometric approaches: (i) generalized least squares (GLS) regression model, (ii) robust regression and (iii) high-dimensional fixed effects. GLS models allow for heteroscedasticity and correlation in error terms by modeling the variance-covariance structure explicitly (Wooldridge, 2010). Robust regression down-weights the influence of outliers and high-leverage points in the data (Huber, 1973; Rousseeuw and Leroy, 1987). As financial indicators such as cash flow can be subject to extreme values, robust regression provides a useful sensitivity analysis to check whether our results are driven by outliers.

Finally, we used the high-dimensional fixed effects estimator (Correia, 2016), which extends the standard fixed effects approach by efficiently absorbing multiple high-dimensional sets of fixed effects (e.g. firm, sector, year and country simultaneously). This allows us to control flexibly for a wide range of unobserved heterogeneity, mitigating concerns about omitted variable bias in multidimensional settings (Guimarães and Portugal, 2010).

To further validate our findings, we used alternative proxies for heavy rain that captured its impact on both property and individuals. Specifically, we considered the occurrence of damages (Damages), injuries (Injured), fatalities (Killed) and a combined measure of any injuries or fatalities (People).

Finally, to ensure the consistency of our results, we conducted additional tests using subsamples. Specifically, given the high representation of Italian firms and firms operating in the construction and wholesale trade sectors in our data set, we excluded these groups separately from the sample. Subsequently, we removed influential observations that could disproportionately affected the estimates. These steps allow us to verify that our main findings were not driven by country-specific effects, sectoral concentration or outliers.

4.2 Empirical strategy: green policies and small and medium-sized enterprises' financial conditions and productivity

To test the effect of green policies on the relationship between heavy rain phenomena and financial conditions – and again productivity – we analyzed the following OLS model:

$$Finance_{i,j,t} = \beta_0 + \beta_1 Green_{j,t} + \beta_2 Controls_{i,t} + Year\,F.E. + \;Country\,F.E. + \;Industry\,F.E. + \;\varepsilon_{i,t} \tag{2}$$

where:

Finance$_{i,j,t}$ = proxy for a company's financial conditions or productivity by company *i* in year *t* in region *j*; and

Green$_{j,t}$ = proxy for the green index for country *i* in year *t*.

Specifically, we used two policy-based country-level indexes from Andres and Mealy (2023):

(1) The green complexity index (GCI): Reflects the country's specialization in green technologies and exports, indicating stronger green competitiveness.

(2) The brown lock-in index (BLI): Measures the degree to which a country's industrial structure is dependent on polluting sectors, indicating transition risk.

A greater GCI means greater green competitiveness, while a greater BLI means a greater transition risk.

Finally, $\text{Controls}_{j,t}$ is the same vector of control variables used in Model (1) for company i in year t in region j and year, country and industry fixed effects are included.

To ensure the reliability of our findings, we performed the same robustness checks described in Model (1). Specifically, we reestimated the specifications using GLS, robust regression and high-dimensional fixed effects. We also replicated the subsample analyses (excluding Italian firms, construction and wholesale trade sectors and influential observations) and adopted alternative environmental indicators derived from the Environmental Performance Index (Wolf *et al.*, 2022). Specifically, we considered PM2.5 exposure (PMd), a widely used proxy for air quality and environmental health; carbon monoxide exposure, another indicator of air quality; the methane emissions growth rate (CHA), capturing the trajectory of greenhouse gas emissions; and the nitrogen oxides (NOx) growth rate (NOx), which reflects industrial pollution, acid rain potential and broader ecosystem vitality.

Table 6 reports the descriptive statistics for all variables analyzed in this study. Appendix 2 provides the correlations between the variables analyzed, while Appendix 3 shows the values of the variance inflation factor (VIF) for the first regression Model (1). As reported, correlations were generally low; the VIF values ranged between 1.12 and 1.61, indicating that multicollinearity was not a problem.

5. Results

5.1 Financial outcomes

Table 7 presents the coefficients and their corresponding statistical significance for the specifications in Model (1). The dependent variable is the cash flow ratio for Columns 1–3, the gearing for Columns 4–6 and the liquidity ratio for Columns 7–9.

The adjusted R-squared reached 0.41. All the control variables present coefficients that are statistically significant at the 0.001*** level, which means that they have been correctly selected.

We identified some significant influence coefficients. The proxies for heavy rain events decreased firms' financial conditions by causing a significant decrease in the cash flow ratio and an increase in gearing. However, the effects of heavy rain events on liquidity were not clear: as reported, in Column 7 the coefficient is positive and statistically significant, while in Column 8 it is negative and significant. Finally, in Column 9 it is not significant. The fact that the effect on liquidity is influenced by the type of proxy used leads us to think that these events affect liquidity differently. A possible interpretation is that the presence of events increased liquidity following measures implemented by local or central authorities – measures that were not sufficient when rainfall was high.

The estimates in Table 7 reveal that heavy rain events significantly deteriorated SMEs' financial conditions, specifically in the decline in cash flow ratios, indicating that recurrent rainfall reduces internal financing capacity, consistent with Myers and Majluf's (1984) theory of financial constraints under adverse shocks. At the same time, gearing ratios increased, showing greater reliance on debt financing, a pattern aligned with Dunz *et al.* (2023), who highlighted that credit market frictions amplify climate shocks by forcing firms into riskier financing structures.

The effect on liquidity was less straightforward: coefficients varied across specifications, sometimes positive and sometimes negative, with one specification yielding insignificant results. This heterogeneity might reflect both firm-level precautionary behavior (cash hoarding during uncertainty) and external support measures such as government relief or emergency credit lines. Chenet *et al.* (2021) argue that public interventions can temporarily

Table 6. Descriptive statistics

Variable	Mean	Median	SD	Min.	Max.
R_Event	64.3040	48.00	58.4358	0.00	390.00
R_Amount	184,386.80	142,513.00	202,867.40	0.00	1,293,828
R_Length	1,408.60	822.00	1671.88	0.00	6,153
Age*	21.3143	19.00	11.7136	5.00	129.00
Size**	1,429.40	1021.62	1,645.55	3.5789	275,505.20
Roe	9.5742	8.64	52.7107	−999.02	982.71
Sales**	1,364.80	1205.84	1,606.03	0.00	270,764.20
Emp	12.1581	9.00	12.3517	0.00	306.00
Ltd	264,556.80	74366.46	623,969.50	0.00	2.48e + 07
IC	21.4319	3.65	78.5526	−100.00	999.67
CF	5.6777	3.98	8.6623	−99.82	99.82
Gear	192.9928	131.02	189.6625	0.00	999.8
Liq	1.1915	1.00	1.5087	0.00	88.94
Prod	25.0874	21.69	17.2005	0.00	99.99
Damages	0.7823	1.00	0.4127	0.00	1.00
Injured	0.3540	0.00	0.4782	0.00	1.00
Killed	0.0980	0.00	0.2973	0.00	1.00
People	0.3660	0.00	0.4817	0.00	1.00
Bli	107.4195	115.00	18.6709	47.00	133.00
Gcp	7.4882	3.00	10.4647	2.00	45.00
PMd	0.0354	0.0332	0.0329	0.0005	0.1870
Coe	0.1580	0.1719	0.0370	0.0016	0.2079
CHA	−0.2674	−0.2670	0.3768	−0.9897	0.8435
Nox	0.4896	0.5743	0.2344	0.0109	0.9805

Note(s): *in years; **in Thousand Euros
Source(s): Authors' own work

offset liquidity pressures, but our findings suggest that such measures are not uniformly effective.

