



Empirical Studies on the Economic Impact of Climate-Related Natural Disasters

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博 士 論 文

平成 30 年 12 月

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経済学専攻

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CONTENTS

Contents	i
List of Figures	iii
List of Tables	iv
1 Introduction	1
References	4
2 The Impact of Climate Variability on Drought Management: Evidence from Japanese River Basins	5
2.1 Introduction	5
2.2 Droughts and the Drought Response in Japan	7
2.3 Empirical Analysis	9
2.3.1 Estimation Framework	9
2.3.2 Data and Variable Description	10
2.4 Results	14
2.4.1 Main Results with Precipitation Variability	14
2.4.2 Temperature Variability	18
2.4.3 Robustness Checks	21
2.5 Conclusions	23
References	25
3 Floods and Exports: An Empirical Study on Natural Disaster Shocks in Southeast Asia	28
3.1 Introduction	28
3.2 Floods and Storms in Southeast Asia	31
3.3 Empirical Analysis	35
3.3.1 Empirical Specification	35

3.3.2	Data Description	36
3.4	Results	37
3.4.1	Main Results	37
3.4.2	Robustness	39
3.4.3	Agricultural and Manufacturing Products	41
3.4.4	Impact of Large-Scale Disasters	44
3.5	Conclusions	46
	References	48
4	Do Natural Disasters Impede Exports? Evidence from Cross-Country Panel Data	52
4.1	Introduction	52
4.2	Global Trends in Floods and Storms	55
4.3	Empirical Analysis	59
4.3.1	Empirical Strategy	59
4.3.2	Description of the Variables	60
4.4	Results	62
4.4.1	Baseline Results	62
4.4.2	Natural Disasters in Developing and Developed Countries	65
4.4.3	Agricultural and Manufacturing Channels	68
4.4.4	Effect of Severe Disasters	70
4.5	Conclusions	72
	References	74
5	Concluding Remarks	77
	Appendix	80
I	Appendix for Chapter 3	80
II	Appendix for Chapter 4	82

LIST OF FIGURES

2.1	Location of dams subjected to water restrictions	9
2.2	Water restrictions during the 2008 drought in Matsuyama city . . .	12
3.1	Natural disasters in Southeast Asia by type (1990–2016)	32
3.2	Number of flood events in Southeast Asia	33
3.3	Number of storm events in Southeast Asia	33
4.1	Trends in the total number of disaster occurrences	56
4.2	Trends in average economic losses relative to GDP	56
4.3	Number of flood events by country	57
4.4	Number of storm events by country	58

LIST OF TABLES

2.1	Descriptions of variables	10
2.2	Descriptive statistics	11
2.3	Main regression results with rain variables (Dependent variable: water restriction rate)	15
2.4	Main regression results with rain variables (Dependent variable: duration of water restrictions)	16
2.5	Regression results with temperature variables (Dependent variable: water restriction rate)	19
2.6	Regression results with temperature variables (Dependent variable: duration of water restrictions)	20
2.7	Robustness checks	22
3.1	Severe disasters in Southeast Asia (1990–2016)	34
3.2	Summary statistics of variables	37
3.3	Main regression results	38
3.4	Alternative specifications of the results	40
3.5	Effect of floods on exports by product group	42
3.6	Effect of storms on exports by product group	43
3.7	Effect of severe natural disasters on exports (measured by the percentile- based cutoff values of the number of people killed by natural dis- asters)	45
4.1	Descriptive statistics of the variables	61
4.2	Main regression results	63
4.3	Alternative specifications with additional control variables	65
4.4	Effect of natural disasters on trade in developing and developed countries	67
4.5	Effect of natural disasters on trade by product group	69

4.6	Effect of large disasters	71
3.A	List of importers used in the analysis	81
4.A	List of countries used in the analysis	82

CHAPTER 1

INTRODUCTION

Natural disasters, with increasing trends in frequency and intensity, have caused significant damage to worldwide economy and human capital. The average number of natural disasters has doubled to 329 events per year in the period from 1998 to 2017 as compared to 165 events in the period from 1978 to 1997 (Wallemacq et al., 2018). Over the last 20 years, a total of 7,255 natural disasters were reported worldwide. Of these events, climate-related disasters, such as floods, storms, and droughts accounted for over 90% of all events. The media coverage of natural disasters has also drawn public attention to devastation caused by record-breaking hurricanes and extreme droughts worldwide. For instance, Hurricane Katrina in 2005 brought severe human and economic damage to the United States with estimated economic losses of USD 156 billion (Wallemacq et al., 2018). Prolonged and extensive droughts, particularly the latest two events in 2011 and 2016 to 2017, have resulted in severe food crises in Ethiopia, Somalia, and Kenya, along with other East African countries (FAO, 2018; FSIN, 2018).

Faced with challenges associated with natural disasters, global efforts and policy responses are urgently needed to mitigate humanitarian and economic crises. Consequently, in 2015, the *Sendai Framework for Disaster Risk Reduction 2015–2030* was implemented as an international response to disaster risks (UNISDR, 2015). This 15-year agreement is the successor of the *Hyogo Framework for Action 2005–2015*, and aims to mitigate disaster risks and losses by setting seven global targets and four priorities for action at local, national, regional, and global levels.

Researchers have also studied the socioeconomic effect of natural disasters on a variety of relevant topics (see Dell et al., 2014; Heal and Park, 2016). One strand of economic literature focuses on the macroeconomic costs of natural disasters. These studies estimate the extent to which the aggregate economy or economic growth is affected by extreme weather events. Moreover, a growing body of research has focused on the broader as-

pects of the economy at micro levels and examined the adverse impact of natural hazards. While existing literature provides important contributions to the understanding of how climate links to socioeconomic outcomes, related studies remain limited due to diverse and complex mechanisms of the relationship between climate and economy.

Therefore, this study has the following objectives. First, it examines the impact of natural disasters on economic activities. In particular, it identifies some economic aspects through which disaster shocks may affect the aggregate economy. Through empirical investigation, this study provides micro evidence of the adverse impact of extreme weather. Second, this study focuses on climate-related disasters: droughts, floods, and storms, to evaluate their damage to economically relevant aspects. The occurrence of this type of disasters is more likely to be driven by climate change. Moreover, climate change alters weather patterns, thereby accelerating the frequency and intensity of these events. By analyzing climate-related disasters, this study could offer suggestions for disaster risk reduction in relation to climate change adaptation and mitigation.

This study also focuses on the contemporaneous and long-term effect of natural disasters. The analysis incorporates the dynamics of the impact, considering the persistence of natural catastrophic events. The impact of natural disasters may continue for a longer period of time, particularly in the case of slow-onset and/or severe disasters. In this study, climate shocks are captured using the estimation approach that considers both immediate and persistent effects.

The remainder of this dissertation is organized as follows. Chapter 2 examines the impact of climate variability on water management under drought conditions. Focusing on drought response actions in Japan, this study evaluates how changes in precipitation and temperature affect water restrictions during droughts. Data used in this study include records of water restrictions imposed in Japanese watersheds, where the representatives of water users curtail water use via a coordination scheme. Chapter 3 investigates the impact of natural disasters on exports using monthly trade data to examine whether climate-related natural hazards affect international trade. Specifically, the analysis focuses on export flows from Southeast Asia where floods and storms have been the most frequent and damaging natural disasters in recent years. In the empirical analysis, using the breakdown of export data makes it possible to investigate the impact of natural disasters in more detail and identify the industries affected by natural disaster shocks. Chapter Chapter 4 provides further analysis of the relationship between natural disasters and international trade using cross-country panel data. Here, the analysis incorporates the impact of climate-related disasters that occurred in both exporting and importing countries. In

addition to the breakdown of export data used in Chapter 3, this chapter also considers countries' development levels to examine the heterogeneous impacts of natural disasters among countries. Chapter 5 concludes by summarizing the results and presenting some policy implications of the findings.

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CHAPTER 2

THE IMPACT OF CLIMATE VARIABILITY ON DROUGHT MANAGEMENT: EVIDENCE FROM JAPANESE RIVER BASINS

2.1 Introduction

Climate change can affect the hydrological cycle of river basins, making water availability more uncertain across time and space (World Bank, 2016). The uncertain availability of water may lead to serious economic consequences because it is essential for various human activities. The impact of climate variability on water resources can have many dimensions, such as population growth, agricultural yield, energy production, human health, urbanization, migration, and conflicts over resources (WWAP, 2015; Dell et al., 2014). Researchers have shown that weather variability induces unfavorable outcomes (Dell et al., 2009; Nordhaus, 2010; Barrios et al., 2006; Chen et al., 2016; Marchiori et al., 2012; McDermott and Nilsen, 2014; Miguel et al., 2004; Dell et al., 2012; Hsiang and Narita, 2012). These social and economic concerns are not only diverse but also important issues that require policy responses. The *Fifth Assessment Report of the Intergovernmental Panel on Climate Change* discusses how climate change is linked to water-related sectors in terms of its impacts, vulnerabilities, and risks (IPCC, 2014). Facing such challenges, the importance of effective water resource management is strongly emphasized in order to alleviate negative impacts of climate change (World Bank, 2016).

This study contributes to the literature on the socio-economic impacts of climate variability. Chen et al. (2016) analyze the impact of climate change on crop production in China. According to their estimation, economic losses in China's corn and soybean production amounted to \$595-858 million over the past decade. McDermott and Nilsen

(2014) investigate environmental impact on energy production. Focusing on the issue of thermal pollution by cooling water used for thermal power generation, they examine how water scarcity and river temperature affect electricity prices. Their study reveals the potential risks of climate change to the energy sector. It is also well known that precipitation shocks and lack of water resources may provoke social disturbances and political instability (World Bank, 2016). Evidence of such issues has been provided by researchers studying the impact of climate variability on violent conflict and crime (Maystadt et al., 2014; Maystadt and Ecker, 2014; Takahashi, 2017; Miguel et al., 2004). There is also growing literature regarding the link between climate variability and migration (Dallmann and Millock, 2017; Barrios et al., 2006; Marchiori et al., 2012).

The objective of this study is to evaluate the impact of climate variability on water resource management. Specifically, we examine how climate variability affects water restrictions in local communities during droughts. Our dataset includes records of water restrictions implemented in river basins in Japan over the last three decades. It allows us to investigate the impact of weather variability on urban water supply in the face of extreme weather events. The analysis also uses drought-related climate variables based on precipitation and temperature. Although the high dependence of water restrictions on weather conditions is expected because of their impact on the water cycle, the extent of such effects has not been studied extensively. This study thus examines changes in precipitation and temperature to evaluate the extent to which they affect water restrictions during droughts.

Several studies include weather variability as a determinant of residential water use (Hoyos and Artabe, 2017; Schleich and Hillenbrand, 2009). These studies suggest that weather conditions affect water consumption. While water consumption simply refers to how much water is used, it does not represent how much water can be used when the availability of water is limited. This study, on the other hand, focuses on water restrictions during droughts and examines how they are affected by weather. Such drought response actions are taken in order to enhance water availability under extreme weather. Therefore, our approach directly investigates decision making for climate change adaptation. Addressing the risks of climate change has become an important policy task for sustainable water management. The results of this study may provide useful information for a better understanding of climatic impacts on urban water management, thereby leading to an effective adaptation strategy for climate change.

The results of our empirical analysis show that climate variability is significantly correlated with water restrictions. We find that a decrease in annual precipitation raises

the restriction rate of water withdrawals and extends the duration of water restrictions. This study also investigates the effect of weather shocks by measures of weather anomalies, which have been proposed in the relevant literature (Barrios et al., 2010; Marchiori et al., 2012). The results from this weather indicator show that a decrease in precipitation anomalies is associated with higher restriction rate and longer restriction period. Moreover, another precipitation measure shows that an additional day without rainfall during a year also affects water restrictions. These findings suggest that changes in rainfall patterns may disturb the management of water resources, leading to more severe water restrictions.

The remainder of the chapter is organized as follows. Section 2.2 provides an overview of drought conditions in Japan and response actions taken in river basins. Section 2.3 describes the method and data. The estimation results are presented and discussed in Section 2.4, and Section 2.5 concludes.

2.2 Droughts and the Drought Response in Japan

Although Japan receives relatively abundant precipitation and seasonal typhoons, the country has suffered droughts and water shortages. One of the reasons for the insufficiency of water resources lies in its geographical conditions. The gradient of Japanese rivers is steeper and its length is shorter compared to rivers around the world (Water Resource Department, Land and Water Bureau, MLIT, 2015). Runoff from precipitation therefore quickly drains to an outlet that eventually flows into the ocean. Consequently, this prevents runoff from remaining in streams and reservoirs. In addition to geographical difficulties, population growth and economic development have boosted water consumption in the last century (Akiyama, 2011). High demand for urban water use caused an imbalance in water supply and demand, particularly during periods of high economic growth. Recently, water resource management is facing an additional challenge from climate change, which is becoming one of the greatest concerns as it triggers extreme weather events including droughts.

Droughts occur in various parts of Japan almost every year, with various degrees of severity. While a drought can be defined in many ways depending on the context, this study refers to a drought as a period of dry weather that causes diminishing water supply and thus requires restrictions on water withdrawals from reservoir dams. Drought-vulnerable areas include many economically important and/or highly populated cities in Japan, including the Tokyo metropolitan area. Recently, in the summer of 2016, Tokyo and its large suburban area experienced a drought for the first time since 2013. Concerns

over a water shortage began in the spring of 2016 when the region received substantially lower precipitation than usual, followed by a lack of snowpack in winter. After the storage level of reservoirs dropped low enough to threaten water supply, the region implemented restrictions on water withdrawals from dams in June. The drought persisted for about three months until September. Before 2013, seasonal droughts also occurred in the Tone River Basin, Tokyo's largest watershed, in 2012, 2001, and 1997. The Tone River Basin has implemented water restrictions 16 times between 1972 and 2016.

The impact of droughts may spread to various aspects in communities, resulting in social, economic, and environmental consequences. In the Tone River Basin mentioned above, water from dams is used for several purposes: water supply for residential, agricultural, and industrial sectors, and hydroelectric power generation. In addition, these dams are also used for controlling floods and stabilizing water flows in rivers. Because almost every river basin in Japan has such multipurpose dams, regional droughts can be a threat to water use in various sectors. Moreover, issues related to droughts and water shortages may significantly affect how local communities collectively manage water resources.

To address droughts at the river basin level, local communities in Japan implement water restrictions as one of the drought response actions. For instance, the Tone River Basin curtails water use from their eight dams located upstream.¹ Water restrictions are introduced via the drought coordination council, which is organized in a river basin in response to a drought. The council originated from the notification issued by the former Japanese Ministry of Construction in 1974, in which the implementation of a council is suggested in river basins facing droughts (Kasensho Kenkyu Kai, 2011). Members of the council include water users such as representatives of water utilities, farmers' groups, and electric power companies, together with river administrators and related government agencies.² In addition to sharing information on drought conditions, the council makes collective decisions on water restrictions. Therefore, the introduction of the council is not only a way to facilitate communications among council members but also to involve water users in the decision-making process for drought management. From this point of view, water restrictions implemented through the drought coordination council can be characterized as collective action in river basin communities.

¹However, this is a rather exceptional case, as water restrictions in most cases involve only one dam. Even in cases in which water restrictions are imposed jointly on multiple dams, only two or three dams are usually involved.

²Note that the groups of stakeholders actually participating in the council depends on the community in question.

2.3 Empirical Analysis

2.3.1 Estimation Framework

Our empirical analysis aims to examine whether and to what extent weather variability affects drought management, with a focus on the relationship between water restrictions and weather variability. The analysis explores river basins that experienced droughts and implemented water restrictions in Japan, which gives us the panel dataset of 60 river basins with the time period from 1984 to 2014. For drought events included in the analysis, the water restrictions that were implemented concern water withdrawals from dams.³ Therefore, we collect climate variables using point data from weather stations based on the locations of dams. Figure 2.1 shows the site of each reservoir dam used in the analysis. The specification of our estimation model is as follows:

$$WaterRestrictions_{it} = \beta_0 + \beta_1 Weather_{it} + \gamma_i + \delta_t + \varepsilon_{it}. \quad (2.1)$$

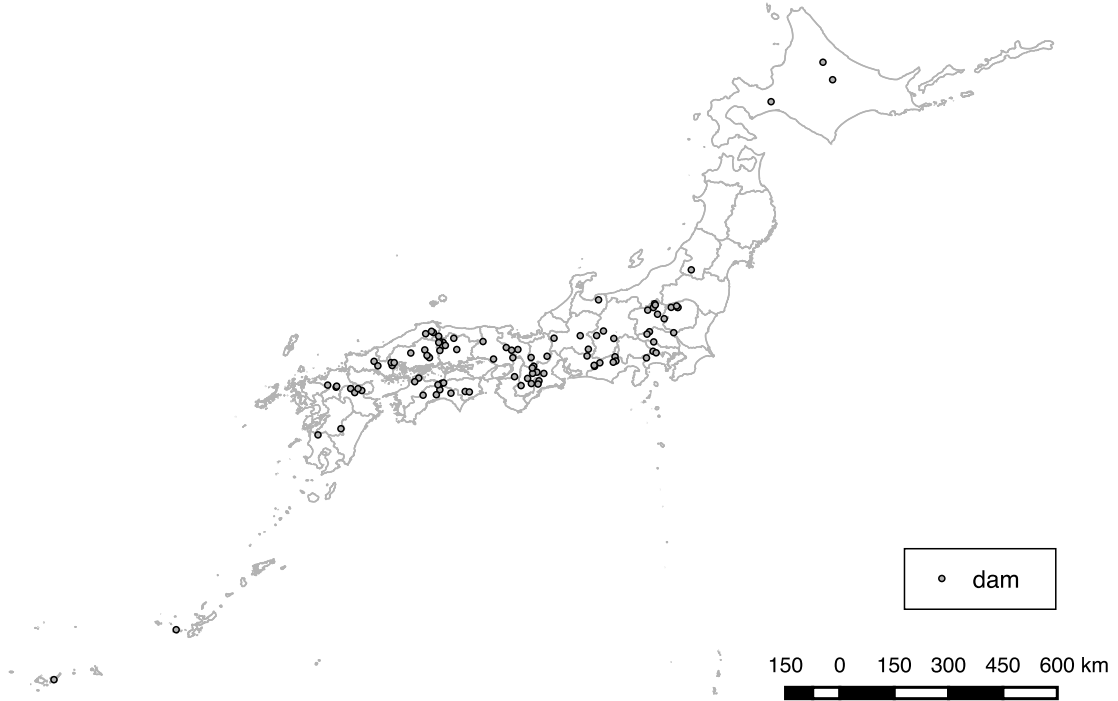


Fig. 2.1 Location of dams subjected to water restrictions

³For this reason, the panel dataset is unbalanced as we only include observations of each river basin after the completion of dams that were subject to the restrictions.

