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Estimating the Impact of Natural Disasters on Caribbean Exports

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Jeremy Smith (Head of the Department of Economics, University of Warwick) and Michael Ward (Head of the Department of Economics, Monash University)

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Estimating the Impact of Natural Disasters on Caribbean Exports

An industry-level analysis

Eleni Sandi*

Abstract

This paper aims to estimate the impact of natural disasters on exports in the Caribbean countries using a panel fixed effects regression. The paper's main contribution lies in identifying the manufacturing industries that are disproportionately affected by natural disasters in the given region. It finds that an additional natural disaster in the Caribbean leads to a significant short-run decrease in total exports, whilst mineral, chemical, paper, textile and metal industries suffer the most. Using alternative disaster measures reveals that deaths have the largest impact on exports, emphasising the Caribbean's high vulnerability to natural shocks. Interestingly, a dynamic model reveals a long-term negative effect on exports that strengthens over time. The main results remain robust to a variety of alternative model specifications. Total disaster effects seem to be driven by disasters in Haiti, although further research on country heterogeneity is recommended. Taken together, these findings are especially alarming in the context of climate change and global warming, as natural disasters are expected to increase in intensity and frequency. Drawing on these results, the policy implication is decreasing the Caribbean's vulnerability by tackling the moral hazard problem of unconditional donor aid.

JEL Classifications: Q54; F14; O10

Keywords: Natural Disaster; Climate Change; Exports; Industry-level

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Appendices link: https://www.dropbox.com/s/ikeu5tddw5rqoc6/Appendices.pdf?dl=0 (includes full regression tables, robustness checks and variable descriptions).
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1 Introduction

From the 2010 Earthquake in Haiti to Hurricane Sandy in 2012, the Caribbean has been hit by some of the 21st century's deadliest natural disasters. Their severe aftermath typically makes media headlines, with reports of fatalities, damages, and calls for international aid attracting global attention.

Central to this paper's motivation is evidence that Small Island Developing States are disproportionately affected by natural disasters. For instance, the IMF reports that the average disaster damage/GDP ratio is 6 times higher in Caribbean countries than larger states (Ötker and Srinivasan, 2018). Alarmingly, projections by the International Panel on Climate Change IPCC (2014) warn that global warming could increase the frequency and intensity of extreme weather phenomena, suggesting natural disasters are a growing concern for the Caribbean.

Whilst natural disasters can obstruct numerous economic activities in vulnerable countries, this paper focuses on their - often overlooked - implications as trade barriers. In the Caribbean context, exports are of particular significance to the region's development agenda (World Bank, 2015), meaning unanticipated export barriers can have sizeable consequences on people's economic livelihoods.

To address the worrying link between trade and natural hazards in at-risk areas, this paper aims to estimate the impact of natural disasters on exports in the Caribbean. Its contribution lies in unpacking the heterogeneity masked by total disaster estimates, and crucially in identifying the most disaster-prone industrial sectors in the region, which appears absent from the literature.

To fulfill its aim, this paper builds on influential studies (Gassebner et al., 2010, Mohan, 2017, Pelli and Tschopp, 2017, Skidmore and Toya, 2007), that show small countries with closely located production facilities experience large supply-side disaster shocks. Therefore, the main hypothesis is that natural disasters will *negatively* and *heavily* affect Caribbean exports in the immediate post-disaster period. The expected disaster mechanisms are direct (damages to physical capital and loss of workers) and indirect (disrupted supply chains due to public infrastructure destruction).

To estimate the natural disaster impact on aggregate exports to the world I construct a panel comprising of 16 Caribbean countries by merging UN ComTrade, EM-DAT and CEPII data. I control for unobserved variables via fixed effects following Mohan (2017).

The main findings confirm the hypothesis that natural disasters have a large, negative and significant short run effect on exports in the Caribbean. The most affected sectors are estimated to be mineral, chemical, paper, textile and metal industries. Concerning mechanisms, the paper only finds evidence in favour of direct channels, whilst casualties have the largest negative impact. Lastly, a dynamic specification reveals large long term disaster effects on exports that intensify over time, mirroring Pelli and Tschopp (2017).

The paper is structured as follows. The next sections summarise the existing literature (2), describe the data sources and main variables (3), present the methodology and baseline specification (4), report the main results and extensions (5), discuss robustness (6) and conclude (7).

2 Literature Review

As discussed in the Introduction, there are alarming environmental concerns about the increase of extreme weather phenomena. Therefore, estimating the economic impact of natural disasters is becoming more common within empirical economic literature.

Disasters and GDP
At large, the literature focuses on macroeconomic effects of natural disasters (GDP level and growth). Most papers utilise cross-country panel regressions, although studies differ in their geographical and temporal coverage. So far, there are no conclusive results about the effect of natural disasters on output.