Overall, Table 7 confirms *H1*: heavy rainfall events negatively affect SMEs' financial conditions. These findings extended prior evidence on catastrophic climate events (Nguyen and Wilson, 2018; Zhao *et al.*, 2024) by showing that even frequent, subcatastrophic rainfall events have measurable effects on SMEs' financing.

5.2 Productivity outcomes

Table 8 show the effects of heavy rain events on firms' productivity. The results document a clear negative relationship between rainfall and productivity. Across all specifications, coefficients are negative and highly significant, with an R^2 of approximately 0.7, confirming strong explanatory power.

The estimates confirmed that firm productivity consistently declined following heavy rainfall, with negative and highly significant coefficients. This underscores how even subcatastrophic, but recurrent weather shocks can generate operational disruptions – including infrastructure damage, transport delays and worker absenteeism – that erode SMEs' efficiency.

These results are consistent with Koetse and Rietveld (2009), who highlight the disruptive role of weather on transport systems, and Wu *et al.* (2023), who show that rainfall shocks reduce industrial activity by limiting logistics and worker availability.

Table 7. Influence of heavy rain events on firms' financial conditions

Variables	(1) CF	(2) CF	(3) CF	(4) GEAR	(5) GEAR	(6) GEAR	(7) LIQ	(8) LIQ	(9) LIQ
R_Event	−0.076*** (−5.49)			1.509*** (3.63)			0.003* (1.66)		
R_Amount		−0.007 (−1.36)			0.603*** (4.10)			−0.004*** (−5.17)	
R_Length			−0.016** (−2.39)			0.462** (2.30)			−0.001 (−1.58)
Age	−0.852*** (−29.48)	−0.852*** (−29.50)	−0.852*** (−29.50)	−17.00*** (−17.76)	−17.02*** (−17.78)	−16.99*** (−17.75)	0.042*** (11.02)	0.043*** (11.10)	0.042*** (11.04)
Size	3.308*** (96.48)	3.310*** (96.57)	3.310*** (96.56)	17.91*** (25.17)	17.93*** (25.20)	17.88*** (25.13)	−0.125*** (−36.14)	−0.126*** (−36.39)	−0.125*** (−36.25)
Roe	0.103*** (153.40)	0.103*** (153.40)	0.103*** (153.40)	−0.405*** (−17.91)	−0.405*** (−17.92)	−0.405*** (−17.92)	0.001*** (21.07)	0.001*** (21.09)	0.001*** (21.08)
Sales	−2.853*** (−59.37)	−2.856*** (−59.46)	−2.855*** (−59.43)	−22.08*** (−23.84)	−22.07*** (−23.84)	−22.04*** (−23.81)	−0.0242*** (−5.24)	−0.0236*** (−5.10)	−0.0239*** (−5.17)
Emp	−0.566*** (−21.53)	−0.566*** (−21.53)	−0.566*** (−21.53)	11.93*** (15.83)	11.94*** (15.84)	11.94*** (15.83)	0.0425*** (12.66)	0.0424*** (12.64)	0.0425*** (12.65)
Ltd	0.076*** (25.59)	0.076*** (25.57)	0.076*** (25.57)	8.180*** (84.47)	8.181*** (84.48)	8.181*** (84.48)	0.007*** (17.36)	0.007*** (17.36)	0.007*** (17.36)
IC	0.009*** (37.95)	0.009*** (37.93)	0.009*** (37.93)	−0.351*** (−56.79)	−0.351*** (−56.78)	−0.351*** (−56.77)	0.001*** (40.81)	0.001*** (40.86)	0.001*** (40.84)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	−0.594 (−0.95)	−0.801 (−1.28)	−0.783 (−1.25)	18.59 (0.47)	18.22 (0.47)	21.66 (0.55)	0.049 (0.15)	0.096 (0.29)	0.068 (0.20)
N	184,768	184,768	184,768	176,643	176,643	176,643	186,156	186,156	186,156
R^2	0.412	0.412	0.412	0.111	0.111	0.111	0.102	0.102	0.102
Adj. R^2	0.412	0.412	0.412	0.111	0.111	0.111	0.102	0.102	0.102

Note(s): This table presents the results of the OLS model. See the text and Appendix 1 for details on the definitions of the variables. In Columns 1–3 the dependent variable is cash flow ratio; in Columns 4–6 the dependent variable is gearing; in Columns 7–9 the dependent variable is liquidity ratio. All models include year, industry, country fixed effects. The sizes of the samples are not the same because of missing data. Coefficients are obtained after controlling for heteroskedasticity. The *t*-statistics are in parentheses ***p-value < 0.01; **p-value < 0.05 and *p-value < 0.1
Source(s): Authors' own work

Table 8. Influence of heavy rain events on firms' productivity

Variables	(1) PROD	(2) PROD	(3) PROD
R_Event	−0.117*** (−4.89)		
R_Amount		−0.095*** (−11.13)	
R_Length			−0.105*** (−9.04)
Age	1.406*** (28.72)	1.411*** (28.81)	1.407*** (28.73)
Size	−1.766*** (−39.33)	−1.775*** (−39.53)	−1.771*** (−39.44)
Roe	−0.029*** (−32.74)	−0.029*** (−32.72)	−0.029*** (−32.73)
Sales	−11.25*** (−160.03)	−11.25*** (−159.92)	−11.25*** (−160.00)
Emp	17.81*** (326.22)	17.80*** (326.27)	17.81*** (326.27)
Ltd	−0.058*** (−12.10)	−0.058*** (−12.09)	−0.058*** (−12.10)
IC	0.0003 (0.61)	0.0003 (0.63)	0.0003 (0.60)
Year F.E.	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Intercept	−19.53*** (−10.84)	−19.03*** (−10.55)	−19.41*** (−10.79)
N	180,718	180,718	180,718
R^2	0.695	0.695	0.695
Adj. R^2	0.695	0.695	0.695

Note(s): This table presents the results of the OLS model. See the text and Appendix 1 for details on the definitions of the variables. The dependent variable is productivity ratio. All models include year, industry, country fixed effects. Coefficients are obtained after controlling for heteroskedasticity. The *t*-statistics are in parentheses ****p*-value < 0.01
Source(s): Authors' own work

This evidence validated *H2* and suggests that operational disruptions – such as infrastructure damage, absenteeism and delays – translated directly into productivity losses. The novelty of our findings lies in showing that even recurrent rain events, rather than catastrophic disasters, have persistent negative effects on SMEs' efficiency.

