Climate Shocks and Corporate Resilience: Extreme Weather Events and EU Solidarity Funds for Adaptation and Mitigation

Nico Rosamilia[§]
Politecnico di Milano, School of Management[‡]

Abstract

I study the effects of Extreme Weather Events (EWE henceforth) on the corporate value of European Small and Medium-sized Enterprises (SMEs hereafter). Additionally, I evaluate whether firms insure against natural disasters. Indeed, I study the effects of the European Solidarity Funds trying to uncover the effectiveness of these funds for climate change adaptation and risk prevention. The existing literature extensively studies the interactions between climate events and financial markets. The empirical literature mainly focuses on the pricing of climate risks for different asset classes. Furthermore, it explores the propagation and amplification of shocks along the supply chain. Conversely, this study contemplates the effect of a broader set of events on the performance of European SMEs investigating the effectiveness of the European Solidarity Funds. My first estimate proposes a difference-in-differences (DiD) strategy with the weather events representing the exogenous shock for the treated group. I should consider that there might be a spatial correlation in the treatment. Additionally, I propose a regression model (Lasso, for variable selection and regularization) to identify the most important variables in determining the allocation of funds by the European Union.

Keywords: Climate finance, European funds, Value of firms.
JEL Classification: L25, G32, Q54.

[§]Email: nico.rosamilia@polimi.it
[‡]Via Raffaele Lambruschini, 20156 Milano, Italia

1 Introduction

The increasing frequency and intensity of EWE pose significant challenges to economies worldwide. In Europe, where SMEs play a crucial role in economic growth and employment, the financial resilience of these firms is increasingly vulnerable to climate-related disruptions. Extreme weather conditions such as droughts, floods, storms, and wildfires not only threaten the operational capacities of firms but also their long-term financial stability. Understanding how SMEs cope with these shocks and whether existing institutional mechanisms, such as the European Union's Solidarity Funds, effectively mitigate the financial impacts of these events is an urgent and underexplored topic.

Existing literature has thoroughly examined the intersections between climate events and financial markets, particularly through the lens of asset pricing. For instance, Hong et al. (2019) analyze how the prices of food stocks efficiently discount the risks associated with rising global temperatures, such as droughts. Similarly, Giglio et al. (2021) explore how climate risks are priced across various asset classes including real estate, equities, and fixed-income securities, providing insights on constructing portfolios to hedge against climate risk. Additionally, Alok et al. (2020) investigate the behavioral biases of managers who underweight disaster-zone stocks, suggesting that proximity to disaster influences risk perception. Alekseev et al. (2022) further demonstrate that mutual fund holdings shift when advisers experience extreme local weather events, affecting their beliefs about climate risks and portfolio construction.

While much of the focus has been on asset pricing, the impact of climate risks on firm performance has also garnered attention. H. H. Huang et al. (2018) examine the consequences of climate-related risks on corporate financing choices, revealing that firms exposed to such risks adjust their capital structure to account for potential disruptions. This growing body of literature underscores the importance of climate risks on financial decision-making but primarily focuses on larger corporations or financial markets.

On the operational side, supply chain dynamics have been a focal point of research. Altay and Ramirez (2010) highlight how the impact of windstorms and floods differs from that of earthquakes, with the specific position of the firm in the supply chain influencing the degree of disruption. Barrot and Sauvagnat (2016) further show that firm-level idiosyncratic shocks propagate through production networks, while Carvalho et al. (2021) quantify how input-output linkages amplify shocks, such as those observed following the 2011 Great East Japan Earthquake. These studies reveal the complex ripple effects that climate shocks can have across industries and geographies.

However, despite this extensive literature on asset pricing and supply chain dynamics, the specific vulnerabilities of SMEs to EWEs have been less studied. SMEs, often lacking the financial buffers and diversification strategies available to larger firms, are particularly susceptible to climate-induced disruptions. This paper seeks to address this gap by focusing on how EWEs affect the financial performance and resilience of European SMEs. Moreover, I evaluate the role of the European Union Solidarity Fund (EUSF) in aiding recovery and fostering climate adaptation among these firms.