Early literature, such as Raddatz (2009), finds large weather-related disasters have a -0.6% effect on real GDP per capita. These findings contrast with Noy (2009), who specifies that disasters have a negative impact only when using property damages to estimate disasters, and no effect for alternative measures, e.g., casualties. More recent literature continues to produce different results. For instance, Cavallo et al. (2013) find that only extremely large natural disasters impede economic growth but only when followed by political revolutions.

However, the literature generally agrees that natural disaster effects are more substantial for small and low-income countries. For example, Noy (2009) finds that states with higher educational attainment, better institutions and trade openness are more resilient to natural disasters and Skidmore and Toya (2007) find that developed countries have fewer deaths and damages.

Econometric Concerns
One could attribute the aforementioned discrepancy in results to the nature of the database used to construct the explanatory disaster variable. Almost all studies use the Emergency Events Database (EM-DAT) by the Centre for Research on the Epidemiology of Disasters, as it is the most comprehensive, publicly available database. However, there is potential selection bias because a disaster needs to surpass certain socioeconomic thresholds to enter the database, making the selection process endogenous (Osberghaus, 2019). Additionally, there are concerns about the measurement accuracy of the variables, particularly for developing countries, as local authorities may exaggerate damages to gain eligibility for larger amounts of foreign aid.

Specific authors (Lee et al., 2018, Gassebner et al., 2010, Silva and Cernat, 2012) have addressed this issue by restricting their dataset to 'severe' disasters. Although this mitigates the above concerns, all authors choose different definitions for severe disasters without acknowledging definitions proposed by other papers.

Disasters and Trade
These issues carry over to a smaller segment of the literature that estimates the impact of natural disasters on international trade. Gassebner et al. (2010) find that disasters negatively affect bilateral trade, via reducing export volumes. However, results are only significant for small exporting countries with geographically concentrated production facilities.

Gassebner et al. (2010) use a particularly useful count variable for disasters, which allows the authors to capture a frequency effect, as most vulnerable regions experience multiple disasters within a year. This count variable contrasts with the less precise binary disaster variable used by most papers, such as Lee et al. (2018), who find non-significant results for exports.

Another strand of this literature focuses on the firm-level trade effects of natural disasters. Specifically, Volpe Martincus and Blyde (2013) find a strong negative impact of diminished transport infrastructure on firms' exports due to an earthquake. However, this study is limited by low external validity, as it only focuses on Chile.

Literature Contribution

A noticeable shortcoming of the literature is the lack of industry-level analysis. Oh (2017) attempts to address this limitation using the 2-digit Bureau of Economic Analysis industry classification. He finds that natural disasters overall decrease total trade by -4.1%, although trade flows for agricultural products increase. The intuition is that agricultural imports rise as they are part of emergency recovery plans. However, Oh (2017) does not mention the effect of natural disasters on exports.

Recently, Pelli and Tschopp (2017) begin filling this gap by analysing the impact of hurricanes on industry-level exports to the USA using a global panel dataset. Interestingly, they find significantly negative results only for capital intensive industries with a comparative disadvantage in trade. They explain this via a build back better mechanism, whereby disaster-hit exporters shift production into comparative advantage industries, also confirmed by Cuaresma et al. (2008).

Lastly, few industry-level papers centre on disaster-prone areas, but restrict their analysis to agricultural sectors. Mohan (2017) and Mohan and Strobl (2013) find strong post-disaster declines in agricultural exports because of crops' exposure to the natural elements.

Despite these contributions to the literature there is, to this author's knowledge, no study on aggregate exports in the Caribbean with a manufacturing sector analysis, a niche this paper hopes to occupy.

3 Data

3.1 Export Data

Data for Caribbean exports to the world was taken from UN ComTrade (2020). This database provides annual export data in nominal trade values (USD) and net weight (kg) classified by commodity type using the Harmonized Commodity Description and Coding System (HS).

Using ComTrade data I constructed an unbalanced panel of 16 Caribbean countries, comprising of 122,068 observations for total annual export values to the rest of the world, disaggregated at 4-digit HS[1] with the earliest and latest years being 1988 and 2019. No zero values are included in this database; therefore, analysis is on the intensive margin.

ComTrade's strengths are its vast geographical and temporal coverage and, crucially, the granularity of its industry-level export data.[2] However, a potential limitation is the panel's highly unbalanced time-dimension, causing some countries in the sample to seem very underrepresented (or over-represented). In Table 28 Appendix C export shares by country fluctuate from 0.59% to 16.35% of the total sample. This hints that examining country heterogeneity could reflect differences in country sample sizes rather than disproportionate disaster impacts.