The dependent variable $WaterRestrictions_{it}$ represents drought response measures, i.e., water restrictions, implemented by a drought coordination council in river basin i in year t . Drought coordination councils are usually organized on the basis of river basins or sub-river basins. Therefore, the cross-sectional unit is defined according to river basins. The explanatory variable, $Weather_{it}$, is a set of climate variability that captures the severity of drought conditions. River basin dummies are captured by γ_i . These time-constant variables control for any unobserved heterogeneity across areas divided by river basins, such as geographical characteristics and cultural background in terms of water use. The other fixed effects δ_t are year-fixed effects, which are time-specific variables controlling for any external event common to all river basins. Finally, ε_{it} is an error term.

2.3.2 Data and Variable Description

Table 2.1 summarizes the variables used in the regression analysis. Table 2.2 presents descriptive statistics of these variables. Two variables are used as dependent variables: the rate of water restrictions on residential water supply and the duration of water restrictions. The former measures the percentage of water that was curtailed during the restriction period, and the latter measures how long such restrictions continued.

Figure 2.2 depicts these two drought response actions, using the 2008 drought in Matsuyama City as an example. The figure shows at what level water restrictions were implemented and revised as daily rainfall changed over the period. In response to a drought, river basin communities collectively make decisions on water restrictions via the drought coordination council. In the case of the 2008 drought in Matsuyama City, the Ishitegawa

Table 2.1 Descriptions of variables

Variable	Unit	Description
Restriction rate	%	Rate of water withdrawal restrictions on residential water supply
Duration	day	Duration of water restrictions
Rain	mm	Annual precipitation
Rain anomalies	-	Deviations of precipitation from the long-term (1983-2014) mean precipitation, divided by its long-term standard deviation
Dry days	day	Annual number of days with precipitation less than 1mm
Avg. consecutive dry days	day	Average annual number of consecutive days with precipitation less than 1mm
Max. consecutive dry days	day	Maximum annual number of consecutive days with precipitation less than 1mm
Temp	°C	Average daily temperature
Temp anomalies	-	Deviations of temperature from the long-term (1983-2014) mean temperature, divided by its long-term standard deviation
Hot days	day	Annual number of days with maximum daily temperature above 30°C threshold
Avg. consecutive hot days	day	Average annual number of consecutive days with maximum daily temperature above 30°C threshold
Max. consecutive hot days	day	Maximum annual number of consecutive days with maximum daily temperature above 30°C threshold

Table 2.2 Descriptive statistics

Variable	Mean	S.D.	Min	Max
Restriction rate	3.12	9.69	0.00	100.00
Duration	9.22	25.92	0.00	190.00
Rain	1926.44	703.65	661.00	5892.00
Rain anomalies	-0.00	0.98	-3.21	3.97
Dry days	232.64	25.51	133.00	294.00
Avg. consecutive dry days	4.76	0.71	2.86	7.83
Max. consecutive dry days	18.28	7.05	6.00	59.00
Temp	13.67	3.04	3.50	25.38
Temp anomalies	0.02	0.98	-4.69	3.51
Hot days	42.09	23.28	0.00	138.00
Avg. consecutive hot days	5.48	3.80	0.00	34.50
Max. consecutive hot days	15.18	11.23	0.00	80.00

Drought Coordination Council organized meetings and set water restrictions from August 4. At the early stages of drought, restrictions are usually imposed with lower rates of withdrawal reduction. The restriction rates are gradually increased as drought conditions worsen. As shown in Figure 2.2, the highest restriction rate (25%) was applied in late September. The restrictions were then relaxed as drought conditions ceased.

Our dataset is composed of the maximum rates of water restriction issued during each drought event. Water restrictions described in this study are associated with reductions of water intake by water utilities. Therefore, the restriction rate of 25% does not imply that percentage of reduction in water supply to citizens. During the drought in 2008, Matsuyama City implemented different types of measures to curtail water use. For instance, the city regulated residential water use by reducing water pressure and closing school and community swimming pools. The duration of water restrictions means the period between the day of implementation and the day of lifting of the restrictions, which is illustrated in the shaded area in Figure 2.2. In this example, the duration of water restrictions is 64 days, from August 4 to October 6.

Data on water restrictions are obtained from *Water Resources in Japan* published by the Japanese Ministry of Land, Infrastructure, Transport, and Tourism. This annual report provides the records of regional drought, including the maximum rates of water restrictions issued during each drought event.⁴ We collect data on these regional droughts and water restrictions, which comprise 301 drought events for models estimating restriction rates and 356 drought events for models estimating restriction duration. Data on restriction rates and duration are used for each river basin in the drought years when water

⁴The document does not report other measures related to the rates of water restrictions.

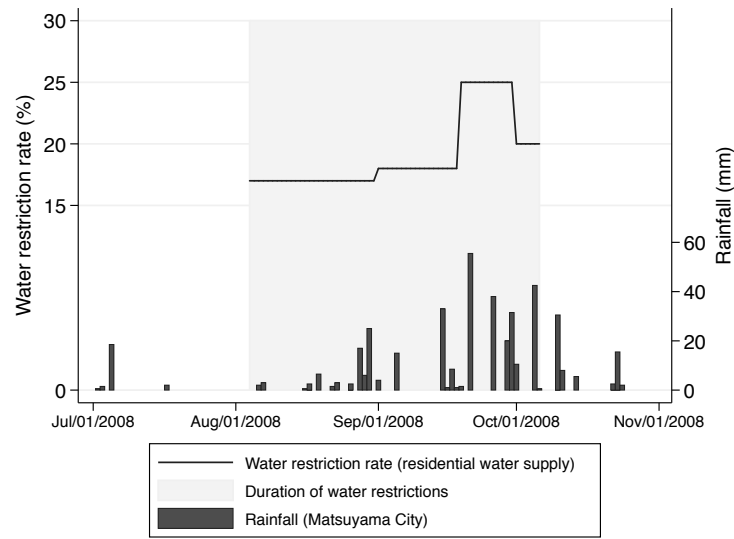


Fig. 2.2 Water restrictions during the 2008 drought in Matsuyama city

Source: Matsuyama City

restrictions were issued. Non-drought years in any river basin are assigned a value of zero.

The variables of interest in this study are a series of weather variability. We compute several types of climate measures based on precipitation and temperature. By including these alternative variables, we intend to capture the weather variability that may affect water availability and drought management. Data on precipitation and temperature are available from the online database of the Japanese Meteorological Agency.⁵ We collect daily data on precipitation and temperature at weather stations geographically closest to each dam, which are calculated with GIS software by using point data of weather stations and reservoir dams.⁶ The data are then aggregated at the annual level. In cases where multiple dams were jointly subject to water restrictions, we average the values of the weather data.

We first use the level measure of weather variables, represented as *Rain* and *Temp*. *Rain* indicates the annual amount of precipitation, whereas *Temp* indicates the average daily temperature during a year. We then construct alternative variables based on these level measures of precipitation and temperature variables. Following Barrios et al. (2010) and Marchiori et al. (2012), we construct the weather anomaly variables, *Rain anomalies*

⁵ Available at <http://www.jma.go.jp/jma/indexe.html>.

⁶ Data on the locations of the dams are obtained from the *National Land Numerical Information download service* run by the Japanese Ministry of Land, Infrastructure, Transport, and Tourism and are available at <http://nlftp.mlit.go.jp/ksj-e/index.html>.

and *Temp anomalies*, by taking the deviation from the long-run mean and dividing it by its long-run standard deviation. The weather anomaly variables are thus computed as follows:

$$Weather\ anomalies_{it} = \frac{Weather_{it} - \mu_i^{LR(Weather)}}{\sigma_i^{LR(Weather)}}, \quad (2.2)$$

where $Weather_{it}$ is the level of precipitation or temperature for river basin i in year t , $\mu_i^{LR(Weather)}$ is the long-run mean for river basin i , and $\sigma_i^{LR(Weather)}$ is its long-run standard deviation.⁷ The normalized measure defined as weather anomalies in Equation 2.2 has been used in the literature on the relationship between climate variability and socioeconomic activities (see Barrios et al., 2010; Dallmann and Millock, 2017; Maystadt and Ecker, 2014; Marchiori et al., 2012). With this approach, weather conditions are captured in a relative sense because anomaly variables take into account weather variations in a particular area. In other words, the anomaly measures indicate how weather conditions of a region in any given year deviate from the average weather conditions (Marchiori et al., 2012).

For precipitation, we use the amount of rainfall, in either absolute or relative terms. In addition to these variables, we further examine three types of variables related to precipitation: *Dry days*, *Avg. consecutive dry days*, and *Max. consecutive dry days*. These variables indicate the number of days without rainfall a river basin had in a year. A dry day is defined as a day with precipitation less than 1 mm. We construct the variable *Dry days* by calculating the annual number of such days without rainfall. Consecutive dry days are defined as the sequence of days without rainfall. *Avg. consecutive dry days* is calculated as the average annual number of consecutive dry days, while *Max. consecutive dry day* is taken as the longest spell of dry days in a given year.

Analogous to the precipitation variables, three temperature variables are also constructed, based on the maximum daily temperature. *Hot days* indicates the total number of days with maximum daily temperature above 30°C (86°F) threshold in a year. Then we calculate the mean number of consecutive hot days to obtain *Avg. consecutive hot days*. *Max. consecutive hot days* is the longest spell of days with maximum daily temperature above 30°C threshold in a given year.

⁷We take the long-run to be a period from 1983 to 2014.

2.4 Results

2.4.1 Main Results with Precipitation Variability

The main results from the regression analysis are presented in Tables 2.3 and 2.4. The panel structure of the data allows us to use alternative estimation approaches; i.e., fixed-effects model and random-effects model. First, we test the validity of these models by using an F -test for the fixed-effects model and the Breusch-Pagan Lagrange multiplier test for the random-effects model. Both tests confirm that these models are more appropriate than the OLS model. Then, we also conduct the Hausman test to compare the fixed-effects and random-effects models. The tests in all models do not reject the null hypothesis that the regressors are uncorrelated with river basin-specific effects. This suggests that the random-effects model is more appropriate; however, the estimates of the fixed-effects model do not considerably differ from those of the corresponding random-effects model. We present the estimation results of both fixed-effects (FE) and random-effects (RE) models, as shown in the tables.

The estimation results using precipitation variability show that the variables have significant impacts on water restrictions. The coefficients of *Rain* are negative and statistically significant as shown in the first and sixth columns in Table 2.3. The estimation results suggest that the restriction rate increases by 0.2% as the level of annual precipitation decreases by 100 mm. The coefficients of *Rain anomalies* in the second and seventh columns are also negative and statistically significant. These coefficients indicate that a one-point decrease in precipitation anomalies leads to an increase in the restriction rate by 1.4%. Moreover, we find that *Dry days* is correlated with the water restriction rate. The coefficients in the third and eighth columns are positive and statistically significant at the 1% level, suggesting that more days without rainfall may lead to stricter water restriction rates. However, we find that the coefficients of *Avg. consecutive dry days* and *Max. consecutive dry days* are not statistically significant. A spell of dry days may not affect the levels of water restrictions if it rains substantially in a short period of time. Potentially, one typhoon with heavy rain brings large amount of water that can be stored in reservoirs.

Table 2.3 Main regression results with rain variables (Dependent variable: water restriction rate)

	FE					RE				
	1	2	3	4	5	6	7	8	9	10
Rain	-0.002* (0.001)					-0.002** (0.001)				
Rain anomalies		-1.428*** (0.398)					-1.423*** (0.397)			
Dry days			0.076*** (0.022)					0.059*** (0.016)		
Avg. consecutive dry days				0.479 (0.482)					0.552 (0.453)	
Max. consecutive dry days					0.062 (0.056)					0.061 (0.052)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.06	0.07	0.06	0.06	0.06					
Within R^2	0.08	0.09	0.08	0.07	0.07	0.08	0.09	0.08	0.07	0.07
Overall R^2	0.04	0.07	0.06	0.06	0.06	0.04	0.07	0.07	0.06	0.06
Standardized coef.	-0.180	-0.144	0.200	0.035	0.044	-0.118	-0.143	0.156	0.040	0.043

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.

Table 2.4 Main regression results with rain variables (Dependent variable: duration of water restrictions)

	FE					RE				
	1	2	3	4	5	6	7	8	9	10
Rain	-0.009*** (0.002)					-0.007*** (0.002)				
Rain anomalies		-5.565*** (0.919)					-5.552*** (0.918)			
Dry days			0.243*** (0.056)					0.198*** (0.048)		
Avg. consecutive dry days				2.581* (1.501)					2.786* (1.514)	
Max. consecutive dry days					0.121 (0.085)					0.124 (0.082)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.14	0.15	0.14	0.13	0.13					
Within R^2	0.16	0.17	0.15	0.14	0.14	0.16	0.17	0.15	0.14	0.14
Overall R^2	0.09	0.13	0.12	0.12	0.11	0.10	0.13	0.13	0.12	0.11
Standardized coef.	-0.257	-0.210	0.240	0.070	0.032	-0.185	-0.209	0.195	0.076	0.033

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.

While the results above show that precipitation affects the intensity of water restrictions, we also find that precipitation variables have significant effects on the duration of water restrictions. In Table 2.4, the coefficients of *Rain* are negative and statistically significant at the 1% level. The findings suggest that a decrease in annual precipitation by 100 mm is associated with an increase in the restriction period by 0.7–0.9 days. Similarly, *Rain anomalies* is also correlated with the duration of water restrictions. The coefficients show that a one-point decrease in precipitation anomalies increases the duration by 5.6 days. Furthermore, the coefficients of *Dry days* are statistically significant and indicate that one additional dry day increases the duration of water restrictions by 0.2 days. The positive sign of the coefficients suggests that more dry days may lead to extended water restrictions. The coefficients of *Avg. consecutive dry days* are also positive and statistically significant. While both variables of the average and maximum consecutive dry days do not show a significant effect on the restriction rate, we find that the average number of consecutive dry days may induce prolonged water restrictions. On the other hand, we do not find the correlation between *Max. consecutive dry days* and the duration of water restrictions.

The results from Tables 2.3 and 2.4 show that variability in precipitation affects both the rate and duration of water restrictions. This suggests that changes in rainfall may bring an adverse impact on drought management. In other words, lower precipitation can cause stringent water restrictions during a drought, in terms of higher restriction rates and longer restriction period. The impacts of precipitation variability have also been observed in other studies. Schleich and Hillenbrand (2009) investigate residential water demand and find that the number of days with rainfall in the summer months affects water consumption, which is similar to our findings on the dry days variable. However, in contrast to our results, they find no significant effect of the amount of rainfall. Barrios et al. (2010) use precipitation anomalies and find that lower rainfall negatively affects the growth rate of GDP per capita in sub-Saharan African countries. In another study, Miguel et al. (2004) use rainfall measures as instrumental variables and show that rainfall shocks have a significant impact on the economic growth rate in sub-Saharan Africa. Although the focuses of their analyses are different, our findings are in line with the relevant literature examining the impact of precipitation variability.

In the bottom row of Tables 2.3 and 2.4, we provide the standardized coefficients of the weather variable included in each model. Both the dependent and independent variables are standardized, meaning that the coefficients are estimated as standard deviation changes in the dependent variable, i.e., the rate or duration of water restrictions, for a

one standard deviation change in the weather variable. The standardized coefficients are useful for comparing variables with different metrics. Because variables are measured by the same metric when standardized, it makes the impacts of variables more comparable to each other. According to the results, for instance, a decrease in the annual precipitation by one standard deviation raises the rate of water restrictions by 0.12–0.18 standard deviations and the duration by 0.19–0.26 standard deviations. The standardized coefficients of the anomaly variable also show that a one standard deviation decrease in precipitation anomalies increases the restriction rate by 0.14 standard deviations and the duration by 0.21 standard deviations. Although the magnitude of the (unstandardized) coefficients of *Rain* are substantially smaller than those of *Rain anomalies* and *Dry days*, the standardized coefficients suggest that the impact of *Rain* is as large as those of the other two precipitation variables.