The EUSF, established to provide financial support to member states after natural disasters, plays a critical role in compensating for damage and funding recovery efforts. Yet, the effectiveness of these funds in helping businesses, particularly SMEs, to adapt and recover from climate shocks remains unclear. This paper investigates whether EUSF allocations have had measurable effects in mitigating the financial impacts of EWEs and promoting long-term resilience among SMEs.

To address these research questions, I employ a Difference-in-Differences (DiD) methodology, treating EWEs as exogenous shocks and investigating the differential effects across firms exposed to these events. Additionally, a LASSO regression model is proposed to identify key variables influencing the allocation of EU funds, potentially uncovering institutional or regional biases in fund distribution. By combining firm-level data from 23 European countries with detailed records of EWEs, this study offers an empirical evaluation of how climate events impact SMEs performance and whether institutional mechanisms like the EUSF serve as effective tools for climate risk mitigation and adaptation. Therefore, this paper aims to uncover the following questions:

- do EWE affect firm performances (total asset, number of employees, etc.)? How much does every single event affect the performance (event-specific risks) and which one is the worst/most persistent (short vs long-term effects)?
- do EU solidarity funds help in mitigation and adaptation?

This research contributes to the growing body of literature on climate finance, SMEs resilience, and public policy, offering new insights into how European firms manage climate risks and the role of EU institutions in supporting them.

2 Data

I combine firm-level data from 23 European countries (over the period 2009-2018, to download data for the period 2018-2024) with a dataset of events. The event data reports the occurrences of extreme weather events (Drought, Extreme Temperature, Flood, Storm, Wildfire) for the countries under consideration. In the matching between the datasets for events and for firms, I have that some countries interested in weather events are not in the dataset of firms, and vice versa. Therefore, I abandon those data. Table 1 shows the distribution of the single unique events for each country in the final matched dataset.

Table 2 shows the distribution of firms among industrial sectors in the financial dataset. I also report the distribution of firms by country in table 3. In this paper, I study the effect of the EU Solidarity Fund Interventions since 2002. The EU allocates these funds for events regarding natural disasters only. Table 4 displays the amount of damage for the type of event and the amount of funds that states received from the EU. The first column for the amount of damage reports data from my dataset, while the second one reports the amount of damage as recorded by the EU. The difference between these amounts comes from discrepancies related to data collection and availability. In other words, some events in my dataset do not report the amount of damage, while the EU dataset does. And vice versa.

3 Empirical Strategy

3.1 The Difference-in-Differences

The difference-in-differences strategy estimates the effect of each type of event on the performance and value of the firms. The estimates are specified for each type of event. The general DID equation is the following:

$$y_{it} = \beta_0 + \beta_1 Event_i + \beta_2 Treatment + \beta_3 Treatment * Post_i +$$
$$\beta_4 Year_t + \beta_5 NACE_i + \beta_6 Country_i + \beta_7 X_{it} + \epsilon_{it} \qquad (1)$$

where y_{it} is the financial variable for observation i at time t, $Event_i$ is a set of binary variables indicating whether the observation occurred during any of the events (Drought, Extreme Temperature, Flood, Storm,

Table 1: Frequency of Unique Events by Country

Country name	Drought	ExtremeTemp	Flood	Storm	Wildfire	Total
Austria	0	2	3	3	0	8
Belgium	0	3	1	6	0	10
Bulgaria	0	4	6	1	0	11
Croatia	0	2	4	1	0	7
Czech Republic	0	4	5	2	0	11
France	0	7	8	15	2	32
Germany	0	5	3	11	0	19
Greece	0	1	3	0	1	5
Hungary	0	2	2	2	0	6
Ireland	0	0	1	3	0	4
Italy	2	5	3	3	1	14
Latvia	0	1	0	0	0	1
Netherlands	0	2	0	6	0	8
North Macedonia	0	2	2	0	0	4
Norway	0	0	0	2	0	2
Poland	1	12	2	5	0	20
Portugal	0	3	1	2	3	9
Romania	0	6	11	2	0	19
Serbia	0	3	0	0	0	3
Slovakia	0	0	1	0	0	1
Spain	0	1	4	5	3	13
Sweden	0	0	0	1	1	2
Switzerland	0	3	0	7	0	10
Total	3	68	60	77	11	219