Furthermore, countries with no reported disasters in the years available by ComTrade were excluded from the sample.[3] Any commodity classified as miscellaneous (code 9000 and above) was also excluded due to the inconsistency and lack of clarity of goods in this category. Transport costs were calculated by dividing net weight by trade value, following Hummels (2007) who discusses that weight/value practically measures how transport costs affect final trade prices. Data availability constraints also contributed to this choice of transport costs calculation.

3.2 Disaster Data

The main explanatory variable for disaster frequency is based on EM-DAT. It is the most commonly used source for international disaster data in the literature, because it is comprehensive, publicly available and regularly updated. It includes all global natural disasters from 1900-2021 fulfilling at least one of the following criteria: a) 10 or more people killed, b) 100 or more people affected, c) state of emergency declared, d) international assistance called (EM-DAT, 2020).

However, the EM-DAT's key weakness is possible selection bias and measurement error, as discussed in the Literature Review. The solution proposed by previous papers is to restrict the sample to the most severe disasters. As a result, the remaining disasters are assumed to be those which would have been included in the EM-DAT regardless of particular socioeconomic characteristics of the affected country. I address this concern by running a model with increased disaster intensity in the Extensions.

Moreover, adjustments were made to the original data set. EM-DAT reports each disaster as one observation, which I used to calculate the total number of disasters that

[1] 1,151 4-digit commodities.

[2] 6-digit HS data was also available, however, due to the large amount of missing commodity codes at 6-digit for the Caribbean countries, this paper employs the more aggregate 4-digit level for which all commodity codes are reported.

[3] Excluded: Anguilla, Antilles, Cayman Islands, Montserrat, Saint Martin.

occurred for each country-year pair.[4] Additionally, this paper focuses on disasters that could affect exports through similar channels (e.g., physical capital shocks). Thus, the following disasters were excluded from analysis: droughts, wildfires, ash fall from volcanic activity and epidemics. The remaining disasters are storms (tropical cyclones), floods (coastal, riverine and flash floods) and earthquakes. Landslides are included; however, not as a standalone category because their occurrence is either linked to floods or earthquakes (Kjekstad and Highland, 2009).

3.3 Additional Controls

TradeProd by CEPII (2020) was used to retrieve control variables for firm size and value-added (000's USD). Firm size was calculated by dividing the number of employees by number of firms. The correlation between log firm size and log value-added variables is 0.618, indicating that despite being similar they still represent different information.

CEPII was chosen as it is the only publicly available database with industry-classified production variables for Caribbean countries. However, a drawback is that CEPII uses the International Standard Industrial Classification (ISIC) Revision 2, which does not concord with ComTrade export data. Also, ISIC excludes primary agriculture. Therefore, I converted HS commodity codes into ISIC to merge the TradeProd and ComTrade datasets.[5] Consequently, this conversion may have impacted results through measurement error. Another crucial weakness is the large amount of missing values, meaning observations are restricted when analysis is run with firm size and value-added controls.

3.4 Descriptive Statistics

Table 1 presents descriptive statistics for the baseline model variables (c = country, i = industry and t = year).

Table 1: Main Variables - Summary Statistics

Variable	Obs.	Mean	S. Dev.	Min	Max
Dependent variable (USD)					
$\ln(\text{Exports})_{cit}$	122,068	3,061,275	60,400,000	1	5,880,000,000
Main explanatory variable					
Disasters_{ct}	122,068	.67	1.03	0	5
Control variables					
$\text{TransportCosts}_{cit}$	119,994	3.27	230.69	0	55,717.18
$\ln(\text{ValueAdded})_{cit}$	12,299	9.41	2.26	.43	14.14
$\ln(\text{FirmSize})_{cit}$	10,856	3.18	1.17	0	7.72

[4] Same for damages, people affected and casualties variables.
[5] Author's own conversion, see Table 27 Appendix C.

Table 2 presents the 15 product groupings (or sections) used for the industry-level analysis. These categories were constructed by grouping 4-digit commodities according to the sections defined by UN Trade Statistics (2016). Machinery has the highest export share, followed by base metals and chemicals. These groups are expected to drive total export effects. Conversely, raw hides have the lowest export share. Table 29 Appendix C indicates that by country, the product groups with the smallest and largest export shares are typically raw hides and machinery, respectively. This suggests similar export compositions across the sample countries.