5.3 *Robustness checks*

Table 9 presents the robustness checks of our main results using GLS (Columns 1 and 4), robust regression (Columns 2 and 5) and high-dimensional fixed effects (Columns 3 and 6). The results remain generally consistent with the baseline OLS estimates: heavy rain reduces cash flow and productivity. These findings demonstrate that the baseline results are not driven by model assumptions, heteroscedasticity or outliers. Consistency across specifications strengthens the support of *H1* and *H2* and the internal validity of our conclusions, in line with standard robustness practices in the climate-finance literature (Agoraki *et al.*, 2024; Zhao *et al.*, 2024).

Subsample tests reported in Table 10 exclude Italian firms (Columns 1 and 4), construction and wholesale trade industries (Columns 2 and 5) and influential observations (Columns 3 and 6). The results remain largely unchanged, indicating that our conclusions are not artifacts of country concentration, sectoral specialization or extreme data points. The persistence of these effects provides further support for *H1* and *H2* This reinforces the generalizability of our findings across countries and industries, despite the uneven distribution of firms in the data set.

Table 9. Robustness check. Influence of heavy rain events on firms' financial conditions and productivity

Variables	(1) CF	(2) CF	(3) CF	(4) PROD	(5) PROD	(6) PROD
R_Event	−0.099*** (−3.58)	−0.040*** (−5.10)	−0.076*** (−2.83)	−0.101* (−1.69)	0.037* (1.86)	−0.117** (−2.17)
Age	−0.745*** (−13.20)	−0.385*** (−23.09)	−0.852*** (−15.42)	2.094*** (17.46)	1.362*** (32.78)	1.406*** (13.12)
Size	2.536*** (46.98)	2.426*** (207.54)	3.308*** (53.46)	−1.402*** (−16.41)	−1.404*** (−48.09)	−1.766*** (−19.64)
Roe	0.091*** (107.96)	0.093*** (364.17)	0.103*** (112.22)	−0.029*** (−42.89)	−0.022*** (−35.31)	−0.029*** (−25.67)
Sales	−1.310*** (−17.68)	−2.564*** (−170.37)	−2.853*** (−35.16)	−8.270*** (−65.61)	−11.24*** (−297.28)	−11.25*** (−84.27)
Emp	0.033*** (9.45)	0.059*** (35.95)	0.076*** (15.20)	−0.017*** (−3.47)	−0.036*** (−8.79)	−0.058*** (−6.58)
Ltd	−0.954*** (−20.61)	0.091*** (6.96)	−0.566*** (−11.61)	10.65*** (90.15)	17.39*** (525.47)	17.81*** (154.36)
IC	0.009*** (32.59)	0.006*** (46.87)	0.009*** (26.91)	−0.003*** (−8.63)	−0.0001 (−0.40)	0.0003 (0.41)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.989 (0.93)	−2.877*** (−3.53)	0.952*** (9.10)	−14.89*** (−4.95)	−20.05*** (−9.97)	5.992*** (28.68)
N	184,768	184,768	184,768	180,718	180,718	180,718
R^2		0.560	0.412		0.743	0.695
Adj. R^2		0.560	0.412		0.743	0.695
R^2 (overall)	0.3998			0.6520		
R^2 (between)	0.4384			0.6883		

Note(s): This table presents the results of the GLS model (Column 1 and 4), robust regression (Column 2 and 5) and high-dimensional fixed effects (Column 3 and 6). See the text and Appendix for details on the definitions of the variables. In Columns 1–3 the dependent variable is cash flow ratio and in Columns 4–6 the dependent variable is productivity ratio. All models include year, industry, country fixed effects. The t-statistics are in parentheses ***p-value < 0.01; **p-value < 0.05 and *p-value < 0.1
Source(s): Authors' own work

Table 10. Subsample analyses. Influence of heavy rain events on firms' financial conditions and productivity

Variables	(1) CF	(2) CF	(3) CF	(4) PROD	(5) PROD	(6) PROD
R_Event	−0.047*** (−3.02)	−0.069*** (−3.75)	−0.065*** (−7.22)	−0.090*** (−3.41)	−0.165*** (−5.34)	−0.014 (−0.66)
Age	−0.999*** (−21.15)	−1.006*** (−27.50)	−0.548*** (−27.58)	0.563*** (7.47)	1.649*** (26.68)	1.395*** (34.47)
Size	3.873*** (76.13)	3.876*** (90.17)	3.087*** (157.96)	−1.533*** (−23.82)	−1.697*** (−29.66)	−1.624*** (−49.54)
Roe	0.101*** (105.33)	0.105*** (125.93)	0.102*** (207.67)	−0.023*** (−19.26)	−0.028*** (−25.87)	−0.025*** (−36.32)
Sales	−3.448*** (−47.90)	−3.164*** (−52.21)	−3.041*** (−118.34)	−12.99*** (−127.29)	−12.53*** (−141.31)	−11.50*** (−238.05)
Emp	0.169*** (23.66)	0.081*** (21.03)	0.069*** (34.65)	−0.113*** (−10.20)	−0.072*** (−11.62)	−0.041*** (−10.39)
Ltd	−0.650*** (−16.03)	−0.704*** (−22.12)	−0.112*** (−6.93)	18.12*** (228.31)	19.28*** (288.87)	18.01*** (426.72)
IC	0.009*** (20.39)	0.009*** (30.33)	0.008*** (44.78)	0.0002 (0.36)	0.001 (1.49)	−0.001*** (−4.26)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	−0.783 (−1.23)	−0.801 (−0.91)	−1.847*** (−11.35)	−18.68*** (−9.97)	−24.65*** (−16.81)	−20.18*** (−54.75)
N	93,126	120,399	174,101	88,863	117,648	171,897
R^2	0.452	0.426	0.524	0.719	0.699	0.757
Adj. R^2	0.451	0.426	0.524	0.719	0.699	0.757

Note(s): This table presents the results of the OLS model. See the text and Appendix 1 for details on the definitions of the variables. In Columns 1–3 the dependent variable is cash flow ratio and in Columns 4–6 the dependent variable is productivity ratio. All models include year, industry, country fixed effects. The sizes of the samples are not the same because of missing data. Coefficients are obtained after controlling for heteroskedasticity. The *t*-statistics are in parentheses
***p-value < 0.01
Source(s): Authors' own work

Table 11. Influence of heavy rain events on firms' financial conditions and productivity with other proxies