2.4.2 Temperature Variability

The regression results using temperature variables are shown in Tables 2.5 and 2.6. The models in Table 2.5 examine the effect on the restriction rate, while the models in Table 2.6 examine the effect on the duration. In Table 2.5, none of the temperature variables are statistically related to the water restriction rate, except *Avg. consecutive hot days*. The coefficients in the fourth and ninth columns are positive and statistically significant at the 10% level, suggesting that a one-day increase in the average spell of dry days is associated with an increase in the restriction rate by 0.2%. While precipitation variables in Table 2.3 are found to be correlated with the restriction rate, we find little evidence of temperature impacts. The findings suggest that water restrictions, in terms of intensity, are affected by precipitation rather than temperature. The results seem reasonable since precipitation is more directly related to water use, storage, and shortage.

Regarding the duration of water restrictions, however, we find significant effects of temperature more clearly. The coefficients of *Temp* are statistically significant as shown in the sixth column in Table 2.6. The coefficients are positive, indicating that a 1°C increase in daily temperature prolongs the duration of water restrictions by 0.7 days. We also find that *Hot days* is statistically correlated with the duration of water restrictions. The coefficients in the eighth column in Table 2.6 show that an additional hot day extends water restrictions by 0.1 days. Likewise, *Avg. consecutive hot days* is statistically related to the duration of water restrictions. The coefficients suggest that the duration of water restrictions increases by 0.8–0.9 days with a one-day increase in the average spell of hot days.

Table 2.5 Regression results with temperature variables (Dependent variable: water restriction rate)

	FE				RE					
	1	2	3	4	5	6	7	8	9	10
Temp	0.373 (0.731)					0.131 (0.160)				
Temp anomalies		0.501 (0.566)					0.483 (0.555)			
Hot days			0.069 (0.051)					0.047 (0.032)		
Avg. consecutive hot days				0.209* (0.111)					0.216** (0.107)	
Max. consecutive hot days					0.016 (0.048)					0.020 (0.042)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.06	0.06	0.06	0.06	0.06					
Within R^2	0.07	0.07	0.08	0.08	0.07	0.07	0.07	0.08	0.08	0.07
Overall R^2	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
Standardized coef.	0.116	0.050	0.167	0.083	0.018	0.041	0.048	0.113	0.086	0.023

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.

Table 2.6 Regression results with temperature variables (Dependent variable: duration of water restrictions)

	FE					RE				
	1	2	3	4	5	6	7	8	9	10
Temp	0.936 (2.299)					0.727* (0.441)				
Temp anomalies		0.960 (1.941)					0.940 (1.925)			
Hot days			0.124 (0.083)					0.125** (0.060)		
Avg. consecutive hot days				0.775** (0.379)					0.854** (0.366)	
Max. consecutive hot days					0.077 (0.082)					0.123 (0.083)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.12	0.13	0.13	0.13	0.13	0.14	0.14	0.14	0.15	0.14
Within R^2	0.14	0.14	0.14	0.15	0.14	0.14	0.14	0.14	0.15	0.14
Overall R^2	0.12	0.11	0.12	0.13	0.12	0.12	0.11	0.12	0.13	0.12
Standardized coef.	0.108	0.036	0.111	0.115	0.033	0.084	0.035	0.113	0.126	0.053

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.

The findings show that water restrictions are affected by higher temperature measured by both levels and frequencies. Although precipitation may be a more robust predictor for drought response actions, temperature conditions are also expected to affect water restrictions. This may be because of the potential demand for water in the hot year: higher temperature induces more water consumption for drinking, gardening, taking showers, etc. Another possible explanation may be that higher temperature results in larger water loss in reservoirs through evaporation. These concerns could cause a river basin to restrict water use in the hot year. The results from temperature variables suggest that potential extreme weather events caused by climate change, such as heat waves and longer summer seasons, could lead to more stringent drought response actions being implemented.

2.4.3 Robustness Checks

We test the robustness of the estimation results by examining alternative weather indicators. We introduce alternative measures of weather anomalies in this section. In the main analysis, weather anomalies are included as a proxy for climatic conditions. To check the validity of the main results, we use alternative definitions of weather variables constructed as follows:

$$Rain\ ratio_{it} = \frac{Rain_{it}}{\mu_i^{LR(Rain)}}, \quad (2.3)$$

$$Rain\ deviation_{it} = Rain_{it} - \mu_i^{LR(Rain)}. \quad (2.4)$$

The definitions of the variables used to compute *Rain ratio* and *Rain deviation* are the same as those in *Weather anomalies*, explained in Section 2.3.2.⁸ Similar to the anomaly variable, the ratio and deviation variables consider the long-run mean value. The rain ratio in Equation 2.3 is computed as the level of the precipitation variable, divided by the long-run mean. The rain deviation in Equation 2.4 is taken as the deviation from the long-run mean precipitation. The Japanese Meteorological Agency regularly releases the ratio and deviation of precipitation and temperature calculated in a similar manner to capture long-term climatic trends. Moreover, the ratio and deviation measures have also

⁸We also compute and test the ratio and deviation variables using temperature. The coefficients of these variables are both statistically insignificant (results not shown); therefore, they do not alter the results presented in Section 2.4.2.

Table 2.7 Robustness checks

	Restriction rate			Duration				
	FE	RE		FE		RE		
	1	2	3	4	5	6	7	8
Rain ratio	-6.623*** (2.357)		-6.615*** (2.348)		-27.525*** (4.564)		-27.454*** (4.554)	
Rain deviation		-0.002* (0.001)		-0.002** (0.001)		-0.010*** (0.002)		-0.010*** (0.002)
River basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	1678	1678	1678	1678	1678	1678	1678	1678
Adjusted R^2	0.07	0.06			0.15	0.14		
Within R^2	0.08	0.08	0.08	0.08	0.17	0.16	0.17	0.16
Overall R^2	0.06	0.06	0.06	0.06	0.13	0.13	0.13	0.13
Standardized coef.	-0.134	-0.109	-0.133	-0.109	-0.207	-0.158	-0.207	-0.158

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by river basin and reported in parentheses. Standardized coef. stands for standardized coefficients of weather variable, indicating a change in the dependent variable measured in units of standard deviations for a one standard deviation increase in the weather variable. FE refers to the fixed-effects model, and RE refers to the random-effects model.

been examined in previous literature (Barrios et al., 2010; Levine and Yang, 2014).⁹ Thus, these variables are suitable for use as alternative indicators.

Table 2.7 presents the estimation results of the ratio and deviation measures. Columns 1–4 provide the results for the restriction rate model, and columns 5–8 provide the results for the duration model. The results of models using alternative variables do not largely differ from the main results in Section 2.4.1. The coefficients of *Rain ratio* are statistically significant and negative as expected. The standardized coefficients in the bottom rows indicate that a one standard deviation decrease in *Rain ratio* increases the restriction rate by 0.13 standard deviations and the duration by 0.21 standard deviations. Likewise, *Rain deviation* is also negatively correlated with both the restriction rate and duration. The standardized coefficients show that a decrease in the deviation measure of precipitation is associated with a 0.11 standard deviation increase in the restriction rate and a 0.16 standard deviation increase in duration. The magnitudes of these standardized coefficients are similar to those of the level and anomaly variables.

2.5 Conclusions

This chapter investigate the impact of weather variability on community-based water management during droughts. To explain how drought management is affected by weather conditions, we analyze water restrictions that were implemented in response to droughts in Japanese river basins from 1984 to 2014. The analysis uses climatic indicators relevant to precipitation and temperature. We construct alternative variables to examine whether and to what extent weather conditions affect water resource management during droughts.

Our study shows that weather variability is significantly related to water restrictions. We find that changes in weather conditions affect not only the amount of water being curtailed but also the duration of restriction implementation. The regression results show that the rate of water withdrawal restriction increases by 0.2% and the restriction period extends by almost a day when annual precipitation decreases by 100 mm. In addition, the impact of weather shocks is estimated using weather anomalies, which capture regional weather variations relative to the average conditions. The results show that a one-point decrease in precipitation anomalies intensifies the restriction rate by 1.4% and the duration by 6 days. These findings suggest that precipitation, measured by both absolute and

⁹Barrios et al. (2010) study the effect of precipitation on economic growth in Africa using the ratio measure along with its interaction terms. Levine and Yang (2014) examine the impact of rainfall on rice production with the deviation measure by taking the log of rainfall and the log of mean rainfall.

relative terms, is associated with drought response actions. When we use dry days, i.e., the number of days without rainfall, as a weather indicator, we also find evidence of a negative impact of weather shocks that cause an increase in the rate and duration of water restrictions. The results of this study suggest that lower precipitation may result in the implementation of more stringent water restrictions.

Furthermore, the regression results show that temperature variability is correlated with water restrictions. The findings suggest that the negative impact of temperature variability on water restrictions may be amplified as temperature conditions become more intense. This has important policy implications regarding drought management in local communities. As climate change is expected to cause more extreme weather events, the potential risks of heat waves or extended summer seasons should be considered in drought management. In addition to concerns for human health, crop losses, environmental damages, etc., the occurrences of such extreme events may have a serious impact through the water supply. Drought coordination councils in Japan can facilitate the management of water supply under drought conditions by providing opportunities to coordinate the water demand of local stakeholders.

We believe that this is one of the few studies that investigate the impact of climate variability on water resource management under extreme weather conditions. Despite the urgent need for adaptation to future climate variability and change, there are few attempts to empirically analyze the topic, especially in the context of drought issues in Japan. This study provides empirical evidence of climatic impact on water availability under drought conditions. The findings suggest an important role of coordination body in enhancing an institutional capacity to adapt to severe weather events. On the other hand, we do not consider how the restrictions on water availability affect the livelihood of water users in river basins. Economic activities and actual water consumption may also be affected by such restrictions under droughts. Future research should thus focus on these aspects to investigate economic consequences of extreme weather events.

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CHAPTER 3

FLOODS AND EXPORTS: AN EMPIRICAL STUDY ON NATURAL DISASTER SHOCKS IN SOUTHEAST ASIA

3.1 Introduction

Natural disasters can cause severe destruction and devastation, leading to significant economic and human damage. According to the Emergency Events Database (EM-DAT), a total of 6,457 weather-related disasters have occurred worldwide between 1995 and 2015 (CRED and UNISDR, 2015). These disasters have caused economic damage of USD 1,891 billion and, on average, affected 205 million people every year. Among such disasters, floods are the most frequent type, accounting for 43% of natural disasters. Over the past two decades, 2.3 million people have been affected by floods, causing economic losses of USD 662 billion. The Intergovernmental Panel on Climate Change (IPCC) reports growing economic losses as a result of floods since the 1970s (IPCC, 2014), a trend that is likely to continue, with flood events projected to increase in certain parts of the world, especially developing nations, where the economic losses relative to GDP are most significant.

The objective of this study is to examine the effects of climate-related disasters on international trade. By using monthly export data from 2004 to 2016, we explore the relationship between natural hazards and the bilateral export flows of four Southeast Asian countries. Southeast Asia provides a good opportunity to analyze this topic for two reasons. First, floods and storms in Southeast Asia are the two most frequent and damaging natural hazards. Between 2006 and 2015, the average annual costs incurred as a result of floods and storms were USD 5.8 billion and USD 2.7 billion, respectively (Guha-Sapir

et al., 2016). Economic losses in lower-income countries are smaller in absolute value compared to those in high-income countries, but are relatively larger as a share of GDP. In this sense, natural disasters can have severe consequences in Southeast Asia. Second, Southeast Asia's exports are a key factor of economic development. In ASEAN countries, for example, the total traded goods amounted to USD 2,270 billion in 2015, accounting for 93% of the region's GDP (ASEAN, 2016). Since more than 70% of the goods are exported outside ASEAN countries, Southeast Asia's export losses caused by natural disasters may also affect other countries' economies through the global supply chain.

Researchers have examined the effects of natural disasters on socioeconomic activities at various levels (El Hadri et al., 2017; Mendelsohn et al., 2011; Anttila-Hughes and Hsiang, 2013; Gassebner et al., 2010; Hsiang, 2010; Hsiang and Narita, 2012; Leiter et al., 2009; Loayza et al., 2012). For example, Hsiang and Narita (2012) use global cross-sectional data from 1950 to 2008 to examine the marginal damage of tropical cyclones. The authors find that an increase in cyclone exposure is associated with greater economic damage and human losses. Loayza et al. (2012) investigate four types of natural hazards using the generalized method of moments (GMM). In their analysis using cross-country panel data, they find that storms negatively affect agricultural growth in developing countries. However, their study shows mixed results for flood impacts. While moderate flooding positively affects economic growth, severe floods have a negative growth effect. By analyzing firm-level data with a difference-in-differences (DID) model, Leiter et al. (2009) also find a positive effect of floods on firms' capital accumulation and employment growth, while demonstrating a negative flood impact on productivity. The effects of natural disasters may not be limited to one country but involve multiple countries through international trade. Oh and Reuveny (2010) examine the effects of climatic disasters and political risk on trade using a gravity model. Their analysis includes bilateral trade data and various types of weather-related disasters, showing that these climatic events reduce imports. Gassebner et al. (2010) also apply a gravity model to bilateral trade data to investigate the impact of large-scale natural and technological disasters. El Hadri et al. (2017) focus on four types of natural disasters to examine their impacts on export values. These studies draw attention to the economic costs of climate change through the trade channel, considering the growing importance of international trade in the world economy. However, the studies analyzing the relationship between climate-related disasters and trade remain limited.

This study is also related to the literature that examines climate impacts on socioeconomic activities (see Dell et al., 2014; Heal and Park, 2016). While researchers have

analyzed and found links between climate and aggregate economic outcomes, recent works emphasize the broader dimensions of socioeconomic activities and explore them as channels through which climate affects macroeconomy. Such channels include agriculture, labor productivity, energy production, migration, health and mortality, and conflicts (Barrios et al., 2006; Cachon et al., 2012; Chen et al., 2016; Di Falco et al., 2012; Marchiori et al., 2012; McDermott and Nilsen, 2014; Miguel et al., 2004; Anttila-Hughes and Hsiang, 2013). Among these channels, agriculture has been the primary focus of climate studies because of the sector's critical dependence on weather conditions. Nevertheless, there is a growing body of literature that investigates the climate impacts associated with non-agricultural outputs. Using international trade data, Jones and Olken (2010) examine the effects of weather shocks on exports and find that a 1 °C increase in temperature reduces export growth by 2.0–5.7 percentage points in poor countries. They further analyze the climate impacts on exports by product and show that temperature shocks in poor countries negatively affect the exports of agricultural and light manufacturing products. Dell et al. (2012) show that temperature shocks affect both agricultural and industrial value-added in poor countries. Hsiang (2010) examines the impact of temperature and cyclones and find that production losses from non-agricultural outputs outweigh those from agricultural ones. The existing literature suggests that economic impacts of extreme weather are not limited to the agricultural sector but also observed in broader aspects of the economy.

This study makes the following contributions to the literature on climate impacts. First, we focus on two types of weather shocks, that is, floods and storms, to investigate the extent to which natural disasters affect exports. While Jones and Olken (2010) estimate the impact of temperature on trade, they do not consider weather-related disasters, which may be highly affected by climate change in terms of intensity and frequency. Second, the analysis uses export data classified by the Harmonized System (HS) code. The breakdown of export data allows us to compare product groups and identify the industries affected by disaster shocks. In addition, monthly data can capture the effect of climate disasters more precisely than annual data used in most studies (Gassebner et al., 2010; Oh and Reuveny, 2010).

The results of the regression analysis show that floods and storms are negatively associated with export values, suggesting that disasters reduce exports from Southeast Asia. The findings suggest that the occurrence of floods has an immediate effect on export values, as well as a persistent impact, sustained in the post-disaster period. To explore this possibility, we include lagged disaster variables in the estimation. We find that these vari-

ables are negatively correlated with exports, showing that flood effects persist for several months. In addition, we find that the exports of both agricultural and manufacturing products are affected by disasters. While many studies on climatic impact focus on agriculture, this study identifies the effects of weather shocks on non-agricultural products. Our findings support recent research findings in that the negative effects of weather shocks tend to prevail for various economic outcomes, including non-agricultural outputs (e.g., Hsiang, 2010; Jones and Olken, 2010).

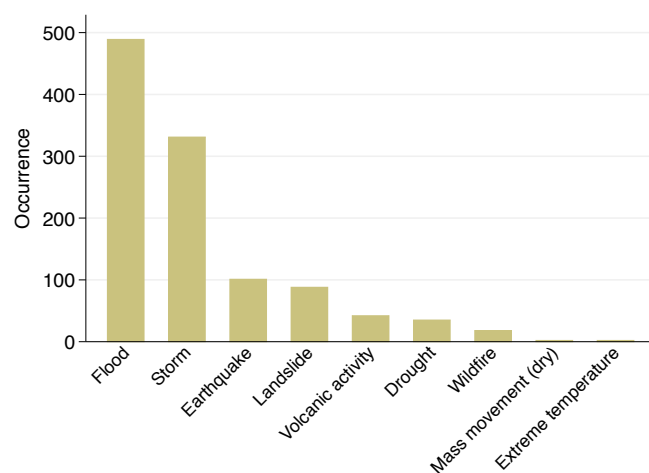
The remainder of this chapter is organized as follows. Section 3.2 provides an overview of flood and storm events in Southeast Asia. Section 3.3 presents the regression model and describes the data employed in the analyses. Section 3.4 discusses the empirical results. Finally, Section 3.5 concludes.