Table 2: Frequency of Firms by NACE Rev. 2

NACE Rev. 2	Freq.	Percent	Cum.
A	28,245	2.07	2.07
B	1,701	0.12	2.20
C	151,199	11.09	13.29
D	11,425	0.84	14.13
E	6,657	0.49	14.61
F	170,947	12.54	27.15
G	348,130	25.54	52.69
H	61,433	4.51	57.20
I	79,154	5.81	63.00
J	55,961	4.11	67.11
K	55,860	4.10	71.21
L	91,654	6.72	77.93
M	149,334	10.95	88.88
N	60,780	4.46	93.34
O	163	0.01	93.35
P	15,155	1.11	94.47
Q	32,037	2.35	96.82
R	18,536	1.36	98.18
S	24,831	1.82	100.00
T	25	0.00	100.00
U	6	0.00	100.00
Total	1,363,233	100.00	

Table 3: Frequency of Firms by Country

Country Name	Freq.	Percent	Cum.
Austria	1,783	0.13	0.13
Belgium	38,032	2.79	2.92
Bulgaria	39,767	2.92	5.84
Croatia	3,301	0.24	6.08
Czech Republic	14,309	1.05	7.13
France	345,936	25.38	32.51
Germany	56,963	4.18	36.69
Greece	144	0.01	36.70
Hungary	96,820	7.10	43.79
Ireland	3	0.00	43.79
Italy	263,389	19.32	63.11
Latvia	676	0.05	63.16
Netherlands	15	0.00	63.16
North Macedonia	12,333	0.90	64.07
Norway	1,244	0.09	64.16
Poland	130,676	9.59	73.75
Portugal	10,326	0.76	74.51
Romania	195,171	14.32	88.83
Serbia	7,788	0.57	89.40
Slovakia	326	0.02	89.42
Spain	140,661	10.32	99.74
Sweden	3,239	0.24	99.98
Switzerland	331	0.02	100.00
Total	1,363,233	100.00	

Table 4: Damage and Funds Amount for Countries by Event Type

Country	Type	TotDamage[$]	TotDamageEUdb[M€]	TotFundEU[M€]
Austria	ExtremeTemp	0	0	0
	Flood	1200000	2125	53.2
	Storm	1001200	0	0
Belgium	ExtremeTemp	0	0	0
	Flood	238146	0	0
	Storm	160000	1425	35.6
Bulgaria	ExtremeTemp	0	876	25
	Flood	387200	801	23.1
	Storm	545000	0	0
Croatia	ExtremeTemp	0	0	0
	Flood	0	310	9.187
	Storm	161000	0	0
Czech Republic	ExtremeTemp	0	0	0
	Flood	1326112	1508	37.7
	Storm	52900	491	12.3
France	ExtremeTemp	0	0	0
	Flood	4654000	1259	31.5
	Storm	7912000	11861.3	422.2
	Wildfire	0	0	0
Germany	ExtremeTemp	0	0	0
	Flood	1.49e+07	2125	53.2
	Storm	9237475	1425	35.6
Greece	ExtremeTemp	0	0	0
	Flood	0	638.9	16.3
	Wildfire	0	0	0
Hungary	ExtremeTemp	0	0	0
	Flood	440000	719	22.5
	Storm	0	0	0
Ireland	ExtremeTemp	0	0	0
	Flood	0	521	13
	Storm	0	0	0
Italy	Drought	3490000	0	0
	ExtremeTemp	132601	0	0
	Flood	115000	1375	34.4
	Storm	2841000	13395.3	294.1
	Wildfire	115000	0	0
Latvia	ExtremeTemp	0	0	0
Netherlands	ExtremeTemp	0	0	0
	Flood	0	0	0
	Storm	982011	1425	35.6
North Macedonia	ExtremeTemp	0	0	0
	Flood	0	0	0
Norway	Storm	0	0	0
Poland	Drought	0	0	0
	ExtremeTemp	0	0	0
	Flood	3180000	719	22.5
	Storm	325000	491	12.3
Portugal	ExtremeTemp	0	0	0
	Flood	0	0	0
	Storm	0	0	0
	Wildfire	732000	1587	53.9
Romania	ExtremeTemp	0	876	25
	Flood	1122428	574.7	14.4
	Storm	7300	0	0
Serbia	ExtremeTemp	0	0	0
Slovakia	Flood	0	205	5.1
Spain	ExtremeTemp	0	0	0
	Flood	597000	0	0
	Storm	2240000	5231	145
	Wildfire	0	129	3.2
Sweden	Storm	0	0	0
	Wildfire	102000	0	0
Switzerland	ExtremeTemp	0	0	0
	Storm	1264000	1425	35.6