Variables	(1) CF	(2) CF	(3) CF	(4) CF	(5) PROD	(6) PROD	(7) PROD	(8) PROD
Damages	−0.091*** (−2.61)				−0.758*** (−12.35)			
Injured		−0.066** (−2.31)				−0.428*** (−8.62)		
Killed			−0.116*** (−2.69)				−1.805*** (−23.34)	
People				−0.093*** (−3.23)				−0.633*** (−12.74)
Age	−0.852*** (−29.49)	−0.854*** (−29.53)	−0.856*** (−29.55)	−0.855*** (−29.56)	1.410*** (28.79)	1.396*** (28.51)	1.350*** (27.56)	1.390*** (28.38)
Size	3.312*** (96.57)	3.312*** (96.58)	3.312*** (96.55)	3.312*** (96.58)	−1.755*** (−39.12)	−1.760*** (−39.23)	−1.747*** (−38.93)	−1.758*** (−39.20)
Roe	0.103*** (153.39)	0.103*** (153.39)	0.103*** (153.37)	0.103*** (153.39)	−0.029*** (−32.65)	−0.029*** (−32.75)	−0.029*** (−32.45)	−0.029*** (−32.74)
Sales	−2.858*** (−59.46)	−2.858*** (−59.47)	−2.859*** (−59.45)	−2.858*** (−59.47)	−11.27*** (−160.23)	−11.26*** (−160.15)	−11.30*** (−160.38)	−11.27*** (−160.22)
Emp	−0.566*** (−21.54)	−0.565*** (−21.51)	−0.564*** (−21.44)	−0.565*** (−21.50)	17.80*** (326.23)	17.81*** (326.30)	17.84*** (326.49)	17.81*** (326.45)
Ltd	0.076*** (25.52)	0.076*** (25.55)	0.076*** (25.54)	0.076*** (25.55)	−0.060*** (−12.34)	−0.059*** (−12.21)	−0.060*** (−12.50)	−0.060*** (−12.26)
IC	0.009*** (37.92)	0.009*** (37.94)	0.009*** (37.95)	0.009*** (37.94)	0.0002 (0.56)	0.0003 (0.63)	0.0003 (0.80)	0.0003 (0.65)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	−0.776 (−1.24)	−0.848 (−1.36)	−0.868 (−1.39)	−0.838 (−1.35)	−19.17*** (−10.66)	−19.82*** (−10.79)	−19.94*** (−11.12)	−19.74*** (−10.64)
N	184,768	184,768	184,768	184,768	180,718	180,718	180,718	180,718
R^2	0.412	0.412	0.412	0.412	0.695	0.695	0.696	0.695
Adj. R^2	0.412	0.412	0.412	0.412	0.695	0.695	0.695	0.695

Note(s): In Columns 1–4 the dependent variable is cash flow ratio; in Columns 5–8 the dependent variable is productivity ratio. All models include year, industry, country fixed effects. See the text and Appendix 1 for details on the definitions of the variables. The sizes of the samples are not the same because of missing data. Coefficients are obtained after controlling for heteroskedasticity. The *t*-statistics are in parentheses ***p-value < 0.01; **p-value < 0.05
Source(s): Authors' own work

Table 11 explores the effect of more severe rainfall events, proxied by damages (Columns 1 and 5), injuries (Columns 2 and 6), fatalities (Columns 3 and 7) and both injuries and fatalities (Columns 4 and 8).

The results show uniformly negative and significant coefficients for both cash flow and productivity. The stronger deterioration compared to baseline measures confirms that the severity of rainfall amplifies financial and operational vulnerability. In other words, it indicates that more severe events – those involving damages, injuries or fatalities – further intensify the negative effects on both cash flow and productivity. This amplifying role of severity strongly confirmed *H1* and *H2*.

5.4 Green policy effects

Table 12 reports the coefficients and their corresponding statistical significance for the specifications in Model (2). The dependent variable is the cash flow ratio for Columns 1 and 2, gearing for Columns 3 and 4 and the liquidity ratio for Columns 5 and 6.

All the control variables present coefficients that are statistically significant at the 0.001*** level, while the adjusted *R*-squared ranges from 0.1 to 0.4.

The results indicate that higher GCI scores improve firms' financial conditions by increasing cash flow and reducing gearing, while lower BLI values (indicating reduced dependence on polluting industries) are also associated with improved outcomes. These findings validated *H3* and demonstrate that institutional environments matter in shaping firms' financial resilience. The results resonate with Shi *et al.* (2022), who document that green financial reforms reduce debt costs for compliant firms, and with Toma and Stefanelli (2022), who highlight the role of banks in integrating climate risk into financial strategies. Our evidence extends these insights by showing that, in the European SME context, national green competitiveness provides a financial buffer against rainfall shocks.

However, the effect on liquidity was ambiguous: GCI was negatively associated with liquidity, while BLI was insignificant. This pattern suggests that while green policies strengthen structural financial resilience, they do not necessarily ease short-term liquidity pressures. Similar ambiguities have been reported by Chenet *et al.* (2021), who note that financial resilience to climate shocks is uneven across dimensions.

Overall, Table 12 supports *H3* and demonstrates that greener institutional environments mitigate the adverse financial impact of heavy rain events, reinforcing the argument that climate policy and financial stability are interdependent.

In Table 13, we examine the impact of green policies on firm productivity. Both the GCI and the BLI show a negative and statistically significant association with firm efficiency. This implies that, although green policies strengthen financial resilience, they may also generate transitional adjustment costs that reduce productivity in the short run.

Unlike financial indicators, the relationship between green policy indexes and productivity is ambivalent. However, although green policies strengthen financial resilience, they may impose short-term compliance and transition costs that reduce firms' operational efficiency. This supports *H4* of an immediate trade-off between financial stability and productivity in the context of green transition policies.

Table 14 reports robustness tests for the green policy regressions using GLS (Columns 1 and 4), robust regression (Columns 2 and 5) and high-dimensional fixed effects (Columns 3 and 6). The results confirm the main findings: green policies improve financial conditions and reduce productivity. The consistency across specifications indicates that our conclusions regarding green policy moderation are robust to model choice. The stability of the results further supports *H3* and *H4*.

Table 12. Influence of green indexes on firms' financial conditions

Variables	(1) CF	(2) CF	(3) GEAR	(4) GEAR	(5) LIQ	(6) LIQ
Gci	0.597*** (3.01)		−64.27*** (−10.52)		−0.249*** (−8.86)	
Bli		−1.891*** (−2.67)		134.3*** (6.67)		0.049 (0.55)
Age	−0.859*** (−30.50)	−0.859*** (−30.51)	−18.52*** (−20.09)	−18.50*** (−20.07)	0.0423*** (11.16)	0.042*** (11.17)
Size	3.330*** (100.02)	3.330*** (100.01)	17.85*** (25.91)	17.85*** (25.92)	−0.129*** (−38.03)	−0.129*** (−38.01)
Roe	0.104*** (158.26)	0.104*** (158.26)	−0.408*** (−18.40)	−0.409*** (−18.47)	0.001*** (20.78)	0.001*** (20.65)
Sales	−2.865*** (−61.47)	−2.864*** (−61.46)	−22.09*** (−24.65)	−22.14*** (−24.70)	−0.026*** (−5.63)	−0.026*** (−5.65)
Emp	−0.562*** (−21.92)	−0.561*** (−21.89)	11.05*** (15.10)	10.98*** (15.00)	0.033*** (9.92)	0.033*** (9.88)
Ltd	0.078*** (26.40)	0.078*** (26.39)	8.260*** (86.06)	8.258*** (86.02)	0.008*** (19.86)	0.007*** (19.78)
IC	0.009*** (38.51)	0.009*** (38.50)	−0.354*** (−57.72)	−0.354*** (−57.67)	0.001*** (41.28)	0.001*** (41.28)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	−0.871 (−1.39)	−0.938 (−1.50)	27.58 (0.68)	32.69 (0.84)	0.112 (0.34)	0.116 (0.35)
N	196,304	196,304	187,778	187,778	197,724	197,724
R^2	0.413	0.413	0.111	0.110	0.103	0.103
Adj. R^2	0.413	0.413	0.110	0.110	0.103	0.102