3.2 Floods and Storms in Southeast Asia

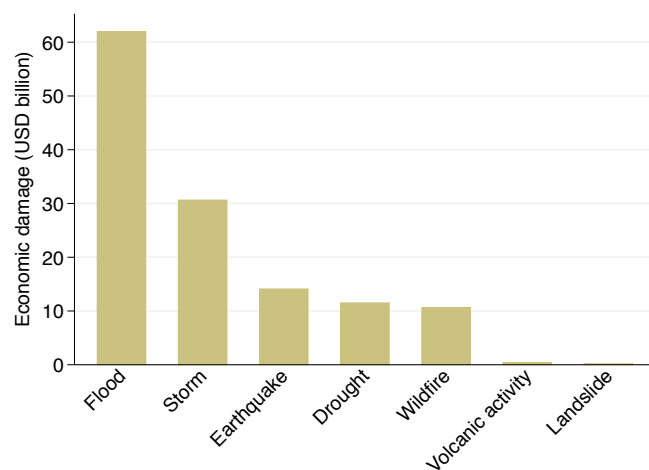
Southeast Asia, as part of the Asia-Pacific region, is one of the most disaster-prone areas in the world. Figure 3.1 depicts the total number of natural disasters and the estimated economic damage in Southeast Asia between 1990 and 2016. As Figure 3.1a shows, flooding is the most frequent disaster type, accounting for almost 500 incidents during this period. Following floods, storms are the second most frequent disaster type, with more than 300 incidents. Similarly, the largest amount of economic damage is incurred from floods and storms, as shown in Figure 3.1b.

Trends in floods and storms in Southeast Asia are illustrated in Figure 3.2 and 3.3 in more detail, respectively. Figure 3.2 shows the annual number of flood events in four Southeast Asian countries: Indonesia, Malaysia, the Philippines, and Thailand. As shown in the figure, the number of floods has been steadily increasing over time. Floods, which were less frequent in the 1990s, have increased about 10–25 times per year and intensified over the past decade. Figure 3.2 also depicts the extent of the damage caused by floods, where the circle-shaped markers indicate the damage by area as a proportion to the number of people affected. The larger circles observed in recent years denote a higher number of people affected by flooding. Figure 3.3 presents the annual number of storm events in Southeast Asia in the same manner. While the figure suggests only a modest increase in the number of storm events, storm damage is likely to increase in the subsequent years. The larger circles in the figure indicate the severe impact of recent storms on countries in terms of human damage.

Table 3.1 presents the five most extreme disasters that have occurred in Southeast Asia



a. Number of disaster occurrences



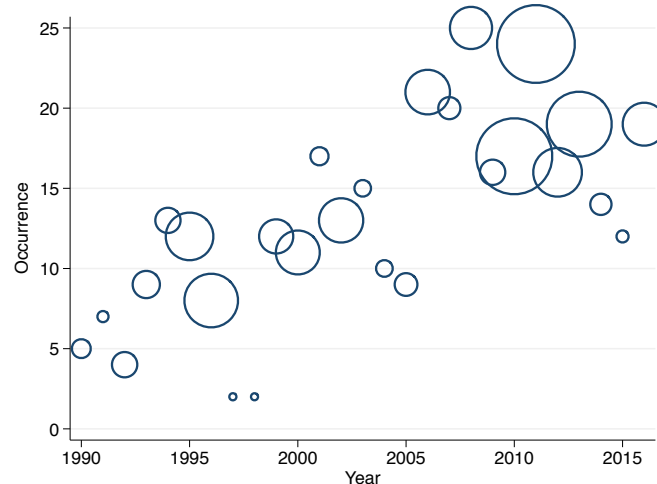
b. Economic damage incurred from disasters

Note: The countries are Brunei Darussalam, Cambodia, Indonesia, Lao People's Democratic Republic, Malaysia, Philippines, Thailand, Timor-Leste, and Viet Nam.
Source: CRED and Guha-Sapir (2017)

Fig. 3.1 Natural disasters in Southeast Asia by type (1990–2016)

between 1990 and 2016. These individual events caused the most costly damage during this period. Flood and storm events are presented by country, along with the year of occurrence, economic damage, death toll, and number of people affected. As the table shows, most severe disasters have taken place after 2010. The most extensive flood occurred in Thailand, followed by Indonesia and the Philippines. On the other hand, the five most damaging storms reported during this period occurred in the Philippines.

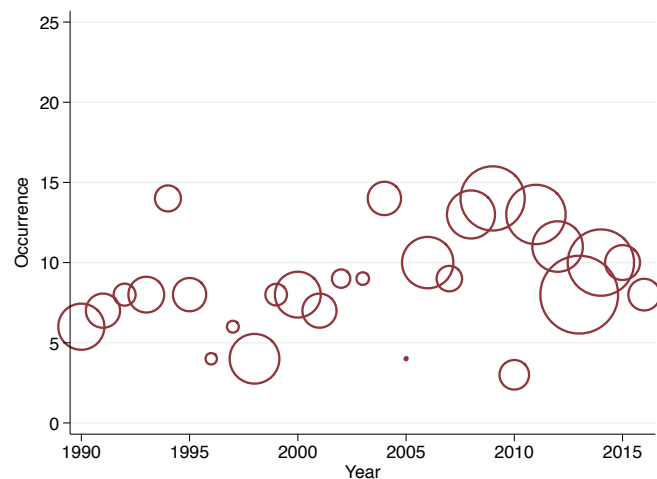
The 2011 flooding in Thailand resulted in more than 800 deaths and affected 9.5 million people across the country, causing economic damage of USD 40 billion. The flood also reportedly destroyed 19,000 houses and damaged around 18,000 km² of farmland



Note: The areas of the circles are proportional to the number of people affected by floods. The countries are Indonesia, Malaysia, Philippines, and Thailand.
Source: CRED and Guha-Sapir (2017)

Fig. 3.2 Number of flood events in Southeast Asia

(World Bank, 2012). The record-breaking precipitation levels and multiple typhoons from May to September are largely responsible for widespread and prolonged flooding. The flood initiated in the northern region of Thailand, inundated 66 of the 77 provinces in the country and reached the Bangkok metropolitan region by November. The primary reason for the devastating economic damage is that the flood affected the central part of the country, where foreign manufacturing firms are concentrated in industrial parks (Oizumi,



Note: The areas of the circles are proportional to the number of people affected by floods. The countries are Indonesia, Malaysia, Philippines, and Thailand.
Source: CRED and Guha-Sapir (2017)

Fig. 3.3 Number of storm events in Southeast Asia

Table 3.1 Severe disasters in Southeast Asia (1990–2016)

Flood					
	Country	Year	Economic damage (million USD)	Death toll	People affected
1	Thailand	2011–2012	40,000	813	9,500,000
2	Indonesia	2013	3,000	34	248,846
3	Philippines	2013	2,190	31	3,096,422
4	Thailand	1993	1,261	23	393,809
5	Indonesia	2007	971	68	217,087

Storm					
	Country	Year	Economic damage (million USD)	Death toll	People affected
1	Philippines	2013	10,000	7,354	16,106,870
2	Philippines	2015	1,500	5	14,100
3	Philippines	2012	898	1,901	6,246,664
4	Philippines	2014	821	111	4,654,966
5	Philippines	2009	585	512	4,478,491

Note: The countries are Indonesia, Malaysia, the Philippines, and Thailand.

Source: CRED and Guha-Sapir (2017)

2012).¹ Manufacturing firms were forced to halt production because of the floodwaters that engulfed these industrial areas. According to the World Bank, the manufacturing sector suffered the highest losses of approximately USD 32 billion from flood damage, followed by the finance and banking, tourism, and housing sectors (World Bank, 2012). Thailand's GDP growth rate in 2011 was 0.84% compared to 7.51% in the previous year. As industrial outputs are a key component of Thailand's GDP, such flood damage is likely to hinder the country's economic growth.

The Philippines is subject to a variety of natural hazards, including floods and storms, ranking third in terms of disaster risk (Kirch et al., 2017). In 2013, the Philippines was hit by Typhoon Haiyan, locally known as Yolanda, one of the strongest typhoons ever recorded in the country's history. The estimated damage by this category five typhoon was approximately USD 10,000 million and over 7,000 people were reported dead or missing. A total of 16 million people, that is, 16% of the country's population, were also affected. Typhoon Haiyan significantly affected the country's agriculture, with more than USD 700 million in damage (FAO, 2015). Crop production in the disaster-affected areas was severely damaged; for instance, the typhoon destroyed 161,400 ha of coconut

¹These areas are covered by the Chao Phraya River Basin that drains through the central region to Bangkok and eventually, into the Gulf of Thailand.

farms, affecting around one million farmers (Bowen, 2015). Furthermore, the destruction of crop production, such as coconut, can cause widespread damage as the Philippines is the world's second largest coconut producer. In addition to farmers, traders, wage earners, processors, and other stakeholders in the industry were also affected by the typhoon (FAO, 2015). Moreover, the typhoon caused severe damage to infrastructure, including electricity, roads, and seaports (World Bank, 2013). Such losses of critical infrastructure could disrupt local and global supply chains, preventing the economy from recovering during the post-disaster period. Therefore, the reconstruction of infrastructure was highly emphasized during the rehabilitation process after Haiyan. The Philippines was also struck by other storms that caused serious damage. As Table 3.1 shows, subsequent typhoons have caused severe losses to the country in recent years.²

3.3 Empirical Analysis

3.3.1 Empirical Specification

Our empirical analysis explores the effects of disasters on international trade. We use data on disasters taken from the EM-DAT to develop panel datasets for four Southeast Asian countries: Indonesia, Malaysia, the Philippines, and Thailand.³ The dataset comprises unbalanced monthly panel data from 2004 to 2016.⁴ The following specification is used to run the regressions:

$$Export_{eimy} = \alpha + \sum_{j=0}^L \beta_j Disaster_{emy-j} + \gamma_e + \delta_{my} + \phi_{em} + \omega_{im} + \varepsilon_{eimy}, \quad (3.1)$$

where $Export_{eimy}$ is the bilateral export values from exporter e to importer i during time period my and $Disaster_{emy-j}$ denotes either a flood or storm event in exporting country. Exporter-specific fixed effects are captured by γ_e , controlling for unobserved heterogeneity across countries. Month-by-year time fixed effects are denoted by δ_{my} . These time-variant variables control for any external event common to all exporting countries in

²In addition, Myanmar was severely hit by Typhoon Nargis in 2008. More than 2.4 million people were affected, and the number of fatalities exceeded 138,000 people. The typhoon caused the second highest economic damage of USD 4,000 million; however, we do not include Myanmar in this analysis due to data availability.

³The analysis includes these four countries because data on either disasters or exports are unavailable for other Southeast Asian countries.

⁴The sample periods for each country are: 2004–2016 (full period) for Malaysia, 2006–2016 for Indonesia, and 2007–2016 for the Philippines and Thailand.

each time period of the sample. ϕ_{em} captures exporter-by-month fixed effects, which account for country-specific seasonal trends affecting production, such as national holidays and cultural events. We also include importer-by-month fixed effects, denoted by ω_{im} , to control for trade externalities on the demand side. Such externalities are exhibited, for example, when importers are hit by natural disasters. Similar to exporting countries, importing countries and areas may also be affected by natural disasters, thereby increasing or decreasing their imports. We consider the seasonality of natural disasters by introducing the interaction term with month. Finally, ε_{eimy} is a disturbance term.

As shown in Equation 3.1, the disaster variable is subject to lags indexed by j . We allow up to a 12-month lag for the disaster variable in the models with lag structures. It is possible that the effects of disasters persist for more than one period when the production of exporting goods is affected by damage to factories and farmlands. Natural disasters also cause the disruption of supply chains, leading to a slowdown in production. Furthermore, severely damaged infrastructure, such as roads, bridges, railways, and seaports, could create difficulties and delays in both domestic and international shipping. The destruction of infrastructure may also prevent workers from commuting to their workplaces. All of these factors can reduce exports in the post-disaster period.

3.3.2 Data Description

Table 3.2 presents the summary statistics of the variables used in the empirical analysis. We have three categories of exports as dependent variables: export values of all products, agricultural products, and manufacturing products. To examine the impact on these export values, this study focuses on floods and storms as representative weather-related disasters.

Data on disasters are from the EM-DAT by the Centre for Research on the Epidemiology of Disasters (CRED) (CRED and Guha-Sapir, 2017). The EM-DAT includes more than 22,000 natural and technological disasters worldwide. The data are provided at the country level and based on information from multiple sources, including international organizations, NGOs, national governments, and insurance companies. Each disaster in the EM-DAT meets one of the following criteria: 10 or more people were reportedly killed, 100 or more people were reportedly affected, a state of emergency was declared, or international assistance was called for. This database has been often utilized in previous studies exploring the effects of natural disasters on socioeconomic activities (El Hadri et al., 2017; Anttila-Hughes and Hsiang, 2013; Hsiang and Narita, 2012; Leiter et al., 2009; Loayza et al., 2012; Oh and Reuveny, 2010).

For the purpose of the present study, we extract data on floods and storms from the

Table 3.2 Summary statistics of variables

Variable	Unit	Mean	S.D.	Min	Max
<i>Export values</i>					
All products	million USD	66.15	253.61	0	3,447
Agriculture	million USD	6.00	26.29	0	750
Manufacturing	million USD	59.63	235.86	0	3,371
<i>Disaster variables</i>					
Flood	dummy	0.34	0.47	0	1
Storm	dummy	0.13	0.33	0	1

EM-DAT to examine their effects on exports. We use a dummy variable that represents the occurrence of disasters. This variable takes the value 1 if a disaster has occurred at least once during a month in a country. The summary statistics in Table 3.2 show that floods are more frequent than storms in the four Southeast Asian countries during the sample period. On average, the occurrence of floods is 0.3 per month, while that of storms is 0.1 per month. As shown in Figure 3.1a, this tendency is in line with the long-term trends in Southeast Asia, where floods are the most frequent disaster type, followed by storms.

Trade data are based on bilateral export flows from Southeast Asia. The data are taken from the International Trade Centre (ITC), a joint agency by the World Trade Organization and United Nations.⁵ The ITC database provides detailed trade data that classify products into groups using HS classification codes, thereby enabling us to investigate the effects of disasters on exports by sector. We obtain monthly export values for all products and disaggregate export values at the two-digit HS code level. The latter is then aggregated to two major sectors: agriculture and manufacturing. In this study, agricultural goods include products with HS codes 1 to 15, whereas manufacturing goods are products with HS codes 16 to 97. The importers include 171 countries, territories, and areas reported in the ITC database that import products from the exporting countries in our dataset (see Appendix Table 3.A).

3.4 Results

3.4.1 Main Results

We run regressions to estimate the effects of floods and storms on export values using the least-squares dummy-variable model. The regression models include up to a 12-month

⁵ Available at <http://www.intracen.org/>.

Table 3.3 Main regression results

	Export values: All products							
	Flood				Storm			
	No lag (1)	3 lags (2)	6 lags (3)	12 lags (4)	No lag (5)	3 lags (6)	6 lags (7)	12 lags (8)
Disaster	-3.133** (0.704)	-2.289*** (0.127)	-1.840*** (0.037)	-2.239*** (0.313)	-1.644 (0.955)	-1.053 (0.872)	-0.338 (1.100)	0.264 (1.326)
L.Disaster		-1.190* (0.412)	-0.723 (0.558)	-1.055 (0.590)		-1.601* (0.523)	-1.330 (0.590)	-1.059 (0.995)
L2.Disaster		-1.846** (0.427)	-1.547*** (0.246)	-1.415*** (0.197)		-1.627 (1.160)	-1.494 (1.137)	-0.468 (1.398)
L3.Disaster		-2.939** (0.576)	-2.541*** (0.371)	-1.994** (0.570)		-1.678* (0.590)	-1.611* (0.582)	-0.127 (1.097)
L4.Disaster			-1.013 (0.436)	-0.434 (0.554)			0.239 (0.669)	1.231 (1.051)
L5.Disaster			-1.277* (0.521)	-0.792 (0.472)			0.185 (0.269)	1.442* (0.580)
L6.Disaster			-2.052 (0.911)	-1.893** (0.519)			1.416 (1.199)	2.289 (1.412)
Observation	90,288	88,236	86,184	82,080	90,288	88,236	86,184	82,080
Adjusted R^2	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79
Exporter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total effect of disaster	-3.133** (0.704)	-8.263*** (0.936)	-10.992*** (1.552)	-14.357** (2.768)	-1.644 (0.955)	-5.959 (2.797)	-2.934 (4.385)	15.574 (12.558)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by exporting country and reported in parentheses.

lag in disaster variables. The models with lag structures allow us to investigate whether a disaster effect appears and persists in the post-disaster period.

The regression results are presented in Table 3.3. Columns 1–4 show the results for flood events and columns 5–8 show the results for storm events. For each disaster type, the models include variables with no lag, three lags, six lags, or 12 lags. In addition, the bottom row of each column presents the total effect of disasters, calculated using the estimated coefficients of the disaster variable and its lagged variables.

According to the results in columns 1–4 in Table 3.3, the occurrence of floods is negatively related to the export values of all products. In column 1, the coefficients of disaster, that is, the immediate effect of floods, are negative and statistically significant: the occurrence of floods reduces export values by USD 3.13 million in a month. This implies that, on average, export losses from floods are approximately 5% of the total export values per month.⁶ The results of the model with no lag show that exports are immediately affected by floods. The effects of floods are also observed in models with lags. In columns 2–4, the immediate impact of floods remains significant, with export losses of approximately 3% of the monthly mean export values. The lagged variables

⁶According to the summary statistics in Table 3.2, the mean export values for all products in the sample are USD 66.15 million.

are also negatively correlated with export values. These results are mostly consistent in magnitude and statistical significance, suggesting that the impact of floods appears two to three months after floods. In these lag models, the coefficients of the cumulative effect reported in the bottom row of Table 3.3 are all negative and statistically significant. For instance, the model with 12 lags indicates that export losses from floods that occurred in a given month are USD 14.36 million, which is equivalent to approximately 2% of the annual mean export values. This shows that the total export losses from floods are more than four times as large as those of USD 3.13 million estimated without lags from the first column. These results suggest that ignoring lagged effects may underestimate flood damage that persists for over a period of time.