Table 2: Product Groups - Summary Statistics

Product Group	Mean Value USD	Export Share % of total exports
Animal products (Meat, fish, dairy produce)	925,629	3.62
Vegetable products (Fats/oils, coffee, tea, spices, cereals etc.)	1,043,406	9.45
Prepared foodstuffs (Tobacco, beverages, sugars, cocoa etc.)	4,699,986	6.75
Mineral products (Salt, ores, mineral fuels)	43,300,000	2.62
Chemicals and allied industries (Chemicals, pharmaceuticals, soap, dyes etc.)	4,658,795	11.88
Plastics and rubbers (Articles thereof)	1,412,260	4.53
Raw hides (Hides, skins, furs, travel goods)	511,761	1.01
Wood and wood products (Wood, charcoal, cork, straw)	79,951	2.92
Paper and paperboard (Wood pulp, paper, paperboard, publications)	918,964	4.05
Textiles (Silk, wool, cotton, apparel, carpets, ropes etc.)	1,990,282	10.55
Footwear and headgear (Footwear, headgear, umbrellas)	1,903,520	2.09
Stone and glass (Stone, plaster, cement, ceramics, glass)	2,578,882	5.63
Base metals (Iron, steel, copper, nickel, lead etc.)	1,747,992	13.08
Machinery (Appliances and electrical equipment)	784,396	18.21
Transportation (Vehicles, aircraft, ships, locomotives)	1,311,219	3.61

Table 3 shows the composition of disasters by type. As storms and floods are over-represented in the sample compared to earthquakes, I anticipate that results will reflect the impact of those two disaster types. Table 4 shows that the Dominican Republic is the country with the highest disaster incidence, however, in terms of intensity Haiti had the highest mean deaths and Cuba had the highest mean damages and people affected. Therefore, there could be heterogeneous disaster effects across countries.

Table 3: Disaster Types

Disaster Type	Number of Disasters	% of Total Disasters
Storms	107	66.05
Floods	50	30.86
Earthquakes	5	3.09
Total	162	100

Table 4: 5 Most Disaster-Prone Countries

Country	No. of Disasters	Mean Damages ('000 USD)	Mean Affected	Mean Deaths
Dominican Republic	47	37,246	186,631	56
Jamaica	21	113,054	95,306	7
Haiti	15	23,564	415,345	217
Bahamas	15	256,417	3,184	4
Cuba	13	430,750	1,170,533	5

Lastly, Table 5 tests for whether mean exports (USD and kg) are lower a year after a disaster hits using difference in means t-tests. The 1990 and 1996 disasters in Haiti were chosen as there were no disasters in the years before or after. The difference in mean exports for both disasters is negative regardless of the export measure used, indicating that exports dropped after each disaster. Additionally, almost all differences are statistically significant at the 1% level. This exercise points towards a negative relationship between disasters and exports, supporting this paper's hypothesis, however, this does not identify causal effects.

Table 5: Haiti 1990 and 1996 Disasters
Before and After

	Mean(1991) - Mean(1989)	Mean(1997) - Mean(1995)
$\ln(\text{ExportsUSD})_{cit}$	-1.864***	-0.465
	(-4.57)	(-1.09)
$\ln(\text{ExportsKG})_{cit}$	-2.009***	-1.212***
	(-5.36)	(-2.99)
N	210	270

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4 Methodology

To estimate the impact of natural disasters on exports in the Caribbean this paper adapts and combines the specifications of Gassebner et al. (2010) and Mohan (2017).

The majority of papers within the literature employ panel data techniques, particularly fixed effects to control for unobserved variables that could affect exports. This paper follows the fixed effects specification suggested by Mohan (2017) due to her similar data structure (panel data with country-product-time dimension) and choice of countries. Hence, I control for country-industry and year fixed effects. Country-industry addresses the likelihood that a certain country may export less or more of a particular commodity. Year fixed effects control for shocks across all countries.

Mohan (2017) also incorporates export determinant controls such as rain fall and temperature as she focuses on agricultural exports. This paper employs export determinant controls that are suitable to the context of manufacturing industries: transport costs, value-added and firm size. I anticipate transport costs to negatively affect exports, whilst value-added and firm size are expected to have a positive effect.

Furthermore, Mohan (2017) uses wind speed as the disaster variable, since her paper focuses exclusively on the trade effects of hurricanes. Authors preferring physical disaster measures argue this method avoids using potentially endogenous EM-DAT data (Strobl, 2012). However, this technique limits studies to publicly available disaster measures. For example, flood intensity is typically measured by water height, however, there is no systematic data collection in the Caribbean for such hydrological indices (Fontes de Meira and Phillips, 2019).

Hence, this paper chooses to estimate disasters using a frequency variable that indicates the number of total disasters for a country-year pair for which comprehensive data could be retrieved, as proposed by Gassebner et al. (2010). This method also has an advantage over binary disaster variables as it can capture the impact of multiple disasters for a given country-year, rather than simply their occurrence or non-occurrence.