The column "TotDamage[$]" shows the total amount of damage, in $, of each type of event for all the countries as recorded in my dataset. The following column reports the same data as recorded in the EU Solidarity Fund Interventions, which also reports the fund allocated to each event for each country in the amount shown in the last column (both in million €- amounts in millions are rounded).

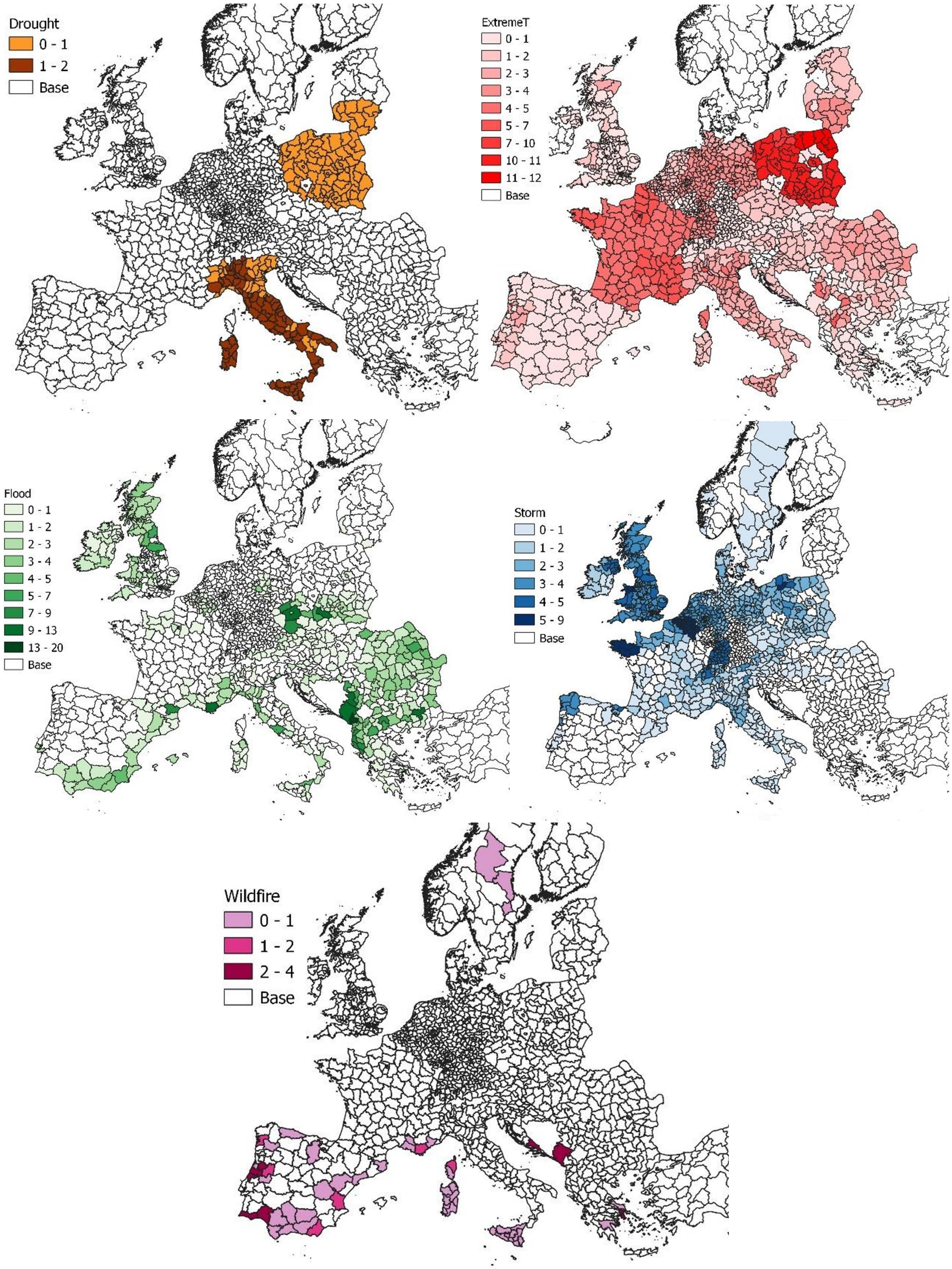

Figure 1: Distribution of extreme weather events by NUTS3 in Europe

or Wildfire) and it equals one only in the year of the event occurrence, $Treatment$ is a time-invariant dummy variable indicating whether observation i is in the treatment group, the interaction term $Treatment * Post_i$ estimates the time-varying effect of the event. I create an indicator variable, $Post_i$, which takes a value of one if the date of observation is in the years following an EWE(it equals one in the year of the event and the following years). $Year_t$ represents the year-fixed effect, $NACE_i$ represents a set of indicator variables for different divisions within the NACE (Statistical Classification of Economic Activities) classification system, and $Country_i$ represents a set of indicator variables for different countries. X_{it} is the set of control variables that slightly changes with respect to the financial variable on the left-hand side. Indeed, in the same fashion of H. H. Huang et al. (2018) I plan to estimate the effect of EWEon Total Assets and financial performance, measured by Return-On-Assets and Cash Flows from Operations. Therefore, when controlling for firm characteristics I may include the natural log of TA (size), the natural log of firm Age, the Number of Employees, Total Debt, and the log of Sales (Sales growth in the growth model). Following the approach of Kingsley and Graham (2017), I incorporate country-level macroeconomic factors: log and annual growth of GDP per capita. I may also use a country-specific Climate Risk Index, measured by annual and long-term CRI scores published by Germanwatch (see H. H. Huang et al. (2018)). ϵ_{it} is the error term.