Columns 5–8 in Table 3.3 present the estimation results for storm events. In contrast to the results for floods, we do not find a statistically significant effect of storms on exports. While the effect of floods is statistically significant both with and without lags, we find little evidence of storm effects on total export values. A possible explanation for the insignificance may be that storms affect exports in various sectors differently. That is, some sectors are affected by storms while others are not. In Section 3.4.3, sectoral differences in the impact of natural disasters are examined by using disaggregate export data.

3.4.2 *Robustness*

This section tests the robustness of the main results. We run regressions using alternative specifications, data, and sample periods to verify the validity of the results in Section 3.4.1. The results of the robustness checks are presented in Table 3.4. The baseline models in columns 1 and 6 show the results for floods and storms, which are the same models as in columns 4 and 8 in Table 3.3, respectively. These baseline models and the rest of the models in Table 3.4 include 12 lags of disaster variables.

Overall, we find that the results for both floods and storms are mostly consistent across alternative models, confirming the robustness of our findings. First, we use an alternative specification by excluding importer-by-month fixed effects. The results are reported in columns 2 and 7. The coefficients appear quite similar to the baseline results in terms of statistical significance, magnitude, and sign, supporting our main results.

Second, we add temperature in the baseline model. Jones and Olken (2010) find that temperature is significantly related to exports. Thus, the exclusion of temperature may suffer from omitted variable bias. For a temperature variable, we use the monthly average temperature of exporting countries taken from the Climate Change Knowledge Portal by

Table 3.4 Alternative specifications of the results

Export values: All products										
Flood										
Storm										
	Exclude Importer ×year FE (2)	Include temperature 2004-2015 (3)	Balanced sample 2007-2015 (4)	Balanced sample 2007-2015 (5)	Baseline (6)	Exclude Importer ×year FE (7)	Include temperature 2004-2015 (8)	Balanced sample 2007-2015 (9)	Balanced sample 2007-2015 (10)	
Disaster	-2.239*** (0.313)	-1.575** (0.391)	-1.556** (0.477)	-1.558** (0.467)	0.264 (1.326)	0.264 (1.310)	0.703 (1.272)	0.683 (1.303)	0.667 (1.287)	
L1.Disaster	-1.055 (0.590)	-0.948 (0.545)	-1.008 (0.629)	-1.007 (0.623)	-1.059 (0.995)	-1.059 (0.982)	-0.445 (1.078)	-0.467 (1.232)	-0.480 (1.097)	
L2.Disaster	-1.415*** (0.197)	-1.221** (0.333)	-1.139** (0.302)	-1.135* (0.365)	-0.468 (1.398)	-0.468 (1.381)	0.660 (1.353)	0.652 (1.441)	0.635 (1.361)	
L3.Disaster	-1.994** (0.570)	-1.797** (0.542)	-1.613* (0.558)	-1.613* (0.564)	-0.127 (1.097)	-0.127 (1.083)	0.554 (1.285)	0.517 (1.415)	0.508 (1.302)	
L4.Disaster	-0.434 (0.554)	-0.259 (0.656)	-0.292 (0.674)	-0.291 (0.670)	1.231 (1.051)	1.231 (1.038)	2.508 (1.317)	2.464 (1.377)	2.460 (1.337)	
L5.Disaster	-0.792 (0.472)	-0.666 (0.628)	-0.525 (0.665)	-0.530 (0.764)	1.442* (0.580)	1.442* (0.573)	1.829* (0.581)	1.832* (0.728)	1.823* (0.597)	
L6.Disaster	-1.893** (0.519)	-1.925** (0.480)	-2.019** (0.548)	-2.016** (0.480)	2.289 (1.412)	2.289 (1.394)	3.174 (1.351)	3.153 (1.408)	3.148 (1.371)	
Temperature		-0.306 (1.501)		-0.042 (1.444)			-0.259 (2.203)		-0.138 (2.147)	
Observation	82,080	73,872	65,664	65,664	82,080	82,080	73,872	65,664	65,664	
Adjusted R^2	0.79	0.79	0.79	0.79	0.79	0.01	0.79	0.79	0.79	
Exporter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Exporter-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Importer-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	
Total effect of disaster	-14.357** (2.768)	-11.859** (3.346)	-12.734** (3.553)	-12.722** (3.156)	15.574 (12.558)	15.574 (12.400)	24.003 (12.248)	23.573 (13.849)	23.451 (12.507)	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by exporting country and reported in parentheses.

the World Bank (World Bank, 2018a).⁷ In columns 3 and 8, the results show that the inclusion of temperature variable does not alter the baseline results, although the sizes of the coefficients are slightly different. For example, the coefficients of flood variables are smaller, except those of the six lags variable. Nevertheless, the statistical significance and sign are consistent with the baseline results.

Third, we estimate the baseline model with the same specification using a balanced sample. This specification uses the sample period starting in 2007, where all exporting countries in the sample have complete monthly data on exports. In columns 4 and 9, the results of the balanced sample do not largely different from the baseline results. In the balanced sample, the magnitudes of coefficients are slightly different, exhibiting similar tendencies to an alternative model with temperature. In addition, the standard errors tend to be larger than the baseline results, given that the number of observations is reduced. Finally, we add the temperature variable to the balanced sample model. The results in columns 5 and 10 are similar to the balanced sample without temperature in that the statistical significance and sign are consistent with the baseline results.

3.4.3 *Agricultural and Manufacturing Products*

The damage from climate-related disasters might be heterogenous among sectors. This section investigates the effects of floods and storms on exports, focusing on specific components of exporting products. The export data are classified into two industrial sectors using the two-digit HS code: agriculture and manufacturing.

Table 3.5 presents the effects of floods on exports by two product groups. Agricultural products are examined in columns 1–4 and manufacturing products in columns 5–8. In column 1, the coefficients of flood are negative and statistically related to the export values of agricultural products. This immediate effect is also correlated with export values when the models include lagged variables, as shown in columns 2–4. The magnitude of these coefficients is slightly smaller than in the model without lags, although the negative signs and statistical significance remain consistent. The coefficients of the total effect of floods indicate that the export losses of agricultural products from floods occurred in a given month are USD 0.73 million in the model with no lag and USD 3.18 million in the model with 12 lags. Comparing these losses with the mean export values of agricultural products in the sample (see Table 3.2), we find that the export losses from floods per month are approximately 4–12% of the mean export values of agricultural products.

⁷The latest year of the sample period for this model is 2015, which was the latest data available at the time of accessing the data.

Table 3.5 Effect of floods on exports by product group

	Export values: Agriculture				Manufacturing			
	No lag (1)	3 lags (2)	6 lags (3)	12 lags (4)	No lag (5)	3 lags (6)	6 lags (7)	12 lags (8)
Flood	-0.732* (0.236)	-0.525* (0.169)	-0.441* (0.164)	-0.487* (0.198)	-2.271** (0.599)	-1.774*** (0.093)	-1.577*** (0.134)	-1.813** (0.320)
L.Flood		-0.354* (0.134)	-0.314* (0.103)	-0.359* (0.131)		-0.759 (0.399)	-0.411 (0.543)	-0.755 (0.590)
L2.Flood		-0.048 (0.248)	0.003 (0.247)	0.020 (0.291)		-1.652** (0.342)	-1.473*** (0.240)	-1.583** (0.341)
L3.Flood		-0.772** (0.197)	-0.598** (0.185)	-0.514* (0.216)		-2.046** (0.452)	-1.922*** (0.305)	-1.761** (0.506)
L4.Flood			-0.356* (0.128)	-0.440* (0.143)			-0.539 (0.411)	-0.141 (0.475)
L5.Flood			-0.238 (0.119)	-0.198 (0.119)			-0.884 (0.414)	-0.648 (0.391)
L6.Flood			-0.488*** (0.055)	-0.450** (0.078)			-1.413 (0.882)	-1.498* (0.613)
Observation	90,288	88,236	86,184	82,080	90,288	88,236	86,184	82,080
Adjusted R^2	0.52	0.52	0.53	0.54	0.78	0.78	0.79	0.79
Exporter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total effect of flood	-0.732* (0.236)	-1.699* (0.595)	-2.432* (0.764)	-3.175* (1.237)	-2.271** (0.599)	-6.230*** (0.881)	-8.219** (1.683)	-10.951** (3.123)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by exporting country and reported in parentheses.

Similarly, we find that floods are associated with reductions in the export values of manufacturing products. The model in column 5 shows that the immediate impact of flood events is statistically correlated with the export values of manufacturing products. The coefficients of flood variables in columns 6–8 are also statistically significant. Moreover, the effect of floods is significant two to three months after the disasters. The cumulative effect in the bottom row of Table 3.5 indicates that, in the model without lags, floods that occurred in a given month reduce the export values of manufacturing products by USD 2.27 million. In the model with 12 lags, floods are associated with export losses of USD 11.00 million. The magnitude of the coefficients of manufacturing exports is larger than those of agricultural exports. However, the results for manufacturing products suggest that their losses are equivalent to 2–4% of the mean export values. These findings suggest that the export losses from floods are larger in agriculture than manufacturing in terms of proportion.

While the impact of storms is statistically insignificant when all exporting products are considered, we find a correlation between storm events and export values classified by sector. Table 3.6 presents the results for the impact of storms on the exports of agricultural and manufacturing products. In columns 1–4, the coefficients of storm are negative and

Table 3.6 Effect of storms on exports by product group

	Export values: Agriculture				Manufacturing			
	No lag (1)	3 lags (2)	6 lags (3)	12 lags (4)	No lag (5)	3 lags (6)	6 lags (7)	12 lags (8)
Storm	-0.518** (0.109)	-0.450** (0.108)	-0.286** (0.088)	-0.164* (0.065)	-1.210 (0.953)	-0.746 (0.927)	-0.446 (1.086)	0.195 (1.284)
L.Storm		-0.476** (0.104)	-0.400** (0.122)	-0.270 (0.126)		-1.369* (0.549)	-1.310 (0.593)	-1.154 (0.945)
L2.Storm		0.006 (0.385)	0.050 (0.384)	0.315 (0.433)		-1.838 (0.803)	-1.789 (0.792)	-1.217 (0.987)
L3.Storm		-0.287** (0.088)	-0.297** (0.087)	-0.062 (0.105)		-1.589** (0.499)	-1.555** (0.478)	-0.658 (0.926)
L4.Storm			-0.352 (0.251)	-0.098 (0.239)			0.274 (0.392)	0.689 (0.685)
L5.Storm			0.148 (0.149)	0.315 (0.163)			-0.155 (0.289)	0.468 (0.456)
L6.Storm			0.572* (0.204)	0.687** (0.206)			0.747 (1.095)	1.230 (1.290)
Observation	90,288	88,236	86,184	82,080	90,288	88,236	86,184	82,080
Adjusted R^2	0.52	0.52	0.53	0.54	0.78	0.78	0.79	0.79
Exporter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total effect of storm	-0.518** (0.109)	-1.206** (0.350)	-0.565 (0.523)	3.366* (1.182)	-1.210 (0.953)	-5.541 (2.432)	-4.235 (3.811)	8.738 (10.924)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by exporting country and reported in parentheses.

statistically significant. These results suggest that the immediate impact of storms reduces the exports of agricultural products by USD 0.16–0.52 million, or approximately 3–8% of the monthly mean agricultural export values. In columns 2 and 3, the lagged variables of storms also show significant impacts on the exports of agricultural products, although only the immediate impact remains statistically significant in the model with 12 lags. By incorporating the breakdown of export data, we find a negative and significant effect of storms on agricultural exports.

Columns 5–8 in Table 3.6 show the results for the impact of storms on the exports of manufacturing products. Although some lagged variables suggest a negative and significant effect of storms, the statistical significance no longer holds in the model with 12 lags. The total effects of storms reported in the bottom row of the table also do not show any correlation with export values. Therefore, we find little evidence of storms affecting the exports of manufacturing products. This result may explain the statistical insignificance of storm impacts in the main result, as manufacturing products account for approximately 90% of all exporting products.

The estimation results by product group suggest that the agricultural and manufacturing sectors suffer export losses caused by natural disasters. Related research by Jones

and Olken (2010) also investigates weather shocks on export values. Using the two-digit SITC data, their study finds that higher temperature negatively affects agricultural and light manufacturing products in poor countries. In a study on the relationship between temperature and economic growth, Dell et al. (2012) find the impact of temperature on agricultural and industrial value-added as potential channels for aggregate outputs. In line with these studies, our results show that both agricultural and manufacturing sectors are negatively affected by climate shocks. In addition, this study identifies the heterogeneous impacts of natural disasters on these sectors.

3.4.4 Impact of Large-Scale Disasters

We conduct additional analyses using an alternative measure for disaster variables. The dummy variable for disaster occurrence used in previous sections does not reflect the size and scale of each disaster event. To incorporate the severity of natural hazards into the analysis, this section thus focuses on the impact of large-scale disaster events in terms of human losses. The results using this alternative disaster variable are reported in Table 3.7.

The severity of natural disasters can be measured based on the number of casualties, economic damage, etc. However, the application of such non-physical disaster characteristics may present issues and, thus, the estimation results should be interpreted with caution. For instance, it is argued that exogeneity of variables cannot be assumed with non-physical disaster characteristics (Hsiang and Narita, 2012). This is because human losses and economic damage as proxies for the scale of disasters may be correlated with other factors, such as GDP, institutions, and the level of development. Loayza et al. (2012) also point out issues of missing data and measurements errors, which weaken data credibility.

Bearing these issues in mind, this study attempts to incorporate the severity of disasters using the distribution of the weighted number of deaths by natural disasters. In the study on natural disasters and economic growth, Cavallo et al. (2013) define a large-scale disaster by introducing the percentile-based cutoff values of the population killed by disasters. According to Cavallo et al. (2013), the 75th percentile cutoff is equal to the mortality rate of approximately seven people per one million inhabitants. Based on this criterion, we construct a dummy variable for severe floods and storms. The variable takes the value 1 if disasters that occurred in a given month killed more than seven per one million people, and 0 otherwise. We use data on total deaths taken from the EM-DAT, defined as the sum of people killed and missing. Data on population in exporting countries are obtained from the World Development Indicators (World Bank, 2018).

Table 3.7 Effect of severe natural disasters on exports (measured by the percentile-based cutoff values of the number of people killed by natural disasters)

	All products							
	Flood				Storm			
	No lag (1)	3 lags (2)	6 lags (3)	12 lags (4)	No lag (5)	3 lags (6)	6 lags (7)	12 lags (8)
Severe disaster	-5.972 (7.492)	-0.996 (7.554)	0.851 (9.021)	1.409 (9.617)	-8.941** (2.697)	-9.505** (2.864)	-9.442* (3.069)	-8.815* (3.087)
L.Severe disaster		0.149 (2.273)	0.149 (2.274)	-0.142 (2.448)		-9.593** (2.826)	-9.656** (2.863)	-10.301** (2.926)
L2.Severe disaster		-9.285*** (1.157)	-8.992*** (1.244)	-10.171*** (0.893)		-9.664** (2.455)	-9.681** (2.460)	-9.564** (2.555)
L3.Severe disaster		1.664 (3.387)	-7.032** (1.358)	-5.768** (1.107)		-9.049** (1.850)	-9.241** (1.879)	-8.858** (2.226)
L4.Severe disaster			7.791*** (0.064)	9.321*** (0.774)			-2.872* (0.959)	-2.620* (0.887)
L5.Severe disaster			-1.749 (1.795)	-2.396 (1.561)			-3.514* (1.326)	-3.369* (1.315)
L6.Severe disaster			4.233 (5.870)	3.903 (7.355)			-2.178 (1.585)	-1.346 (1.726)
Observation	90,288	88,236	86,184	82,080	90,288	88,236	86,184	82,080
Adjusted R^2	0.79	0.79	0.79	0.79	0.79	0.79	0.79	0.79
Exporter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total effect of disaster	-5.972 (7.492)	-8.468 (8.712)	-4.751 (11.874)	1.044 (16.029)	-8.941** (2.697)	-37.811** (9.949)	-46.583** (13.002)	-44.591* (16.509)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by exporting country and reported in parentheses.

The results for floods show that severe events affect exports in the post-disaster period. We find a negative and significant effect of severe flooding two to three months after disasters. These findings are consistent with the main result; moreover, the coefficients become larger compared to the corresponding coefficients in models in Table 3.3. This suggests that severe floods cause greater export losses than average floods. On the other hand, we do not find an immediate impact of floods from the zero lag variable. Together with the main results, these findings suggest that an immediate effect is driven by less severe floods. As can be expected, the results imply that the impact of severe floods likely appears and persists in the post-disaster period, while average floods have short-term effects.

The results for storms show both immediate and persistent impacts of severe storms on exports. In contrast to the main results, the coefficients of severe storms for the 0–5 lag variables are negatively correlated with export values. The cumulative effects of severe storms are also negative and statistically significant in all specifications. For storms, extreme disasters harm total exports immediately and persistently.