The main specification also hinges on the assumption that natural disasters are exogenous to economic activity. Elsner and Bossak (2001) find the occurrence of one natural disaster does not inform about the probability of another occurring. Hence, industries do not base their production or location choices on disaster likelihood (Pelli and Tschopp, 2017). Therefore, the baseline model is as follows:

$$\begin{aligned} ln(Exports)_{cit} = \beta_1 Disasters_{ct} + \beta_2 TransportCosts_{cit} + \beta_3 ln(ValueAdded)_{cit} + \\ + \beta_4 ln(FirmSize)_{cit} + \eta_{ci} + \sigma_t + \epsilon_{cit} \end{aligned} \tag{1}$$

Where $ln(Exports)_{cit}$ is the log of total export value (USD) to the world for country c, industry i and year t. $Disasters_{ct}$ indicates the total number of disasters for each country and year. The coefficient of interest is β_1 as this indicates the impact of an additional disaster on percentage of total export value to the world. According to the hypothesis in the Introduction, β_1 is expected to be negative. η_{ci} are country-industry fixed effects[6] and σ_t are year fixed effects. Standard errors are clustered by 2-digit HS to account for correlation between observations within each 2-digit category (Wooldridge, 2001).

[6] Industry FE at 4-digit HS.

5 Results

5.1 Main Results

Table 6 shows the development of the baseline specification, which explores the relationship between disaster frequency and total exports. It reveals that the coefficient on disaster frequency is negative in columns (2)-(6). Column (6) presents the final specification results, suggesting that one additional disaster causes a short-run export decrease of -22.8%, verifying the paper's main hypothesis.

As anticipated, this estimate is larger than coefficients reported by global studies, e.g., Gassebner et al. (2010) who find -1.8% export decreases on average. However, it is strikingly similar to the -22% export decline for financially isolated disaster-struck countries found by Felbermayr and Gröschl (2013). Importantly, the large magnitude confirms the theory that small, developing countries are especially impacted by natural disasters as postulated by Noy (2009) and Skidmore and Toya (2007).

Table 6 also reveals that the estimated disaster effect on exports changes from positive to negative between columns (1) and (2). This sign flip was caused by adding controls and not by the change in sample composition (samples in columns (2) onward are much smaller) since when running the regression without controls on column (6)'s smaller sample, the disaster coefficient remains positive. Additionally, transport costs are surprisingly not significant, possibly because total instead of bilateral exports were used.

Columns (3)-(6) indicate that negative disaster effects become significant with the inclusion of fixed effects, showing that they are controlling for important omitted variables. Encouragingly, disaster effects persist in the final specification (column (6)), which is also the strictest model. Nevertheless, this estimate conceals multiple heterogeneous effects, as explored in the next subsections.

Table 6: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(exp)	ln(exp)	ln(exp)	ln(exp)	ln(exp)	ln(exp)
Total Disasters	4.516***	-0.0228	-0.324***	-0.238***	-0.301**	-0.228**
	(0.0680)	(0.0887)	(0.0551)	(0.0525)	(0.131)	(0.102)
Transport Costs		0.00256	-0.000511	0.00203	0.00198	-0.00105
		(0.00232)	(0.00104)	(0.00209)	(0.00206)	(0.000793)
ln(ValueAdded)		0.913***	0.268**	-0.0167	-0.0169	-0.0760
		(0.0786)	(0.131)	(0.120)	(0.119)	(0.0669)
ln(FirmSize)		0.235	0.0500	0.212	0.220	0.0291
		(0.266)	(0.147)	(0.269)	(0.276)	(0.0840)
Country FE	No	No	No	Yes	Yes	No
Industry FE	No	No	Yes	No	No	No
Year FE	No	No	No	No	Yes	Yes
Country-Industry FE	No	No	No	No	No	Yes
N	122,068	7,404	7,345	7,404	7,051	7,051
Adj. R^2	0.321	0.866	0.634	0.017	0.022	0.805

Standard errors clustered at 2-digit HS in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Extensions

5.2.1 Industry Heterogeneity

This subsection explores the possibility that disasters may affect certain industries more than others. For this purpose, the baseline specification has been relaxed, as the country-industry and year fixed effects were absorbing most of the variation in the model, making it difficult to observe industry heterogeneity. This is not unexpected, as due to the high industry disaggregation and multiple countries, country-industry fixed effects create numerous controls. Therefore, I use a less restrictive model with industry and year fixed effects.[7]

Tables 7-9 present results for different sub-samples corresponding to each general product group as defined in the Data Section.[8] They indicate that the following industries are negatively affected by disasters: mineral, chemical, paper, textile and metal, whilst the remaining industries are left unaffected.[9] The disaster coefficients on impacted industries show a very large disaster effect, implying that exports completely halted immediately post-disaster. Textiles report the smallest decline in exports, at 46.4%.