Note(s): In Columns 1 and 2 the dependent variable is cash flow ratio; in Columns 3 and 4 the dependent variable is gearing; in Columns 5 and 6 the dependent variable is liquidity ratio. All models include year, industry, country fixed effects. See the text and Appendix 1 for details on the definitions of the variables. The sizes of the samples are not the same because of missing data. Coefficients are obtained after controlling for heteroskedasticity. The *t*-statistics are in parentheses
***p-value < 0.01
Source(s): Authors' own work

Table 13. Influence of green indexes on firms' productivity

Variables	(1) PROD	(2) PROD
Gci	−0.918*** (−2.74)	
Bli		−2.499** (−2.16)
Age	1.350*** (28.66)	1.349*** (28.65)
Size	−1.716*** (−39.71)	−1.715*** (−39.69)
Roe	−0.030*** (−34.22)	−0.030*** (−34.27)
Sales	−11.38*** (−167.77)	−11.38*** (−167.76)
Emp	17.79*** (337.65)	17.79*** (337.66)
Ltd	−0.059*** (−12.29)	−0.060*** (−12.34)
IC	0.0003 (0.62)	0.0003 (0.62)
Year F.E.	Yes	Yes
Country F.E.	Yes	Yes
Industry F.E.	Yes	Yes
Intercept	−19.80*** (−10.94)	−19.87*** (−11.00)
N	192,264	192,264
R^2	0.698	0.698
Adj. R^2	0.697	0.697

Note(s): The dependent variable is productivity ratio. All models include year, industry, country fixed effects. See the text and Appendix 1 for details on the definitions of the variables. Coefficients are obtained after controlling for heteroskedasticity. The *t*-statistics are in parentheses ***p-value < 0.01; **p-value < 0.05
Source(s): Authors' own work

Table 15 shows the subsample robustness of the green policy models. Excluding country-specific (Columns 1 and 4), sectoral groups (Columns 2 and 5) or influential observations (Columns 3 and 6) does not alter the main results, confirming that the moderating role of green indexes is not driven by sample composition. This external validity of our findings across diverse European contexts reinforces the confirmation of *H3* and *H4*.

Table 16 presents the results obtained with alternative environmental indicators derived from the Wolf *et al.* (2022). The results show that higher levels of PM2.5, Co., methane and NOx are significantly associated with worse financial conditions. These findings reinforce the conclusion that firms located in more polluted environments or in economies where environmental performance is weaker, face additional financial burdens. This interpretation is consistent with Bolton and Kacperczyk (2021), who documented higher financing costs for environmentally risky firms, and with Shi *et al.* (2022), who showed that poor environmental governance amplifies financing constraints.

In contrast, in three of our four specifications, environmental degradation appears to correlate with higher productivity, possibly because firms in heavily polluting or carbon-intensive industries maintain short-term efficiency gains at the expense of environmental sustainability. This trade-off echoes prior evidence that transition costs and compliance requirements can temporarily reduce efficiency while fostering long-term resilience (Shi *et al.*, 2022; Zhao *et al.*, 2024).

Overall, the results in Table 16 confirm the robustness of the main findings. By using alternative environmental proxies, we provided further evidence that environmental quality and pollution trends materially shape firms' financial conditions. The results on productivity highlight a persistent tension: While greener institutional and environmental settings foster financial resilience, they may temporarily constrain operational efficiency, especially for

Table 14. Robustness check. Influence of heavy rain events on firms' financial conditions and productivity

Variables	(1) CF	(2) CF	(3) CF	(4) PROD	(5) PROD	(6) PROD
Gci	0.584*** (4.37)	0.433*** (3.76)	0.597*** (4.18)	−0.763*** (−5.08)	−0.456 (−1.63)	−0.918*** (−5.12)
Age	−0.747*** (−13.51)	−0.398*** (−24.39)	−0.859*** (−15.97)	2.014*** (17.52)	1.311*** (32.80)	1.350*** (13.11)
Size	2.545*** (48.43)	2.464*** (215.06)	3.330*** (55.52)	−1.307*** (−15.86)	−1.367*** (−48.63)	−1.716*** (−19.83)
Roe	0.092*** (111.26)	0.094*** (374.09)	0.104*** (115.71)	−0.029*** (−44.66)	−0.023*** (−36.74)	−0.030*** (−26.85)
Sales	−1.293*** (−17.70)	−2.607*** (−176.25)	−2.865*** (−36.37)	−8.461*** (−68.45)	−11.36*** (−311.36)	−11.38*** (−88.17)
Emp	0.034*** (9.89)	0.060*** (36.29)	0.078*** (15.71)	−0.018*** (−3.73)	−0.036*** (−8.87)	−0.059*** (−6.69)
Ltd	−0.960*** (−21.01)	0.100*** (7.73)	−0.562*** (−11.82)	10.80*** (93.78)	17.35*** (542.93)	17.79*** (159.92)
IC	0.010*** (33.37)	0.007*** (47.36)	0.009*** (27.28)	−0.003*** (−8.76)	−0.0002 (−0.46)	0.0003 (0.41)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.646 (0.60)	−2.890*** (−3.52)	0.733*** (20.01)	−15.60*** (−5.20)	−19.72*** (−9.89)	5.286*** (84.15)
N	196,304	196,304	196,304	192,264	192,264	192,264
R^2		0.561	0.413		0.745	0.698
Adj. R^2		0.561	0.413		0.745	0.697
R^2 (overall)	0.4005			0.6570		
R^2 (between)	0.4363			0.6934		

Note(s): This table presents the results of the GLS model (Column 1 and 4), robust regression (Column 2 and 5) and high-dimensional fixed effects (Column 3 and 6). See the text and Appendix 1 for details on the definitions of the variables. In Columns 1–3 the dependent variable is cash flow ratio and in Columns 4–6 the dependent variable is productivity ratio. All models include year, industry, country fixed effects. The *t*-statistics are in parentheses ***p-value < 0.01
Source(s): Authors' own work

Table 15. Subsample analyses. Influence of heavy rain events on firms' financial conditions and productivity