3.5 Conclusions

This chapter examines the effects of natural disaster shocks on exports in Southeast Asia. We focus on the two most frequent weather-related disasters: floods and storms. The panel dataset comprises monthly export data for four Southeast Asian countries between 2004 and 2016. In the empirical analysis, we investigate the extent to which floods and storms affect bilateral export flows. In addition, export data are divided into agricultural and manufacturing product groups to explore the effects of disasters by sector.

The regression results show a significant effect of natural disasters on exports, suggesting that flood and storm events reduce export values. In the case of floods, the occurrence of flooding is significantly correlated with total export values. The results show that the impact of floods appears within a month of the onset of a disaster. The findings also suggest that the immediate effect of floods leads to a reduction in bilateral export flows from a Southeast Asian country by 3–5% of the mean export values. This study also analyzes models with lag structures and finds that flood impacts persist in the post-disaster period. When considering 12-month lags, we find that the total effect of floods occurred in a given month causes export losses, as much as 2% of the annual mean export values.

Furthermore, this study suggests that natural hazards have a significant impact on exports across industrial sectors. We find that floods negatively affect exports of both agricultural and manufacturing products. While there is no clear evidence of storm impacts on total export values, we find that storms negatively affect agricultural exports. The classified export data lead to more detailed findings of disaster impacts in the context of exports. Climate impacts on agriculture are in line with the findings presented in the literature (for example, Dell et al., 2012; Jones and Olken, 2010). In addition, we also find the impact of weather shocks on manufacturing, which have not been largely emphasized in previous studies. This result also offers support to the studies examining the effects of weather shocks on firm-level labor productivity (Cachon et al., 2012; Li et al., 2016).

The results of this study suggest international trade as a channel through which climate may affect aggregate economic outputs. A better understanding of the channels and mechanisms of the relationship between climate and economy is important to achieve economic development while facing the risks of climate change. For developing countries, particularly those where exports play a crucial role in boosting economic growth, disaster shocks can be of great concern and need immediate policy responses. Such issues also relate to developed countries, whose firms are located in disaster-prone regions and who trade various products through a global supply chain. Therefore, this study highlights the

need for business entities and policymakers to pay more attention to the risks associated with extreme weather events in the context of international trade.

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CHAPTER 4

DO NATURAL DISASTERS IMPEDE EXPORTS? EVIDENCE FROM CROSS-COUNTRY PANEL DATA

4.1 Introduction

Between 1998 and 2017, the Emergency Events Database (EM-DAT) recorded 7,255 natural disasters, of which over 90% are classified as climate-related disasters such as floods, storms, droughts, and extreme temperature (Wallemacq et al., 2018). These climate-related disasters have cost USD 2,245 billion over the past two decades. In 2017, the two most frequent climatic disasters, floods and storms, alone affected 80 million people and caused economic losses of USD 300 billion (CRED, 2018). Given the increasing frequency and intensity of natural disasters, researchers have been studying the impact of climate shocks on various socioeconomic activities including international trade. The adverse effect of natural disasters can impede trade by disturbing economic activities through capital and human damage. These disaster risks in trade may thus pose serious issues because exports are an important component of the aggregate economy, particularly in many emerging countries. The World Bank estimates that natural disasters force 26 million people into extreme poverty each year (Hallegatte et al., 2017). However, few studies examine the causal mechanisms of climate impacts on international trade in countries closely interrelated through global supply chains.

This study fills this gap in the literature by providing empirical evidence of the effect of natural disasters on international trade. We estimate whether and to what extent floods and storms affect exports using cross-country panel data on bilateral trade flows. The application of bilateral data provides a large sample size as well as enables us to examine the impact of climate-related disasters in both exporting and importing countries. The analysis is enriched by studying whether the effects of disasters are heterogeneous among

these countries in terms of their development levels, industrial sectors, and the severity of disasters. We also consider the persistence of disaster impacts by including lagged disaster variables in the estimation models.

This study is related to the literature that examines the relationship between climate and economy. A small yet increasing number of studies analyze the impact of climate shocks on international trade. Jones and Olken (2010) examine the effect of temperature on export growth and find that a 1°C rise in temperature leads to a decline in annual export growth by 2.0–5.7 percentage points in poor countries. They also use the breakdown of export data to demonstrate that temperature shocks in poor countries reduce the exports of agricultural and light manufacturing products. Loayza et al. (2012) use cross-country panel data to analyze the impact of four types of natural disasters on economic growth. They find that agricultural growth in developing countries is negatively affected by storms. The results for floods in their study show mixed results depending on the severity of the disaster: the negative effects of severe floods diminish the positive growth effects of moderate floods. Gassebner et al. (2010) and Oh and Reuveny (2010) apply a gravity model to their studies of the relationship between disasters and trade. Gassebner et al. (2010) estimate the impact of large-scale natural and technological disasters and find that their occurrence reduces bilateral trade flows. Oh and Reuveny (2010) use various types of climatic natural disasters to investigate the relationship between disasters, political risks, and bilateral trade. The more recent study by Dallmann (2018) also adopts a gravity equation approach and examines the impact of climate variability on international trade. Detailed analyses at the product level reveal the significant effects of higher temperature on exports of agricultural and manufacturing products.

The strands of the existing literature on related topics focus on the multidimensional impacts of extreme weather and natural hazards (see Dell et al., 2014; Heal and Park, 2016). For instance, Noy (2009) investigates a series of country characteristics to estimate the macroeconomic costs of natural disasters. The results of these analyses suggest that developing countries and smaller economies are more vulnerable to natural disasters, resulting in greater output losses. Dell et al. (2012) examine the relationship between temperature and the macroeconomy, showing that higher temperature negatively affects economic growth in poor countries. Their study also reveals the negative effects of temperature in the agricultural and industrial sectors as potential channels through which climate shocks affect the aggregate economy. Focusing on the Caribbean and Central America, Hsiang (2010) analyzes the effect of temperature and tropical cyclones and finds that total output losses in non-agricultural production exceed those in agricultural

production. These studies of climate impacts suggest the heterogeneous effects of climate shocks among countries and regions based on their socioeconomic factors, e.g., economic levels and industrial sectors.

Our study contributes to the literature in the following aspects. First, it focuses on floods and storms as representative examples of weather-related disasters. The adverse effects of natural disasters could be caused by both the sudden and the slow onset of disaster events. While studies such as Jones and Olken (2010) and Dallmann (2018) provide important evidence of temperature effects on trade, the temporary impact of climate may not be fully captured by temperature shocks. Using monthly data and lagged disaster variables, this study identifies the contemporaneous and dynamic effects of natural disasters more precisely. Second, the use of bilateral trade data enables us to estimate the disaster impacts on trade flows in the origin and destination countries. Similar to exporting countries, the economic activities of partner countries may also be affected when a nation is hit by a natural disaster. Therefore, the analysis of disaster impacts should include such a geographical aspect in the context of international trade. Third, this study explores the heterogeneous impacts of natural disasters on trade. For instance, we examine whether disasters affect developing and developed countries differently by considering a country's adaptive capacity to climate shocks. Such characteristics could leave a country vulnerable to natural disasters, leading to larger trade losses. Therefore, this study can also provide suggestive evidence of the potential disaster risks in the context of international trade.

The results of the empirical analysis show the negative effects of natural disasters on bilateral export flows. We find that flood events in exporting and importing countries reduce export flows. These findings suggest that exporters' floods have a contemporaneous effect, reducing exports within a month of the onset of the events. In addition, the results for the lagged disaster variables show that flood impacts persist in both exporting and importing countries several months after disasters. We also find evidence of the persistent effect of storms in the post-disaster period. However, storm events do not have a robust and cumulative effect on exports.

Moreover, the results of this study provide evidence that the effects of natural hazards are heterogeneous in several aspects, reflecting the country's vulnerability to natural disasters. First, we find that floods cause larger export losses in developing countries than developed countries. In developing countries, both exporters and importers are inflicted by floods immediately and persistently. While the results for storms show a positive impact on trade flows in developing countries, we find a negative and significant effect of storms in developed countries. Second, the results show the heterogeneous impacts of dis-

asters in industrial sectors. We find that agriculture is more sensitive to natural disasters than manufacturing. These findings suggest that floods and storms in exporting countries lead to a reduction in agricultural exports. On the contrary, manufacturing exports in both exporting and importing countries decline because of floods. Third, this study examines the effect of large-scale disasters based on the estimated damage. The results show that floods and storms cause greater export losses when estimating severe disaster events.

The remainder of this chapter proceeds as follows. Section 4.2 presents an overview of global natural disasters, focusing on trends in floods and storms over time. Section 4.3 provides the empirical strategy for the analysis and describes the data used in the estimation. Section 4.4 presents and discusses the empirical results and Section 4.5 concludes.

4.2 Global Trends in Floods and Storms

Floods and storms have been the most frequent natural disaster types over the past two decades. According to the EM-DAT, about 70% of recorded climate-related disasters are categorized into these types (Wallemacq et al., 2018). Between 1998 and 2017, 3,148 flood events occurred worldwide, accounting for 43% of all natural disasters. During this period, floods affected two billion people and caused economic losses of USD 656 billion. Storms are the second most frequent type, with 2,049 recorded events or 28% of natural disasters. Over the past two decades, USD 1,330 billion of economic losses have been incurred as a result of storms, making it the costliest disaster type followed by earthquakes and floods.

Figure 4.1 shows the trends in the number of disaster events in developing and developed countries from 1990 and 2015. As illustrated in Figure 4.1a, floods are more frequent in developing countries than developed countries. The annual average number of floods during this period was 107.5 in developing countries and 26.7 in developed countries. The number of flood events in developing countries has been increasing steadily over time, especially since in the 2000s. More recent years have witnessed roughly 100 flood events in developing countries every year. Figure 4.1b presents the number of storm occurrences. Compared with floods, there is little difference in occurrences between developing and developed countries. On average, 58.2 annual events occur in developing countries and 36 in developed countries. Similar to floods, more storm events occur in developing countries than developed countries.

Figure 4.2 illustrates the trends in estimated economic losses by disaster type. Economic losses are calculated as a percentage of GDP using the average values of each

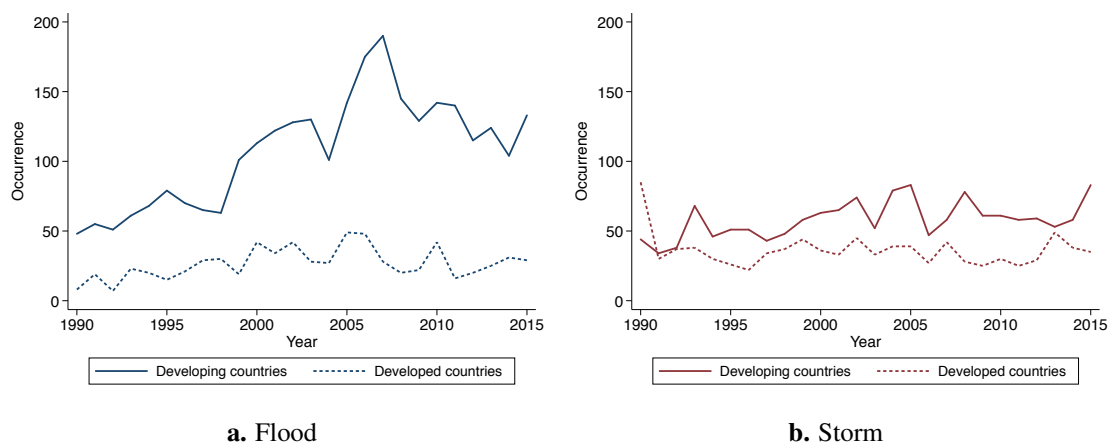


Fig. 4.1 Trends in the total number of disaster occurrences

Note: Data on floods include 169 countries, among which 130 are classified as developing countries and 39 as developed countries. Data on storms include 166 countries, among which 123 are classified as developing countries and 43 as developed countries. Source: CRED and Guha-Sapir (2018)

country's economic losses. In relative terms, damage incurred by floods is similar in developing and developed countries over time, as shown in Figure 4.2a. Yet, average economic losses are slightly larger in developing countries (0.6%) than developed countries (0.2%). Figure 4.2b depicts that storms cause as much damage as floods despite the relatively small number of occurrences. Notably, storms in developing countries cause much greater economic losses in relative terms. While there are fluctuations by year, the mean economic losses in developing countries are 3.5%. By contrast, the economic losses caused by storms in developed countries are 0.1% on average, similar to those of floods.

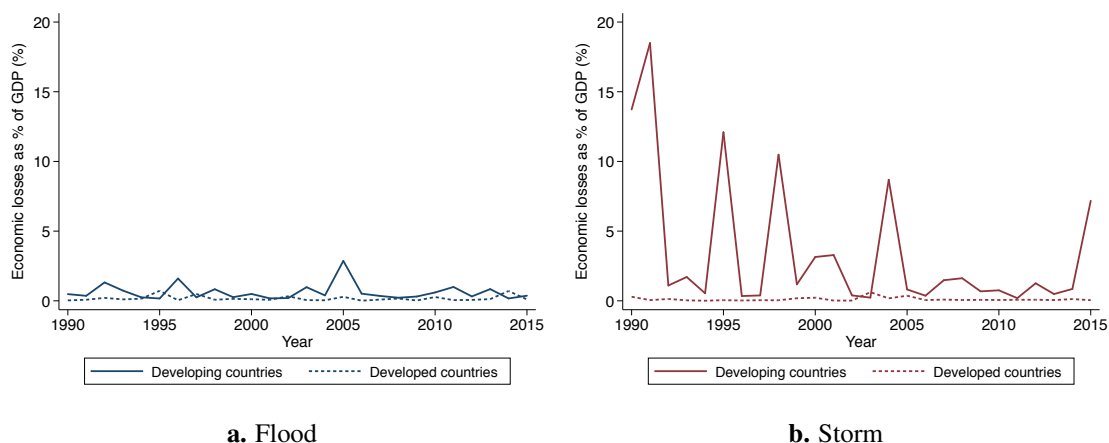
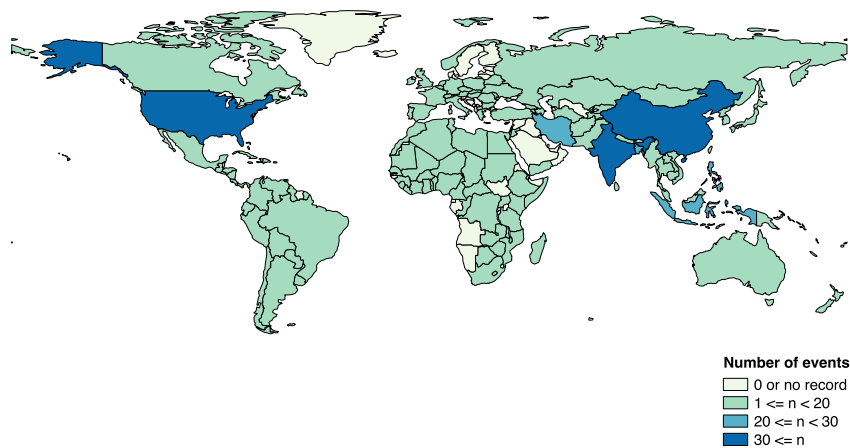
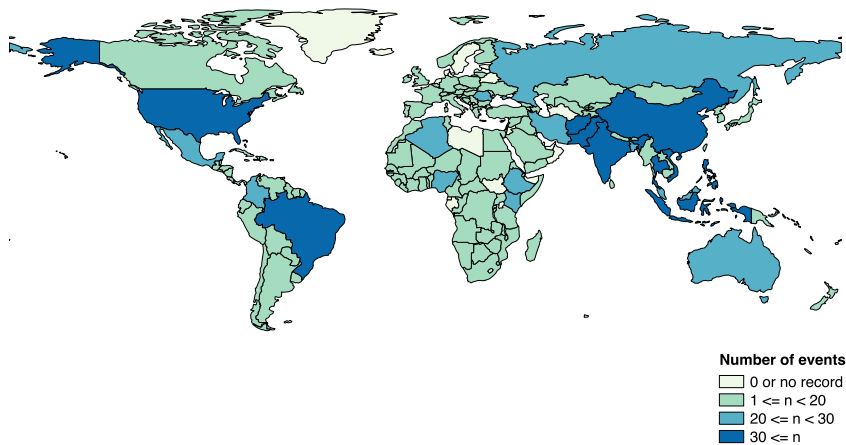


Fig. 4.2 Trends in average economic losses relative to GDP

Note: Economic losses and GDP are in constant 2010 US dollars. Data on floods include 169 countries, among which 130 are classified as developing countries and 39 as developed countries. Data on storms include 166 countries, among which 123 are classified as developing countries and 43 as developed countries. Source: CRED and Guha-Sapir (2018)



a. Years from 1990 to 1999



b. Years from 2000 to 2009

Fig. 4.3 Number of flood events by country

Source: CRED and Guha-Sapir (2018)

These figures depict the frequency and damage of floods and storms as global trends. Yet, natural disasters may occur more frequently in some countries or regions than others. To further understand the trends in floods and storms, Figures 4.3 and 4.4 show the number of disaster occurrences by country in two periods. In Figure 4.3, the number of flood events in the 1990s and 2000s is illustrated with two maps. The darker colors in the figures indicate a higher number of flood events in Asia-Pacific, North America, and South America. In the 2000s, floods became more frequent in many countries, particularly those in South Asia, Southeast Asia, Central America, and South America. Some