Surprisingly, processed food sectors (foodstuffs, animal and vegetable products), which use primary agricultural inputs, were unaffected. Mohan (2017) finds that agricultural crops in the Caribbean are significantly impacted by hurricanes, however, it seems that these agricultural losses are not translated into the food processing sector. This could be due to the storage of primary goods in protective warehouses before their processing.

The results resemble those of Pelli and Tschopp (2017), who find that capital intensive industries are most affected by hurricanes because there is larger scope for physical damages. This explanation emphasises the capital damages channel, but I would also highlight that certain industries were purely unfortunate in terms of their location (e.g., caught in the epicentre of a storm).

The results also echo findings by Volpe Martincus and Blyde (2013) who find that earthquakes negatively affect exports for various manufacturing sectors. They claim that industries with heavier goods are disproportionately impacted through their increased transport costs, as longer routes/detours need to be taken when public infrastructure is destroyed.

I explored this mechanism by interacting disaster frequency and transport costs[10], however, the interaction coefficient was not significantly negative for any of the affected industries.[11] Hence, disaster impact does not increase with transportation costs, which this also weakens the likelihood that disaster effects are running through the public infrastructure channel.[12]

[7] Country and year fixed effects remained restrictive.

[8] Regressions suffer from small sample size using this method. However, when regressing industry dummies interacted with disasters on the full sample most results appear insignificant.

[9] The following industries were omitted as disaster coefficients were zero: plastics, footwear, machinery and transportation.

[10] See Tables 14-18 Appendix A.

[11] Only animal products had a significantly negative interaction coefficient.

[12] Sytsma (2020) also finds a weak infrastructure channel for US ports, as disaster-hit ports divert exports to non-affected ones.

Table 7: Industry Heterogeneity I

	(1)	(2)	(3)	(4)
Sub-sample	ln(Animals)	ln(Veg)	ln(Food)	ln(Mineral)
Total Disasters	0.0351	0.355	0.408	-2.552**
	(0.364)	(0.250)	(0.247)	(0.150)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	334	266	653	256
Adj. R^2	0.595	0.659	0.721	0.805

Standard errors clustered at 2-digit HS in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Industry Heterogeneity II

	(1)	(2)	(3)	(4)
Sub-sample	ln(Chemical)	ln(Hides)	ln(Wood)	ln(Paper)
Total Disasters	-1.075***	-0.910	-0.899	-2.891**
	(0.372)	(1.048)	(0.778)	(0.424)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1,234	34	260	383
Adj. R^2	0.649	0.706	0.638	0.805

Standard errors clustered at 2-digit HS in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Industry Heterogeneity III

	(1)	(2)	(3)
Sub-sample	ln(Textile)	ln(Stone)	ln(Metal)
Total Disasters	-0.464*	-4.860	-2.677**
	(0.234)	(1.802)	(0.472)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	1,139	399	747
Adj. R^2	0.631	0.734	0.766

Standard errors clustered at 2-digit HS in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.2 Alternative Disaster Measures

To shed more light onto the channels through which disasters impact exports, this section runs the baseline specification with alternative disaster measures. I distinguish between total monetary damages inflicted by disasters[13], the total number of people affected[14] and the total number of deaths.[15]

These measures represent the main mechanisms proposed by several authors: destroyed productive capital/public infrastructure (Hsiang and Jina, 2014, Oh and Reuveny, 2010) and human capital losses (Gassebner et al., 2010).

Table 10 presents results of the baseline specification using alternative measures for disasters. Columns (1)-(3) indicate that all disaster measures yield significantly negative disaster coefficients. However, the magnitudes for direct damages to physical capital and people affected are quite low. Contrarily, column (3) shows that disaster induced deaths have the most sizeable impact out of the three measures, as an additional death leads to a -0.16% decrease of total exports.

The magnitude for the total deaths coefficient may be larger as it could also be capturing a lack of solid shelter from disasters, implying low quality housing and factory construction. This is not surprising as Skidmore and Toya (2007) find that developing countries suffer from more disaster induced deaths than wealthier countries. The intuition is that people in lower-income countries have less private demand for safety, meaning they are less willing to pay additional costs for safer construction, better housing location etc., leading to higher casualties and vulnerability to disasters.

Hence, it seems that the impacted industries in the previous section did suffer to a small extent from physical damages, but mostly from deaths reflecting the low-quality construction of these industries' facilities.