β_0 is the intercept term, while β_1 measures the average difference in the outcome between treatment and control (with respect to the specific event). In fact, the coefficient for $Event_i$ represents the immediate or contemporaneous effect of experiencing an event (the treatment) on the outcome variable. β_2 measures the average difference in outcome between the treatment group (independently of the type of event) and the control group. Indeed, I also regress $Treatment$ because when specifying a single event (e.g., drought) I need to account for firms that are not affected by drought but belong to the treatment group. The variable of interest is the interaction term. It estimates the time-varying effect of the event by allowing the effect of the event to perpetuate across different years in the post-treatment period. In other words, it indicates the effect of the event over time. A positive (negative) coefficient means that the effect of the event increase (decrease) the outcome variable in the years after the occurrence.

I run regressions for the single events in order to gauge their specific effect on the TA of firms and their performance. In equation (1) I encounter multicollinearity issues regarding the dummies $Event$, $Treatment$, and $Post$. Therefore, I split the model regressing $Event$ and $Treatment$ first, and then the interaction term $Treatment * Post$ to capture the effect of the event in the aftermath of the shock (in the same fashion of Q. Huang et al. (2022)). I show the specification of the model split in the next chapter.

3.2 Lasso and Fund Allocation Strategy

I propose to use LASSO to select the most important variables in the allocation process of the funds. The "received_funds" is binary, therefore I would use the “logit” specification. Select(bic) regularize the estimate using Bayesian Information Criterion for variable selection (I may discuss alternatives). The result should highlight the variables selected by the model with the corresponding coefficients. I should be careful in the estimate because there may be institutional and or regional criteria influencing the allocation of funds. I should also include control variables.