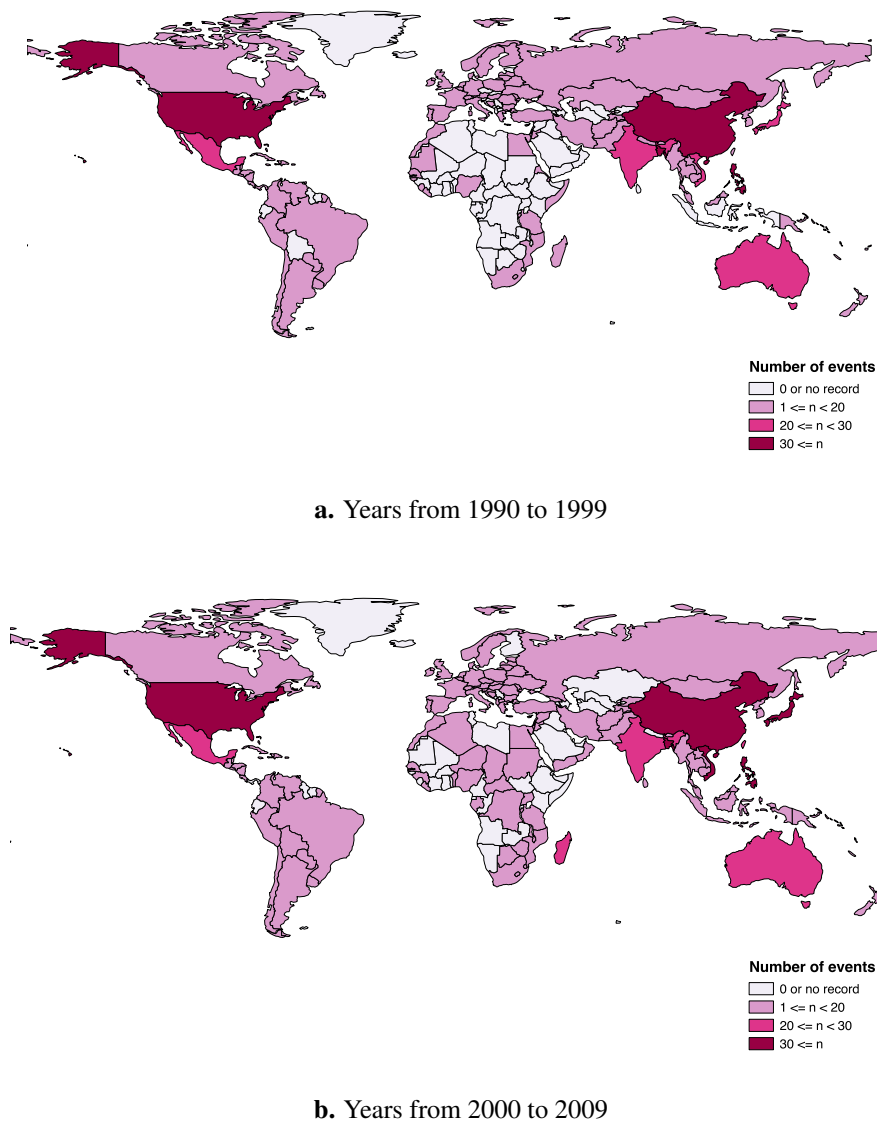


Fig. 4.4 Number of storm events by country

Source: CRED and Guha-Sapir (2018)

European countries and African countries have also observed more flood events than their neighboring countries.

Figure 4.4 presents the number of storm events in the same manner. The 1990s saw more storm events in some countries such as China, Bangladesh, the Philippines, and the United States. Similar to the case of floods, storms tend to be more frequent in Asia-Pacific, North America, and Central America. However, the following decade witnessed more storms in a number of countries, particularly those in Southeast Asia and Africa. Although the levels of frequency are moderate, these regions were distinctively hit by

more storms compared with the previous decade.

The figures in this section show the increasing trends in the occurrence and damage of floods and storms globally over recent decades. While the number of the disaster events has increased over time, more countries have also become exposed to them, implying that natural disasters may cause more damage to the affected countries, especially to poor people who are the most vulnerable. In absolute terms, the disasters in high-income countries account for a large proportion of the economic losses considering their high asset values (Wallemacq et al., 2018). However, low-income countries are among the most affected nations when losses are measured relative to their economic levels. In these countries, the socioeconomic impact of natural disasters may thus be significant. Therefore, the damage inflicted by natural disasters in poor countries cannot be ignored or underestimated.

4.3 Empirical Analysis

4.3.1 Empirical Strategy

This empirical analysis investigates the impact of natural disasters on international trade. We use data on bilateral trade flows to consider the effect of disasters in both exporting and importing countries. The dataset consists of 86 countries with disaster and bilateral export data from 2006 and 2015, comprising unbalanced monthly panel data (see Table 4.A in the Appendix for the countries included in the analysis). As the model takes an exponential form for the export data, this study uses a pseudo-maximum-likelihood (PML) estimation method. Santos Silva and Tenreyro (2006) argue that log-linearized models using ordinary least squares lead to biased estimation results and suggest employing a PML estimator. We adopt their approach and use the Poisson PML (PPML) and Gamma PML (GPML) estimators. The estimation equation is formulated as follows:

$$Export_{eit} = \exp\left(\alpha + \sum_{j=0}^L \beta_j Disaster_{et-j} + \sum_{j=0}^L \gamma_j Disaster_{it-j} + \lambda_e + \mu_i + \phi_t\right) + \varepsilon_{eit}, \quad (4.1)$$

where $Export_{eit}$ is the bilateral export values from exporter e to importer i at time t . $Disaster$ denotes the type of natural disaster; i.e., flood or storm. As Equation 4.1 shows, natural disasters in both exporting and importing countries are included in the model.

Country-specific fixed effects are captured by λ_e for exporting countries and μ_i for importing countries. These exporter and importer fixed effects control for any unobserved aspects of country heterogeneity including multilateral resistance terms. Popularized by Anderson and van Wincoop (2003), multilateral resistance refers to the trade barrier for a pair of countries/regions while trading with all other trading partners. Because the presence of multilateral resistance causes omitted variable issues and thereby leads to biased coefficient estimates, exporter and importer fixed effects are used as a solution in a gravity equation for bilateral trade (Head and Mayer, 2014). Time fixed effects, denoted by ϕ_t , are year-by-month dummies accounting for any external events common to all countries over time. ε_{eit} is an error term.

To explore the dynamics of disaster impacts, we also form the model with a lag structure. The model includes 12 lags of the disaster variables, indexed by j . We assume that the effect of natural disasters on trade persists for more than one month because of the destruction caused by disasters. For instance, agricultural production may be affected when farmland is damaged by floodwater or crops are destroyed by storms. Exports can also be affected when domestic and international supply chains are disrupted by severely damaged infrastructure. These negative impacts on production assets could reduce exports for a considerably long period; therefore, it is important to take into account lagged variables for estimating the disaster impacts.

4.3.2 *Description of the Variables*

Table 4.1 presents the descriptive statistics of the variables used in the analysis. Export values are shown in millions of US dollars. The export values of all products are used in the main empirical analysis. In a further analysis, we examine the trade values in the agricultural and manufacturing sectors.

Data on natural disasters are taken from the EM-DAT provided by the Centre for Research on the Epidemiology of Disasters at the University of Louvain (CRED and Guha-Sapir, 2018). The EM-DAT is the most comprehensive disaster database of natural and technological disasters worldwide. The data in the EM-DAT are collected from several sources such as international organizations, NGOs, national governments, and insurance companies. Each disaster event recorded in the database satisfies at least one of the following criteria: 10 or more people were reportedly killed; 100 or more people were reportedly affected, injured, or homeless; or a state of emergency was declared and/or an appeal for international assistance was launched. The EM-DAT has been used in a number of previous studies to analyze the economic impact of disasters (Anttila-Hughes and

Table 4.1 Descriptive statistics of the variables

Variable	Unit	Mean	S.D.	Min	Max
<i>Bilateral export values</i>					
All products	million USD	100.457	683.578	0	33,561
Agriculture	million USD	21.599	356.141	0	27,962
Manufacturing	million USD	94.723	653.086	0	32,393
<i>Disaster variables</i>					
Flood	dummy	0.114	0.318	0	1
Storm	dummy	0.022	0.146	0	1

Hsiang, 2013; Gassebner et al., 2010; Hsiang and Narita, 2012; Leiter et al., 2009; Loayza et al., 2012; Oh and Reuveny, 2010). We employ the event-based data on disasters from this database to construct a monthly panel dataset.

The EM-DAT classifies natural disasters into several types of which we examine floods and tropical storms.¹ The variables for floods and storms represent the occurrence of these disaster types. We use a dummy variable that takes 1 if a disaster occurred at least once during a month in a given country and 0 otherwise. Floods are a more frequent disaster type than storms according to the descriptive statistics. Table 4.1 shows that the mean occurrences of floods and storms are 11.4% and 2.2% per month, respectively. Our sample thus accords with global trends, where floods are a more frequent disaster type than storms, as described in Section 4.2.

For the trade data, we use the bilateral export values from the International Trade Centre, a joint agency created by the World Trade Organization and United Nations.² The data on exports and imports provided by the International Trade Centre are based on the Harmonized System (HS) classification codes. From this database, we use the export values of all products and the disaggregated export values at the two-digit HS code level. We then aggregate the export data with two-digit HS codes into two product groups: agricultural and manufacturing goods. The former includes products with HS codes 1 to 15 and the latter with HS codes 16 to 99. The mean export values in Table 4.1 show that agricultural products account for approximately 20% of exports and manufacturing products for 80%.

¹Tropical storms are categorized as a subtype of *storms* along with convective storms and extra-tropical storms. For the detailed classification of disasters, see the EM-DAT website (CRED and Guha-Sapir, 2018).

²Available at <http://www.intracen.org/>.

4.4 Results

4.4.1 Baseline Results

We estimate the models based on Equation 4.1 to investigate the effect of natural disasters on bilateral trade flows. All the specifications include 12 lags of the disaster variables to examine whether the effect of floods and storms persist in the post-disaster period. This study also considers disaster events in both exporting and importing countries to explore the impact on trade flows of disasters that occur in origin and destination states.

Table 4.2 presents the main estimation results. We estimate the models using the PPML and GPML estimators for each disaster type. Columns 1 and 2 show the results for floods and columns 3 and 4 show the results for storms. For the lagged variables, the results of the one-to-three-month lags are reported to show the effect of natural disasters over the past three months. We also present the total effects of disasters in exporting and importing countries, as shown in the bottom rows of each column. The total effects consider all disaster occurrences in the present and past 12 months, calculated using the estimated coefficients of the disaster variable and its lagged variables.

The results in Table 4.2 show that floods are negatively correlated with exports of all products. In column 1, the coefficients of exporters' disasters are negative and statistically significant, indicating that floods reduce exports by 1.1% within a month of the onset of the disasters. The results for exporters also suggest that flood impacts persist in the post-disaster period. The coefficients of the exporters' lagged variables are negative and statistically significant. As for importing countries, the immediate effect of floods exhibits a negative sign, although the coefficients are not statistically significant. On the contrary, the results of the importers' lagged disaster variables show negative and statistically significant effects. These findings suggest that, similar to exporters, importers are affected by flood events in their countries, thereby decreasing their trade flows. In the bottom rows of column 1, the cumulative effect of floods is presented for exporters and importers. The results suggest that floods in both exporting and importing countries reduce exports. The magnitudes of the coefficients are similar: total export losses are 13.2% as a consequence of exporters' floods and 10.5% for those of importers. The results using the GPML estimator in column 2 also show similar results. In the GPML model, the total effect of importers' floods is not statistically significant, while some of the lagged variables exhibit a negative and statistically significant effect of floods. Nevertheless, the coefficients and negative signs are mostly consistent with the results using the PPML

Table 4.2 Main regression results

	Dependent variable: Exports All products			
	Flood		Storm	
	Poisson (1)	Gamma (2)	Poisson (3)	Gamma (4)
<i>Exporter</i>				
Disaster _{et}	-0.011*** (0.004)	-0.031*** (0.007)	-0.008 (0.006)	-0.024** (0.010)
L.Disaster _{et}	-0.016*** (0.003)	-0.017** (0.007)	-0.026*** (0.009)	0.007 (0.016)
L2.Disaster _{et}	-0.010*** (0.003)	-0.013 (0.010)	-0.016 (0.011)	-0.039*** (0.012)
L3.Disaster _{et}	-0.014*** (0.003)	-0.001 (0.008)	-0.017** (0.007)	-0.027** (0.013)
<i>Importer</i>				
Disaster _{it}	-0.011 (0.007)	-0.022*** (0.007)	-0.009 (0.007)	0.010 (0.012)
L.Disaster _{it}	-0.016** (0.006)	-0.016** (0.006)	-0.021** (0.010)	-0.021* (0.011)
L2.Disaster _{it}	-0.015** (0.006)	-0.016** (0.007)	-0.018 (0.011)	-0.004 (0.011)
L3.Disaster _{it}	-0.011** (0.005)	0.001 (0.008)	-0.022 (0.015)	-0.002 (0.010)
Constant	9.695*** (0.476)	10.277*** (0.414)	9.664*** (0.476)	10.260*** (0.415)
Exporter fixed effects	Yes	Yes	Yes	Yes
Importer fixed effects	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes
Observation	787,321	787,321	787,321	787,321
Pseudo R-squared	0.789		0.789	
RESET test p-value	0.074	0.000	0.075	0.000
<i>Total effect of disaster in</i>				
Exporting country	-0.132*** (0.036)	-0.116** (0.047)	-0.122 (0.094)	-0.224*** (0.081)
Importing country	-0.105** (0.044)	0.001 (0.048)	-0.169 (0.150)	0.075 (0.082)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by country-pair and reported in parentheses.

estimator.

Table 4.2 also presents the results for tropical storms in columns 3 and 4. The results from the model using the PPML estimator show that the immediate impacts of exporters' and importers' storms are negative but not statistically related to exports. The lagged

disaster variables, on the contrary, suggest a negative correlation between storms and exports. For example, the coefficients of the one-month lagged variables indicate that export losses from exporters' and importers' storms are 2.6% and 2.1%, respectively. Similar to this result, the model using the GPML in column 4 shows a negative and statistically significant impact of storms. However, the coefficients of the cumulative effect reported in the last rows show mixed results for the effect of tropical storms. The results from the PPML model are not statistically significant, while the results from the GPML model show a negative effect of exporters' storms on exports.

To compare the model specifications used in Table 4.2, we run Ramsey's regression specification error test (RESET) (Ramsey, 1969). The RESET test checks if the model in question is correctly specified by running a regression with the fitted values as an additional regressor in the original model. In this study, we use the squared terms of the fitted values of each original model. In the PPML models for floods and storms, the test does not reject the null hypothesis that the coefficient of the squared terms of the fitted values is 0 at the 5% level, suggesting that the models are correctly specified. By contrast, the models using the GPML estimator do not pass the RESET test. These findings mean that the model using the PPML estimator is more appropriate than that of the GPML estimator. Therefore, the following part of this study mainly discusses the results of the PPML model.

In Table 4.3, we test the robustness of the baseline results. These robustness checks use alternative specifications by introducing additional control variables that measure country size. We use data on land area and population taken from the World Development Indicators (World Bank, 2018). These variables are not only important determinants of trade flows but are also related to disaster impacts. Small countries tend to be more vulnerable to natural disaster shocks than large countries. For instance, the same scale of tropical storm would cause larger damage to a country such as Costa Rica than a country such as the United States by affecting a higher proportion of the land, population, and economy. We check the validity of the effect of natural disasters while controlling for country size using these variables. All the models in Table 4.3 use the PPML estimator and include 12 lags of the disaster variables. Columns 1 and 5 show the baseline models for floods and storms, which correspond to columns 1 and 3 in Table 4.2.