Table 10: Alternative Disaster Measures

	(1) ln(exp)	(2) ln(exp)	(3) ln(exp)
Damages	-0.0000380***		
	(0.00000622)		
Affected		-0.00000124***	
		(0.000000190)	
Deaths			-0.00164***
			(0.000256)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes
N	7,051	7,051	7,051
Adj. R^2	0.806	0.806	0.806

Standard errors clustered at 2-digit HS in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[13] 000's USD.

[14] Homeless or injured.

[15] Casualties and missing people.

5.2.3 Disaster Type Heterogeneity

Previous literature has alluded that the impact of different disaster types varies (Oh, 2017). Table 11 presents the break-down of total disaster effect on total exports by type. Columns (1) and (2) read that an additional storm and flood lead to a 59.1% and 24% decrease of total exports, respectively. Tembata and Takeuchi (2019) find comparably large estimates for floods but no storm effects on exports in Southeast Asian countries. This contradiction is attributed to the relatively larger storm frequency in the Caribbean compared to other regions.

The coefficient on earthquakes was zero, and hence was omitted from Table 11. This is possibly because earthquakes are largely under-represented in the sample. In column (3) all disaster types are controlled for, showing that storms absorb the variation caused by floods, implying that the two are linked, as floods may follow severe storms[16] (Heger et al., 2008).

Table 11: Disaster Type Heterogeneity

	(1) ln(exp)	(2) ln(exp)	(3) ln(exp)
Storms	-0.591**		-0.536*
	(0.250)		(0.272)
Floods		-0.240*	-0.0641
		(0.131)	(0.140)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes
N	7,051	7,051	7,051
Adj. R^2	0.805	0.805	0.805

Standard errors clustered at 2-digit HS in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.4 Disaster Intensity

This subsection addresses a distinct feature of the disaster literature, which is defining a decision-rule to restrict analysis to the severest disasters. The purpose of this is to address potential endogeneity issues with EM-DAT data as was discussed in previous sections.

Previous studies have all used different severity decision rules. To avoid favouring one decision-rule over the others, this paper employs its own method. As the deaths variable was previously shown to have the largest impact on exports, it will be used as the best measure for disaster severity. Therefore, I created a severe disaster dummy variable equalling 1 for disasters with casualties above or equal to the 99th percentile (912 deaths) and zero otherwise[17], which I then interacted with the total disaster frequency variable.

Table 12 shows the baseline specification in column (1), the impact of severe disasters in column (2) and the interaction between severe and total disasters in column (3).

[16] Correlation between floods and storms: 0.281
[17] The total deaths distribution is heavily skewed, with casualties still low at the 75th and 90th percentiles.

As expected, in column (2) the severe dummy coefficient is larger than the baseline specification and significance has increased. Column (3) indicates that disaster frequency affects exports more critically when disasters are severe, i.e., have a high death toll, which is especially alarming in light of the IPCC's projections of increasing natural disaster intensity.[18]

This extension also highlights that a decision-rule is not necessary in the context of this paper. As Caribbean countries inherently have intense and frequent disasters, there seems to be less incentive for governments to exaggerate their severity, which would introduce upwards bias in the baseline disaster estimator. This method may be useful with a global cross-country sample, as there may be large differences in the way disasters interact with countries' socio-economic variables and therefore, their entry into the EM-DAT.

Table 12: Decision Rule

	(1) ln(exp)	(2) ln(exp)	(3) ln(exp)
Total Disasters	-0.228**		-0.180*
	(0.102)		(0.103)
Severe Dummy		-1.733***	
		(0.283)	
Total*Severe Disasters			-1.636***
			(0.286)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes
N	7,051	7,051	7,051
Adj. R^2	0.805	0.806	0.806

Standard errors clustered at 2-digit HS in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.5 Disaster Persistence

Lastly, this section explores whether the negative effects of disasters on exports are temporary or persist over time. Following, Yang (2008) who shows that it takes about 3 years for countries to adjust from hurricane damages, I modified the baseline specification to include lagged disaster variables for one to three years after a disaster had struck.

Table 13 presents results from this dynamic specification, with the long-run disaster coefficients reported at the bottom of the table. The cumulative coefficients in columns (2)-(4) indicate that negative disaster effects not only persist over time, but also become stronger (from around -1.8 to -4.7).[19]

Interestingly, these results mirror Pelli and Tschopp (2017), who find that the long-run coefficient for hurricane impact on exports increases over time from -2 to -6. This may seem counter intuitive as one would expect countries to rebuild from damages and effects to subside. However, Pelli and Tschopp (2017) explain this through a creative destruction

[18] Severe dummy coefficient in column (3) omitted due to zero estimate.