Variables	(1) CF	(2) CF	(3) CF	(4) PROD	(5) PROD	(6) PROD
Gci	0.490* (1.93)	0.667** (2.53)	0.590*** (4.55)	1.415*** (3.58)	−0.710* (−1.67)	−0.742*** (−2.64)
Age	−0.992*** (−22.45)	−1.018*** (−28.61)	−0.555*** (−28.59)	0.560*** (8.13)	1.558*** (26.35)	1.350*** (34.71)
Size	3.839*** (80.04)	3.894*** (93.69)	3.113*** (163.41)	−1.456*** (−24.35)	−1.652*** (−30.28)	−1.574*** (−49.94)
Roe	0.103*** (112.15)	0.106*** (130.44)	0.102*** (214.24)	−0.025*** (−21.74)	−0.029*** (−27.42)	−0.025*** (−38.29)
Sales	−3.407*** (−50.45)	−3.170*** (−54.20)	−3.050*** (−122.15)	−13.05*** (−138.40)	−12.62*** (−148.85)	−11.64*** (−250.28)
Emp	0.174*** (25.29)	0.082*** (21.74)	0.071*** (35.75)	−0.113*** (−10.55)	−0.072*** (−11.69)	−0.042*** (−10.66)
Ltd	−0.640*** (−16.71)	−0.702*** (−22.62)	−0.111*** (−7.01)	18.07*** (245.04)	19.24*** (299.71)	17.98*** (441.07)
IC	0.009*** (21.58)	0.009*** (30.79)	0.008*** (45.91)	0.0003 (0.50)	0.001 (1.60)	−0.001*** (−4.30)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	−1.065* (−1.67)	−1.070 (−1.21)	−1.971*** (−15.20)	−18.89*** (−10.08)	−25.05*** (−17.27)	−20.67*** (−80.75)
N	104,662	128,818	185,030	100,409	126,073	182,923
R^2	0.448	0.426	0.524	0.722	0.702	0.759
Adj. R^2	0.448	0.426	0.524	0.722	0.702	0.759

Note(s): This table presents the results of the OLS model. See the text and Appendix 1 for details on the definitions of the variables. In Columns 1–3 the dependent variable is cash flow ratio and in Columns 4–6 the dependent variable is productivity ratio. All models include year, industry, country fixed effects. The sizes of the samples are not the same because of missing data. Coefficients are obtained after controlling for heteroskedasticity. The *t*-statistics are in parentheses
***p-value < 0.01; **p-value < 0.05 and *p-value < 0.1
Source(s): Authors' own work

Table 16. Influence of heavy rain events on firms' financial conditions and productivity with other proxies

Variables	(1) CF	(2) CF	(3) CF	(4) CF	(5) PROD	(6) PROD	(7) PROD	(8) PROD
PMd	−5.992*** (−3.61)				8.225*** (3.23)			
COe		−2.339*** (−2.87)				−0.763 (−0.66)		
CHA			−0.161*** (−3.50)				0.737*** (9.44)	
NOx				−0.040 (−0.28)				1.361*** (5.98)
Age	−0.860*** (−30.52)	−0.859*** (−30.50)	−0.859*** (−30.51)	−0.859*** (−30.50)	1.351*** (28.67)	1.350*** (28.66)	1.351*** (28.69)	1.349*** (28.65)
Size	3.331*** (100.04)	3.330*** (100.01)	3.330*** (100.02)	3.330*** (100.01)	−1.716*** (−39.71)	−1.716*** (−39.70)	−1.717*** (−39.75)	−1.717*** (−39.72)
Roe	0.104*** (158.27)	0.104*** (158.26)	0.104*** (158.21)	0.104*** (158.25)	−0.029*** (−34.22)	−0.030*** (−34.25)	−0.029*** (−34.09)	−0.029*** (−34.16)
Sales	−2.863*** (−61.43)	−2.864*** (−61.46)	−2.865*** (−61.46)	−2.865*** (−61.47)	−11.38*** (−167.78)	−11.38*** (−167.77)	−11.38*** (−167.81)	−11.38*** (−167.78)
Empl	−0.561*** (−21.89)	−0.561*** (−21.90)	−0.562*** (−21.91)	−0.562*** (−21.91)	17.79*** (337.63)	17.79*** (337.63)	17.79*** (337.69)	17.79*** (337.62)
Ltd	0.078*** (26.33)	0.078*** (26.44)	0.078*** (26.36)	0.078*** (26.40)	−0.059*** (−12.23)	−0.059*** (−12.32)	−0.058*** (−12.16)	−0.058*** (−12.15)
IC	0.009*** (38.50)	0.009*** (38.49)	0.009*** (38.49)	0.009*** (38.50)	0.0003 (0.63)	0.0003 (0.62)	0.0003 (0.65)	0.003 (0.63)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	−0.675 (−1.07)	−0.442 (−0.69)	−0.948 (−1.51)	−0.864 (−1.38)	−20.07*** (−11.09)	−19.65*** (−10.81)	−19.45*** (−10.77)	−20.17*** (−11.08)
N	196,304	196,304	196,304	196,304	192,264	192,264	192,264	192,264
R^2	0.413	0.413	0.413	0.413	0.698	0.697	0.698	0.698
Adj. R^2	0.413	0.413	0.413	0.413	0.697	0.697	0.698	0.697

Note(s): In Columns 1–4 the dependent variable is cash flow ratio; in Columns 5–8 the dependent variable is productivity ratio. All models include year, industry, country fixed effects. See the text and Appendix 1 for details on the definitions of the variables. The sizes of the samples are not the same because of missing data. Coefficients are obtained after controlling for heteroskedasticity. The *t*-statistics are in parentheses ***p-value < 0.01
Source(s): Authors' own work

SMEs with a limited capacity to absorb compliance costs. The partial trade-off between financial conditions and productivity outcomes is consistent with transitional effects, confirming *H3* and *H4*.

Taken together, the results across Tables 7–16 provide consistent evidence that heavy rainfall events deteriorate SMEs' financial conditions and productivity (*H1* and *H2*), while stronger green policy environments mitigate these adverse financial effects but introduce short-term productivity costs (*H3* and *H4*). This coherent set of findings underscores both the vulnerability of SMEs to recurrent climate shocks and the critical, though complex, role of green policies in shaping financial resilience.

6. Conclusions

In this paper, we analyzed the effects of heavy rain events on the financing of a sample of 49,809 European SMEs. Starting with data from the ESWD, we used different proxies for heavy rain events that measure the presence of heavy rain, the amount and the length of rain and their impact on things and people. Through quantitative analyses, we investigated how these proxies affect the financial outcomes and profitability of firms located in the same region.

The results demonstrate that heavy rains deteriorate firms' financial conditions by decreasing the cash flow ratio and increasing gearing. However, the effects on liquidity remain ambiguous. Our results indicated that SMEs that experienced extreme weather events presented worse productivity.

Our results contribute to the understanding of climate change's impact on firms' financing and productivity and are robust to a series of alternative tests, subsample analyses and proxies.