4 Peliminary findings

I show the first regression considering all EWE together in the section below. Additionally, in the last section I determine costs and sales statistics to use for the EU solidarity funds regressions. These are very preliminary results. Indeed, the final paper requires more complex analysis and data elaboration.

4.1 Difference in differences

Preliminary results from the difference-in-differences analysis assessing the impact of natural disasters on European firms' financial performance, focus on log total assets (column 1) and log operating revenue (column 2). The DiD coefficient for both dependent variables is positive and statistically significant at the 1% level, suggesting that events reduce firms' total assets and operating revenue.

The table includes controls for year, country, firm, sector, and size, indicating a comprehensive approach to account for potential confounding factors, thereby enhancing the robustness of the results. The high R^2 values of 0.935 and 0.883 signify that the model explains a substantial portion of the variance in the outcomes. To mitigate confounding effects, the analysis excludes instances where firms experienced natural disasters in consecutive years, further supporting the validity of the findings.

Table 5: Regression table

	Log total asset (1)	Log operating revenue (2)
DiD result:	-0.0603*** (0.00101)	-0.0685*** (0.00140)
Controls:		
Year-fixed:	✓	✓
Country-fixed:	✓	✓
Firm-fixed:	✓	✓
Sector-fixed:	✓	✓
Size-fixed:	✓	✓
Observation:	7,392,956	6,916,240
R^2:	0.935	0.883

Notes: The table shows the results of log total assets and log operating revenue for European firms that suffered from all types of natural disasters. To avoid confounding effects, in this table, I exclude all the cases where the firms experienced natural disasters in two consecutive years.

4.2 Average Comparison for Costs and Sales

Prior to studying the dynamics involving the EU funds, I determine averages for Costs and Sales and compare the change in "Costs" and "Sales" in the tables below. I first calculate the average for the two years following the event and then determine the change with respect to the average for the three years before the event.

Table 6: Percentage change in costs after each event (timing) for firms receiving funds

	Summary Statistics					
Variable	*e(count)*	*e(sum_w)*	*e(sum)*	*e(mean)*	*e(min)*	*e(max)*
`pct_change_event1_costs`	76128	76128	6573167	86.34	-2036.24	3014792
`pct_change_event2_costs`	21850	21850	934408.1	42.76	-1114.20	96169.67
`pct_change_event3_costs`	0	0	0	.	.	.
`pct_change_event4_costs`	0	0	0	.	.	.

Table 7: Percentage change in costs after each event (timing) for firms NOT receiving funds

	Summary Statistics					
Variable	*e(count)*	*e(sum_w)*	*e(sum)*	*e(mean)*	*e(min)*	*e(max)*
`pct_change_event1_costs`	1237843	1237843	2.58e+08	208.68	-1148223	5.34e+07
`pct_change_event2_costs`	167846	167846	1.11e+07	65.86	-88150	850863.1
`pct_change_event3_costs`	34431	34431	907958.3	26.37	-1070.67	105437.5
`pct_change_event4_costs`	0	0	0	.	.	.

Table 8: Percentage change in sales after each event (timing) for firms receiving funds

	Summary Statistics					
Variable	*e(count)*	*e(sum_w)*	*e(sum)*	*e(mean)*	*e(min)*	*e(max)*
`pct_change_event1_sales`	122069	122069	1.08e+08	885.54	-11131.43	5.44e+07
`pct_change_event2_sales`	44024	44024	7.94e+07	1804.55	-11131.43	5.44e+07
`pct_change_event3_sales`	0	0	0	.	.	.
`pct_change_event4_sales`	0	0	0	.	.	.

I run T-test for "pct_change_costs_event1" and "pct_change_sales_event1" where I choose the groups on the basis of received funds. In the same fashion, I have statistics for event 2 (not reported to avoid an overwhelming presentation).