[19] Two-year disaster lag omitted due to collinearity.

argument; natural disasters give comparative disadvantage exporters the opportunity to shift production into comparative advantage industries.

Here, the long-term estimates may also be capturing this reallocation of resources, which is a lengthy process that continues and strengthens 3 years post-disaster.

Table 13: Disaster Dynamics

	(1)	(2)	(3)
	ln(exp)	ln(exp)	ln(exp)
Disasters$_{ct}$	-0.228**	-0.180*	0.975*
	(0.102)	(0.103)	(0.503)
Disasters$_{ct-1}$		-1.636***	-3.104***
		(0.286)	(0.730)
Disasters$_{ct-3}$			-2.554**
			(1.057)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes
Cumulative Effect After:			
One Year		-1.816***	
		[0.000]	
Three Years			-4.683***
			[0.000]
N	7,051	7,051	7,051
Adj. R^2	0.805	0.806	0.806

Standard errors clustered at 2-digit HS in parentheses

p-values in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Robustness

This section examines the robustness of the main results. One of the potential drawbacks of the baseline model is that exports are measured in values (USD), capturing price fluctuations unrelated to disaster frequency. For instance, a decrease in export quantity post-disaster may actually increase export values, causing a downward bias on results as argued by El Hadri et al. (2018). Therefore, the baseline model was re-run using net weight (kg) instead of values (USD) as the dependent variable. Estimation results are shown in Table 22 Appendix B.1, indicating that the disaster effect is larger (suggesting downward bias in the baseline specification) but remains negative and significant, confirming the main results.

Furthermore, I test for a variety of different fixed effects combinations and also cluster standard errors at country instead of industry-level. Most specifications produce a significantly negative disaster effect on exports, which further supports the main results. Moreover, the baseline specification remains the most suitable model for the data. For further details, see Table 24 Appendix B.3.

Additionally, I explore the impact of value-added and firm size variables on the total disaster coefficient. This was prompted by the counter-intuitively negative value-added coefficient appearing in the main results, which indicated a potential measurement error problem caused by the conversion between ISIC and HS classifications. Future research could reconcile this limitation by running this analysis with the same classification throughout all industry-level variables. Table 23 Appendix B.2 shows a specification without value-added and firm size controls. Clearly, the two variables control for crucial export-determinants, as the disaster coefficient turns positive without them. This highlights the importance of these controls, despite their potential measurement error.

Lastly, I check for heterogeneous disaster effects across countries in Table 25 Appendix B.4. I find that only Haiti's exports are significantly negatively affected by disasters. However, this could be attributed to highly unbalanced country sub-sample sizes, inviting future research on country heterogeneity to confirm this result. Nevertheless, this hinted that total effects may be driven by Haiti, which I test for in Table 26 Appendix B.4. Without Haiti, disaster impact turns positive, insinuating the main results are reflecting Haitian disasters. This is plausible as Haiti has the highest mean deaths, suggesting high disaster vulnerability.

7 Conclusion

This paper finds evidence that natural disasters have a short run negative effect on exports in the Caribbean using a fixed effects model. The main results are mainly driven by storms as they are the most frequent natural disaster in the region. This study contributes to the few industry-level analyses within the disaster literature by showing that mineral, chemical, paper, textile and metal industries suffer from lower exports in one of the world's most disaster-prone areas.

Precisely explaining why certain industries are affected more than others remains challenging since natural disasters hit industries at random. However, there is evidence that effects are mostly running through the casualties channel, which also reflects the lack of good quality construction practices in affected industries. Long term disaster effects on exports were also uncovered, which showed the export decline intensifying even 3 years post-disaster. Similarities with Pelli and Tschopp (2017) suggest that certain comparative disadvantage exporters were hit by disasters, who chose to reinvest into more competitive industries. The main results are generally robust to alternative specifications. I also test for country heterogeneity, revealing that results are possibly driven by disasters in Haiti as they have the highest casualties. However, further research is advised due to aforementioned data constraints.

As this paper finds large and long-term economic costs to disasters, it is clear that reactive policies focused on continuous damage reconstruction are not sustainable. Unfortunately, the unconditional nature of international aid creates a moral hazard problem as domestic governments are not incentivised to take precautionary measures and rather rely on reconstruction financed by international donors. Therefore, this paper recommends the increase in conditional international aid. Example conditions could be for domestic governments to monitor disaster insurance coverage in the most disaster-prone industries, enforce land-use and construction rules, and finance scientific research for disaster prediction, especially for storms (Charvériat (2000) mentions forecasting is shockingly underfunded by Caribbean governments). These measures would help pave the way towards necessary climate change preparedness and long-term resilience in the Caribbean.

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