In this paper, we also tested whether green policies could help firms mitigate their worse financial conditions. We found that green measures led to improvements in firms' cash flow ratio and gearing, while the effect on liquidity was negative. However, these measures deteriorated firms' productivity.

The findings of this study offer a range of implications that are relevant to both academic and applied fields, such as public policy and entrepreneurial finance. These implications are best understood in light of the theoretical framework and hypotheses, which posited that heavy rain events function as exogenous shocks that deteriorate firms' financial and operational conditions (*H1* and *H2*), while greener institutional environments improve SMEs' financial resilience (*H3*) but may reduce their productivity in the short term due to transitional costs (*H4*).

From a theoretical standpoint, the results provide empirical support for financial theories emphasizing the vulnerability of SMEs to external shocks, particularly those lacking diversified funding sources or structural resilience (Myers and Majluf, 1984; Abdulsaleh and Worthington, 2013). The observed deterioration in cash flow and increase in gearing following rainfall events confirm that climate shocks disrupt internal financing capacity and induce greater reliance on debt, especially among SMEs with limited access to equity markets. These dynamics are consistent with findings in the literature that have shown how climate risk can increase credit constraints and tighten financing conditions (Bolton and Kacperczyk, 2021; Dunz *et al.*, 2023).

The results also contribute to the operational literature on climate and firm productivity (Koetse and Rietveld, 2009; Wu *et al.*, 2023), reinforcing the view that even subcatastrophic, frequent weather events can lower efficiency by disrupting logistics, damaging physical assets and reducing labor availability. This extends previous research that has focused on temperature or single-event shocks, by emphasizing the cumulative effects of precipitation-based disruptions on smaller, regionally embedded firms.

Importantly, the evidence regarding liquidity presents a more nuanced picture. In some cases, liquidity ratios improved postrainfall, suggesting the possible effect of public support mechanisms or precautionary cash accumulation by firms. This aligns with observations that public responses to extreme weather – such as financial relief or temporary credit facilities – may temporarily offset liquidity pressures (Chenet *et al.*, 2021). However, the heterogeneity of outcomes across proxies indicates that liquidity remains a complex and context-dependent dimension of climate resilience.

The role of national green policies, captured through the GCI and the BLI, proves to be particularly instructive. Firms operating in greener policy environments exhibit improved financial metrics following heavy rain events – specifically higher cash flow and lower gearing – suggesting that policy-led environmental capacity may indeed buffer the adverse financial consequences of climate shocks. This empirical result validates *H3* and reinforces institutionalist perspectives in climate finance, which argue that the broader regulatory and technological context significantly shapes firm-level exposure and adaptation (Toma and Stefanelli, 2022; Andres and Mealy, 2023).

However, the results regarding productivity are more ambivalent. While green policy indicators correlate positively with financial stability, they are also associated with reduced productivity in several model specifications. This supports *H4*, which anticipated a short-term trade-off between environmental compliance and operational efficiency. The findings resonate with work by Shi *et al.* (2022) and Zhao *et al.* (2024), who reported that green financial regulations, while critical for long-term resilience, may impose adjustment costs that temporarily hinder output, particularly for resource-constrained firms.

These insights are also of practical relevance. Entrepreneurs and SME managers should recognize that recurring weather events are not isolated anomalies but structural features of a changing climate. As such, building resilience – both financial and operational – must become a central strategic concern. Investing in liquidity management, diversification of funding and alignment with national environmental strategies could not only enhance climate preparedness but also improve access to ESG-sensitive finance in the long run.

For policymakers, the results underscore the importance of viewing climate adaptation and green transition as complementary goals. Rainfall-induced financial stress on firms is not just an environmental issue but also an economic and financial stability concern. While green policies help reduce firms' vulnerability, they may also create productivity pressures if not adequately supported. Therefore, a dual approach is needed: one that strengthens firms' environmental resilience while simultaneously supporting innovation, productivity-enhancing investments and transitional financing tools for SMEs.

6.1 Limitations and directions for further research

This study is not without limitations, which also paves the way for future research avenues. First, the analysis focused exclusively on SMEs across 27 EU countries. While this choice was justified by data availability and the economic relevance of SMEs, it limited the generalizability of the results to larger firms or to economies outside Europe. Future studies could extend the analysis to large corporations, listed firms and non-European contexts, to explore whether firm size, market structure or institutional environments condition the effects of climate shocks on financing and productivity.

Second, the study examined a single type of climate event – heavy rainfall – while other recurrent extreme weather phenomena (such as droughts, heatwaves, hailstorms, windstorms, avalanches or floods) may generate distinct financial and operational impacts. Comparative research across different event types would help to differentiate the mechanisms through which climate shocks propagate into firm-level outcomes.

Third, our reliance on quantitative data constrains our ability to capture firm-level heterogeneity in adaptation strategies. Future research could complement econometric approaches with survey-based or qualitative case studies, providing deeper insights into how

SMEs perceive climate risks, access emergency relief or redesign business models in response to recurrent shocks.

Fourth, although the inclusion of green policy indexes (GCI and BLI) and additional environmental proxies (PM2.5, Co., methane and NOx) broadens the institutional perspective, these indicators remain country-level aggregates. They cannot capture within-country differences or the role of regional and local policy interventions, which are often decisive in shaping firms' resilience. Therefore, further work could use regional green policy measures or study sector-specific regulations to provide a more granular understanding.

Fifth, our findings suggest an ambiguous role of liquidity and a possible trade-off between financial stability and productivity in the context of green policies. Future studies could investigate these dynamics using longitudinal data to assess whether the observed short-term productivity losses are offset by long-run efficiency gains or whether they vary systematically across industries with different capital intensities and environmental exposures.

Finally, given the increasing relevance of financial intermediation and ESG-sensitive investment, an important direction for future research lies in exploring how banks, investors and insurance markets incorporate frequent weather shocks into credit risk assessments, lending practices and insurance coverage. Such studies could clarify how climate risk is transmitted from the real economy to the financial sector and how institutional innovation (e.g., green bonds, climate insurance schemes and blended finance instruments) may mitigate this propagation process.

Taken together, these directions highlight the need for multicountry, multimethod and multilevel analyses to deepen our understanding of how recurrent climate shocks affect firms and how green policy frameworks can balance resilience, sustainability and productivity in the long run.

Notes

[1.] Countable events, that are recorded on a per event basis, are as follows: lesser whirlwinds, funnel clouds, gust front vortices, tornadoes or waterspouts, avalanches and damaging lightning strikes. Uncountable events, that are recorded per observation, are: severe hailfall, severe wind gust, heavy rain, heavy snowfall and ice accumulations.

[2.] Extreme rainfall on consecutive days is reported separately in at most 24-hour periods.