Table 9: Percentage change in sales after each event (timing) for firms NOT receiving funds

	Summary Statistics					
Variable	*e(count)*	*e(sum_w)*	*e(sum)*	*e(mean)*	*e(min)*	*e(max)*
`pct_change_event1_sales`	1388498	1388498	-4.48e+08	-322.41	-3.10e+08	2.70e+08
`pct_change_event2_sales`	186484	186484	-6.34e+07	-340.17	-7.87e+07	1.82e+07
`pct_change_event3_sales`	46550	46550	3141990	67.50	-4835.71	602798.6
`pct_change_event4_sales`	0	0	0	.	.	.

Table 10: Two-sample t test with equal variances for the percentage change of Costs after event1

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
0	1,237,843	208.6787	54.11261	60,204.82	102.6199	314.7376
1	76,128	86.34361	40.03402	11,045.91	7.877137	164.8101
Combined	1,313,971	201.591	51.03022	58,495.21	101.5735	301.6084
diff		122.3351	218.428		-305.7763	550.4465

T-test Results

Parameter	Value	
diff = mean(0) - mean(1)	122.3351	
t	0.5601	
H0: diff = 0		
Degrees of freedom	1.3e+06	
Alternative Hypotheses		
Pr(T < t)	0.7123	Ha: diff < 0
Pr(|T| > |t|)	0.5754	Ha: diff ≠ 0
Pr(T > t)	0.2877	Ha: diff > 0

Table 11: Two-sample t test with equal variances for the percentage change of Sales after event1

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
0	1,388,498	-322.4093	432.5841	509,733.5	-1,170.259	525.4406
1	122,069	885.5375	466.4496	162,969.9	-28.69608	1,799.771
Combined	1,510,567	-224.7951	399.4096	490,894.9	-1,007.624	558.0341
diff		-1207.947	1465.491		-4,080.259	1664.366

T-test Results

Parameter	Value	
diff = mean(0) - mean(1)	-1207.947	
t	-0.8243	
H0: diff = 0		
Degrees of freedom	1.5e+06	
Alternative Hypotheses		
Pr(T < t)	0.2049	Ha: diff < 0
Pr(|T| > |t|)	0.4098	Ha: diff ≠ 0
Pr(T > t)	0.7951	Ha: diff > 0

References

Alekseev, Georgy, Ian Appel, and Steve Slezak (2022). "Heat and corporate risk-taking". In: *Management Science* 68.1, pp. 81–106.

Alok, Shashwat, Meghana Ayyagari, and Alexander Koch (2020). "Do managers misreact to salient risks? Evidence from mutual fund flows". In: *Review of Financial Studies* 33.9, pp. 4041–4083.

Altay, Nezih and Angel Ramirez (2010). "Impact of disasters on firms in different sectors: Implications for supply chains". In: *Journal of Supply Chain Management* 46.4, pp. 59–80.

Barrot, Jean-Noël and Julien Sauvagnat (2016). "Input specificity and the propagation of idiosyncratic shocks in production networks". In: *Quarterly Journal of Economics* 131.3, pp. 1543–1592.

Carvalho, Vasco M, Makoto Nirei, Yukiko Saito, and Alireza Tahbaz-Salehi (2021). "Supply chain disruptions: Evidence from the Great East Japan Earthquake". In: *Quarterly Journal of Economics* 136.2, pp. 1255–1321.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Andreas Weber (2021). "Climate change and long-run discount rates: Evidence from real estate". In: *Review of Financial Studies* 34.8, pp. 3527–3571.

Hong, Harrison, Frank W Li, and Jiangmin Xu (2019). "Climate risks and market efficiency". In: *Journal of Econometrics* 208.1, pp. 265–281.

Huang, Henry He, Joseph Kerstein, and Chong Wang (2018). "The impact of climate risk on firm performance and financing choices: An international comparison". In: *Journal of International Business Studies* 49, pp. 633–656.

Huang, Qiping, Yongjia Li, Meimei Lin, and Garrett A McBrayer (2022). "Natural disasters, risk salience, and corporate ESG disclosure". In: *Journal of Corporate Finance* 72, p. 102152.

Kingsley, Allison F and Benjamin AT Graham (2017). "The effects of information voids on capital flows in emerging markets". In: *Journal of International Business Studies* 48, pp. 324–343.