[3.] To reference countries' regions for statistical purposes, the EU has developed a classification known as NUTS (Nomenclature of Territorial Units for Statistics). NUTS divides each EU country into three levels:

NUTS 1: major socioeconomic regions, with a population from 3,000,000 to 7,000,000

NUTS 2: basic regions (for regional policies) with a population from 800,000 to 3,000,000

NUTS 3: small regions (for specific diagnoses) with a population from 150,000 to 800,000

The NUTS 2024 classification is valid from January 1, 2024. It lists 92 regions at NUTS 1, 244 regions at NUTS 2 and 1 165 regions at NUTS3 level.

NUTS is used for collecting, developing and harmonizing European regional statistics, carrying out socioeconomic analyses of the regions and framing of EU regional policies. Source: https://ec.europa.eu/eurostat

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Further reading

Orbis Bureau Van Dijk Database (2026), available at: www.bvdinfo.com

Appendix 1

Table A1. Variable source and definition

Variable	Definition	Source
R_Event	Natural logarithm of total heavy rain events calculated as ln (1 + number of heavy rain events). Heavy rain is defined as rain falling in such large amounts, that significant damage is caused or no damage is known, but exceptionally high. Precipitation amounts have been observed within a period of at most 24 h. Extreme rainfall on consecutive days must be reported separately in at most 24-hour periods	ESWD
R_Amount	Precipitation amount float opt in millimetres	ESWD
R_Length	Duration of accumulation float opt in hours	ESWD
Damages	Dummy variable equal to 1 if there is any property, crop or forest damage caused by heavy rain events and equal to 0 otherwise	ESWD
Injured	Dummy variable equal to 1 if there are any people injured by heavy rain events and equal to 0 otherwise	ESWD
Killed	Dummy variable equal to 1 if there are any people killed by heavy rain events and equal to 0 otherwise	ESWD
People	Dummy variable equal to 1 if there are any people injured or killed by heavy rain events and equal to 0 otherwise	ESWD
Age	Natural logarithm of the age of the company, calculated as ln [1 + (year of the analysis – year of incorporation)]	Orbis bureau van Dijk
Size	Natural logarithm of total assets calculated as ln (1 + total assets). Data on total assets are collected in euros	Orbis bureau van Dijk
Sales	Natural logarithm of revenues from sales, calculated as ln (1 + sales) Data on sales are collected in euros	Orbis bureau van Dijk
Roe	Return on equity (ROE) using Net income, in percentage, calculated as (Net income/Shareholder funds) * 100	Orbis bureau van Dijk
Emp	Natural logarithm of the total number of employees of the company, calculated as ln (1 + employees)	Orbis bureau van Dijk
Ltd	Natural logarithm of the long-term debt of the company, calculated as ln (1 + long term debt)	Orbis bureau van Dijk
IC	Interest cover calculated as operating profit/interest paid	Orbis bureau van Dijk
CF	Cash flow/Operating revenue, in percentage, calculated as (Cash flow/Operating revenue) * 100	Orbis bureau van Dijk
Gear	Gearing, in percentage, calculated as (noncurrent liabilities + Loans)/Shareholders funds) * 100	Orbis bureau van Dijk
Liq	Liquidity ratio calculated as (current assets – Stocks)/current liabilities	Orbis bureau van Dijk
Prod	Productivity, in percentage, calculated as (Cost of employees/Operating revenue) * 100	Orbis bureau van Dijk
Gci	Green complexity index. It measures countries' green competitiveness based on the number and PCI of green products they are competitive in	Green transition navigator
Bli	Brown lock-in index. It measures a country's transition risk, based on the share of low-complexity brown products in its export basket	Green transition navigator

(*continued*)

Table A1. Continued

Variable	Definition	Source
PMd	PM2.5 exposure calculated using the number of age-standardized disability-adjusted life-years lost due to exposure to fine air particulate matter smaller than 2.5 micrometers (PM2.5) It is commonly used as a measure of ambient particulate matter pollution, air quality and environmental health	Environmental performance index
COe	Carbon monoxide exposure. It is measured using the population-weighted annual average concentration of the air pollutant at ground level It is commonly used as a measure of air quality and environmental health	Environmental performance index
CHA	Methane emissions growth rate. It is calculated as the average annual rate of increase or decrease in raw methane emissions. It is then adjusted for economic trends to isolate change due to policy rather than economic fluctuation It is commonly used as a measure of methane intensity trend and climate change mitigation	Environmental performance index
NOx	Nitrogen monoxide and nitrogen dioxide (NOx) growth rate. It is calculated as the average annual rate of increase or decrease in NOX. It is then adjusted for economic trends to isolate change due to policy rather than economic fluctuation It is commonly used as a measure of pollution emissions and ecosystem vitality	Environmental performance index

Source(s): Authors' own work

Appendix 2

Table A2. Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
R_Event	1																	
R_Amount	0.594	1																
R_Length	0.934	0.729	1															
Damages	0.339	0.28	0.316	1														
Injured	0.47	0.765	0.581	0.361	1													
Killed	0.215	0.368	0.287	0.178	0.361	1												
People	0.477	0.758	0.589	0.371	0.976	0.429	1											
Age	0.049	0.024	0.047	−0.015	0.017	−0.035	0.014	1										
Size	0.068	0.032	0.082	−0.025	0.047	0.012	0.05	0.299	1									
Sales	0.029	−0.023	0.016	0.027	−0.018	0.001	−0.019	−0.118	−0.111	1								
Emp	0.044	0.022	0.035	0	−0.004	−0.014	−0.001	0.16	0.376	0.077	1							
Roe	−0.256	0.021	−0.223	−0.01	−0.048	0.017	−0.032	0.039	0.178	−0.068	0.065	1						
Ltd	−0.154	−0.061	−0.136	−0.044	−0.076	−0.014	−0.071	0.057	0.111	−0.016	0.262	0.115	1					
IC	0.062	0.017	0.05	0.013	−0.009	−0.006	−0.013	−0.045	−0.082	0.252	0.026	−0.188	−0.034	1				
CF	−0.03	−0.079	−0.053	0.034	−0.065	−0.029	−0.066	−0.052	0.203	0.431	−0.133	0.099	−0.005	0.134	1			
Gear	0.036	0.012	0.038	−0.007	0.018	−0.014	0.018	0.007	0.123	−0.116	−0.035	0.185	0.028	−0.169	−0.052	1		
Liq	−0.027	0.003	−0.006	−0.056	0.033	−0.007	0.028	0.01	−0.105	0.076	−0.05	−0.033	0.066	0.126	0.078	−0.05	1	
Prod	−0.095	−0.015	−0.097	−0.013	−0.01	−0.017	−0.013	0.033	−0.137	−0.107	−0.205	0.036	0.582	−0.014	−0.041	0.052	0.165	1

Source(s): Authors' own work

Appendix 3

Table A3. VIF

Variable	VIF
Age	1.19
Size	1.48
Sales	1.12
Emp	1.57
Roe	1.51
Ltd	1.61
IC	1.15

Note(s): Values are referred to the model in Table 7 – column 1
Source(s): Authors' own work

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