Overall, the results with these alternative specifications are robust to the baseline results. In columns 2 and 6, we first include the land area of exporting and importing countries. The results show that the coefficients of the disaster variables are similar to the baseline results in terms of statistical significance, size, and sign. Second, we add popula-

Table 4.3 Alternative specifications with additional control variables

	Dependent variable: Exports All products							
	Flood				Storm			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Exporter</i>								
Disaster _{et}	-0.011*** (0.004)	-0.011*** (0.004)	-0.010** (0.004)	-0.010*** (0.004)	-0.008 (0.006)	-0.008 (0.006)	-0.006 (0.006)	-0.006 (0.006)
L.Disaster _{et}	-0.016*** (0.003)	-0.016*** (0.003)	-0.015*** (0.003)	-0.015*** (0.003)	-0.026*** (0.009)	-0.026*** (0.009)	-0.024*** (0.008)	-0.024*** (0.008)
L2.Disaster _{et}	-0.010*** (0.003)	-0.010*** (0.003)	-0.009*** (0.003)	-0.009*** (0.003)	-0.016 (0.011)	-0.017 (0.011)	-0.015 (0.009)	-0.015 (0.009)
L3.Disaster _{et}	-0.014*** (0.003)	-0.014*** (0.003)	-0.013*** (0.003)	-0.013*** (0.003)	-0.017** (0.007)	-0.018** (0.008)	-0.014* (0.007)	-0.015** (0.007)
<i>Importer</i>								
Disaster _{it}	-0.011 (0.007)	-0.011* (0.006)	-0.009 (0.006)	-0.009 (0.006)	-0.009 (0.007)	-0.009 (0.007)	-0.006 (0.007)	-0.006 (0.007)
L.Disaster _{it}	-0.016** (0.006)	-0.016** (0.006)	-0.013** (0.006)	-0.013** (0.006)	-0.021** (0.010)	-0.021** (0.009)	-0.019** (0.009)	-0.019** (0.009)
L2.Disaster _{it}	-0.015** (0.006)	-0.015*** (0.006)	-0.014** (0.006)	-0.014** (0.006)	-0.018 (0.011)	-0.018 (0.011)	-0.016 (0.011)	-0.016 (0.010)
L3.Disaster _{it}	-0.011** (0.005)	-0.011** (0.005)	-0.009* (0.005)	-0.009* (0.005)	-0.022 (0.015)	-0.022 (0.015)	-0.019 (0.014)	-0.019 (0.014)
<i>Controls</i>								
ln Land area _{et}		6.651*** (2.532)		8.607*** (2.361)		6.241** (2.565)		8.284*** (2.369)
ln Land area _{it}		1.657 (4.858)		3.420 (4.594)		1.433 (4.803)		3.340 (4.523)
ln Population _{et}			1.118*** (0.375)	1.164*** (0.378)			1.151*** (0.384)	1.197*** (0.387)
ln Population _{it}			1.524*** (0.251)	1.534*** (0.252)			1.548*** (0.264)	1.558*** (0.265)
Constant	9.695*** (0.476)	-113.447 (84.351)	-36.578*** (8.779)	-215.842*** (78.908)	9.664*** (0.476)	-104.078 (84.130)	-37.607*** (9.070)	-210.881*** (77.982)
Exporter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	787,321	787,321	787,321	787,321	787,321	787,321	787,321	787,321
Pseudo R-squared	0.789	0.789	0.789	0.790	0.789	0.789	0.789	0.789
<i>Total effect of disaster in</i>								
Exporting country	-0.132*** (0.036)	-0.136*** (0.036)	-0.118*** (0.034)	-0.122*** (0.034)	-0.122 (0.094)	-0.130 (0.095)	-0.105 (0.082)	-0.114 (0.082)
Importing country	-0.105** (0.044)	-0.106** (0.044)	-0.083** (0.042)	-0.085** (0.041)	-0.169 (0.150)	-0.170 (0.148)	-0.150 (0.144)	-0.154 (0.142)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by country-pair and reported in parentheses.

tion into the equation and report the estimation results in columns 3 and 7. The inclusion of population does not change the results of the baseline models. Third, the coefficients of the disaster variables are also similar to the baseline results when both control variables are included, as shown in columns 4 and 8. Moreover, the total effects of floods and storms are mostly consistent across the alternative models, supporting the robustness of our findings.

4.4.2 Natural Disasters in Developing and Developed Countries

This section examines the heterogeneous impacts of natural disasters, with a particular focus on country characteristics. We divide the sample into developing and developed

countries to analyze the effect of disasters in countries at different levels of development based on the classification by the United Nations Statistics Division (see Table 4.A in the Appendix).³

Table 4.4 presents the results. For both exporters and importers, we interact disasters with a dummy variable for a country's development level; i.e., developing or developed. In column 1, the coefficients of the interaction between the zero lag flood variable and developing country are negative and statistically significant for both exporters and importers. The results suggest that floods in developing countries have an immediate negative effect on bilateral trade, with monthly export losses of 2.4% from exporters' floods and 3.2% from importers' floods. Using the lagged variables, we also find that floods in developing countries negatively affect exports in the post-disaster period. By contrast, the immediate effect of floods is not statistically related to exports when interacted with developed countries. Although the interaction terms of the lagged variables and developed countries show a negative correlation with exporters' past flood events, the effect of importers' floods tends to be not significant. The total effect of floods is also heterogeneous among developing and developed countries. In developing countries, the coefficients of the total effect of floods suggest that exporters' and importers' floods reduce bilateral trade flows by 13.3% and 29.2%, respectively. In developed countries, trade losses incurred by exporters' floods are 12.5%, whereas importers' floods do not have a significant effect. The significance and larger size of the coefficients for developing countries indicate larger export losses, suggesting that developing countries are more vulnerable to floods. We also estimate the model using the GPML estimator and find similar results, as shown in column 2. Nevertheless, the RESET test suggests that the PPML model is a more appropriate specification.

Columns 3 and 4 of Table 4.4 show the results for storms. In contrast to floods, the results from the PPML model exhibit a positive effect of the interactions between storms and developing countries. For developed countries, the effects of exporters' and importers' storms tend to be negative, suggesting that storms in developed countries cause bilateral export flows to decline. The coefficients of the total effect of storms indicate that trade losses are 28.8% from exporters' storms and 33.5% from importers' storms. It is assumed that developed countries are more resilient to natural disasters, considering their economic capabilities to adapt to external shocks. Yet, interestingly, we find that developed countries suffer from tropical storms. The cumulative effect of storms also shows the opposite effects of storms in developing and developed countries; that is, positive for

³ Available at <https://unstats.un.org/home/>.

Table 4.4 Effect of natural disasters on trade in developing and developed countries

	Dependent variable: Exports All products			
	Flood		Storm	
	Poisson (1)	Gamma (2)	Poisson (3)	Gamma (4)
<i>Exporter</i>				
Disaster $\times$ developing country _{et}	-0.024*** (0.009)	-0.037*** (0.010)	0.006 (0.005)	-0.028** (0.014)
L.Disaster $\times$ developing country _{et}	-0.012*** (0.004)	-0.021** (0.010)	0.008* (0.004)	0.013 (0.021)
L2.Disaster $\times$ developing country _{et}	-0.015*** (0.006)	-0.012 (0.014)	0.029*** (0.007)	-0.044*** (0.015)
L3.Disaster $\times$ developing country _{et}	-0.010* (0.005)	0.003 (0.011)	0.012* (0.007)	-0.033* (0.017)
Disaster $\times$ developed country _{et}	-0.005 (0.004)	-0.014** (0.006)	-0.012 (0.008)	-0.020** (0.008)
L.Disaster $\times$ developed country _{et}	-0.016*** (0.004)	-0.008 (0.005)	-0.045*** (0.009)	-0.012 (0.009)
L2.Disaster $\times$ developed country _{et}	-0.007* (0.004)	-0.015*** (0.005)	-0.041*** (0.008)	-0.017* (0.010)
L3.Disaster $\times$ developed country _{et}	-0.015*** (0.003)	-0.012* (0.006)	-0.033*** (0.010)	-0.007 (0.009)
<i>Importer</i>				
Disaster $\times$ developing country _{it}	-0.032*** (0.008)	-0.022*** (0.008)	0.005 (0.006)	0.011 (0.014)
L.Disaster $\times$ developing country _{it}	-0.023*** (0.004)	-0.021*** (0.008)	0.013** (0.006)	-0.026* (0.013)
L2.Disaster $\times$ developing country _{it}	-0.035*** (0.007)	-0.022** (0.009)	0.021** (0.010)	-0.002 (0.013)
L3.Disaster $\times$ developing country _{it}	-0.028*** (0.006)	-0.004 (0.010)	0.010* (0.006)	-0.004 (0.012)
Disaster $\times$ developed country _{it}	-0.002 (0.009)	-0.019** (0.009)	-0.013 (0.010)	0.005 (0.018)
L.Disaster $\times$ developed country _{it}	-0.011 (0.010)	-0.000 (0.008)	-0.038*** (0.012)	-0.005 (0.020)
L2.Disaster $\times$ developed country _{it}	-0.007 (0.009)	0.003 (0.007)	-0.040*** (0.012)	-0.004 (0.017)
L3.Disaster $\times$ developed country _{it}	-0.004 (0.008)	0.017** (0.008)	-0.038* (0.020)	0.008 (0.018)
Constant	9.724*** (0.476)	10.287*** (0.414)	9.668*** (0.476)	10.257*** (0.415)
Exporter fixed effects	Yes	Yes	Yes	Yes
Importer fixed effects	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes
Observation	787,321	787,321	787,321	787,321
Pseudo R-squared	0.789		0.789	
RESET test p-value	0.074	0.000	0.075	0.000
<i>Total effect of disaster in</i>				
developing country (exporter)	-0.133** (0.056)	-0.157** (0.063)	0.226*** (0.048)	-0.314*** (0.107)
developing country (importer)	-0.292*** (0.064)	-0.034 (0.062)	0.182* (0.096)	0.031 (0.091)
developed country (exporter)	-0.125*** (0.045)	-0.010 (0.038)	-0.288*** (0.101)	0.046 (0.094)
developed country (importer)	-0.037 (0.058)	0.097 (0.060)	-0.335* (0.184)	0.277 (0.193)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by country-pair and reported in parentheses.

developing countries and negative for developed countries. In column 4, we find a negative impact of storms in developing countries from the GPML model. However, this specification does not pass the RESET test.

These estimation results suggest that natural disasters have heterogeneous effects in countries at different development levels in line with the literature. Jones and Olken (2010) examine weather shocks on export values and find that higher temperature negatively affects export growth in poor countries. In a study investigating the impact on the macroeconomy, Noy (2009) demonstrates the negative effect of natural disasters in developing countries, but not in developed countries. Loayza et al. (2012) also examine the relationship between natural disasters and economic growth, finding that developing countries are more sensitive to natural disasters, while their positive or negative impacts vary by sector and disaster type. In line with these previous studies, our results find diverse natural disaster impacts by a country's economic level. We find that developing countries suffer more export losses from floods in both origin and destination states. Storms in developing countries, on the contrary, tend to positively impact export flows. Furthermore, we find that developed countries also suffer export losses from tropical storms.

4.4.3 *Agricultural and Manufacturing Channels*

We further analyze the relationship between natural disasters and trade to explore the channels through which floods and storms may affect bilateral export flows. Some sectors, particularly agriculture, may be more sensitive to extreme weather, as revealed in the literature on climate impacts (Dallmann, 2018; Dell et al., 2012; Jones and Olken, 2010; Loayza et al., 2012). This study thus investigates the export flows of agricultural and manufacturing products to identify the industries affected by natural disaster shocks.

Table 4.5 shows the estimation results for exports by product group. The results for agricultural exports are reported in columns 1 and 2 for floods and storms, respectively. The results for manufacturing exports follow in the remaining two columns. In column 1, we find that both immediate and past flood events are negatively associated with agricultural exports. The coefficients of the total effect of floods indicate that export losses associated with exporters' floods are 17.3%. While we also find negative effects of floods from importers' disaster variables, the coefficients of the total effect are not significant. Taken together, the results suggest that a decline in agricultural exports derives from floods in exporting countries. Similarly, we find that storms in exporting countries decrease agricultural trade flows. The cumulative effects of exporters' storms are statistically related to agricultural exports, reducing trade flows by 24.4%.

Table 4.5 Effect of natural disasters on trade by product group

	Dependent variable: Exports			
	Agriculture		Manufacturing	
	Flood (1)	Storm (2)	Flood (3)	Storm (4)
<i>Exporter</i>				
Disaster _{et}	-0.020*** (0.008)	0.016 (0.018)	-0.010** (0.004)	-0.007 (0.007)
L.Disaster _{et}	-0.022*** (0.007)	-0.021 (0.014)	-0.016*** (0.003)	-0.027*** (0.010)
L2.Disaster _{et}	-0.015** (0.006)	-0.015 (0.013)	-0.010*** (0.003)	-0.017 (0.012)
L3.Disaster _{et}	-0.015*** (0.005)	-0.028*** (0.010)	-0.014*** (0.003)	-0.017** (0.008)
<i>Importer</i>				
Disaster _{it}	-0.018** (0.007)	0.001 (0.008)	-0.011 (0.007)	-0.009 (0.008)
L.Disaster _{it}	-0.012** (0.006)	-0.003 (0.009)	-0.016** (0.007)	-0.021** (0.010)
L2.Disaster _{it}	-0.013* (0.007)	0.004 (0.016)	-0.015** (0.006)	-0.017 (0.012)
L3.Disaster _{it}	-0.012** (0.005)	-0.007 (0.008)	-0.011** (0.005)	-0.021 (0.015)
Constant	8.452*** (0.390)	8.424*** (0.389)	9.414*** (0.496)	9.382*** (0.496)
Exporter fixed effects	Yes	Yes	Yes	Yes
Importer fixed effects	Yes	Yes	Yes	Yes
Year-by-month fixed effects	Yes	Yes	Yes	Yes
Observation	643,542	643,542	777,811	777,811
Pseudo R-squared	0.891	0.891	0.791	0.791
<i>Total effect of disaster in</i>				
Exporting country	-0.173** (0.088)	-0.244* (0.140)	-0.133*** (0.038)	-0.118 (0.097)
Importing country	-0.097 (0.074)	0.076 (0.132)	-0.106** (0.046)	-0.167 (0.155)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by country-pair and reported in parentheses.

For manufacturing products, we find that flood events have immediate and persistent effects that reduce exports. The results of the total effect of floods show that the coefficients are negative and statistically significant for both exporters and importers. These findings indicate that export losses in manufacturing are 13.3% from exporters' floods and 10.6% from importers' floods, implying that flood events harm the manufacturing production processes of both exporters and importers. In importing countries, a slow-

down in production as a result of floods may cause supply chain disruptions in manufacturing, leading to a decrease in import flows. This description, however, does not apply to storms, for which we find that the total effect on manufacturing exports is insignificant in both origin and destination countries.

The analysis of exports by sector provides interesting findings. When comparing the significance and magnitude of the coefficients, the total effects of disasters show that agriculture is more sensitive to natural disasters than manufacturing. These results imply that natural disasters proportionally cause more export damage to agriculture than to manufacturing. Moreover, the results for storms show that exporters' storms negatively affect exports of agricultural products. While we do not find clear evidence of the impact of storms on total exports, the breakdown of export data by sector reveals a negative impact of storms on exports through agriculture.

4.4.4 Effect of Severe Disasters

This section reexamines the effect of natural disasters using an alternative measure of the disaster variables. The effect of natural disasters may differ substantially depending on their severity. This additional analysis considers several types of estimated damage in terms of human and economic losses to incorporate the severity of natural hazards into the analysis.

In previous sections, we used dummies for the flood and storm variables. Although it is also possible to use other measures that reflect the size and scale of disasters; e.g., the number of casualties and economic loss, estimating disaster impacts using such non-physical data may raise some issues. First, there may be endogeneity problems associated with non-physical disaster characteristics (Hsiang and Narita, 2012). Human losses and economic damage may be correlated with other factors related to a country's attributes such as GDP, institution, and development level. In that case, the exogeneity of the variables no longer holds in the estimation model. Second, the presence of missing data and measurement errors in the database has also been pointed out (Loayza et al., 2012). Therefore, the use of non-physical disaster characteristics could reduce the credibility of the estimation results.

With these caveats in mind, we attempt to estimate the effect of large-scale disasters using an alternative variable based on the estimated damage reported in the EM-DAT. Following Felbermayr and Gröschl (2014) and Gassebner et al. (2010), we adapt the classification of natural catastrophes by Munich Re (2006) to define a large-scale disaster that meets the following criteria: 1,000 or more people were killed, 100,000 or more

Table 4.6 Effect of large disasters

	Dependent variable: Exports All products	
	Flood (1)	Storm (2)
<i>Exporter</i>		
Large disaster _{et}	-0.030*** (0.006)	-0.003 (0.011)
L.Large disaster _{et}	-0.022*** (0.004)	0.019*** (0.007)
L2.Large disaster _{et}	-0.020*** (0.007)	0.004 (0.007)
L3.Large disaster _{et}	-0.010* (0.005)	0.009 (0.008)
<i>Importer</i>		
Large disaster _{it}	-0.040*** (0.007)	-0.028** (0.012)
L.Large disaster _{it}	-0.019*** (0.005)	-0.015 (0.010)
L2.Large disaster _{it}	-0.021** (0.009)	-0.014 (0.009)
L3.Large disaster _{it}	-0.023*** (0.005)	-0.015* (0.008)
Constant	9.651*** (0.477)	9.662*** (0.476)
Exporter fixed effects	Yes	Yes
Importer fixed effects	Yes	Yes
Year-by-month fixed effects	Yes	Yes
Observation	787,321	787,321
Pseudo R-squared	0.789	0.789
<i>Total effect of disaster in</i>		
Exporting country	-0.149** (0.058)	0.031 (0.066)
Importing country	-0.214*** (0.053)	-0.275** (0.136)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by country-pair and reported in parentheses.

people were affected, or economic damage exceeded USD 1 billion. The dollar values for economic damage are converted into constant 2010 US dollars using the US GDP deflator to make the damage comparable over time. The data on the GDP deflator are taken from the World Development Indicators (World Bank, 2018).

Table 4.6 presents the results for the effect of large-scale disasters. In column 1, the coefficients of exporters' variables are negative and statistically significant, suggesting that severe floods have immediate and persistent impacts on exports. Similarly, importers' variables show that floods in importing countries lead to a decline in trade flows. These findings are consistent with the baseline results in Table 4.2, showing a negative effect of floods in both exporting and importing countries.

In column 2, exporters' immediate storm effect appears to be negative but not statistically significant. We also find that the coefficients of the lagged variables are not sig-

nificant, except the variable with a one-month lag showing a positive effect of exporters' storms. Nevertheless, the total effect of exporters' storms is insignificant. The results for importers' storms reveal the immediate effect of storms, suggesting that severe storms in importing countries reduce trade flows. We also find a negative effect of severe storms from the importers' variable with three lags.

Overall, the results show that export losses are induced by severe floods in both exporting and importing countries. We also find that severe storms in importing countries cumulatively affect bilateral trade. Moreover, the results indicate larger coefficients of severe disasters than those of average disasters (see Table 4.2). These findings suggest that large-scale natural disasters can cause a greater reduction in exports.

4.5 Conclusions

This study investigates the effect of natural disasters on bilateral trade. We use cross-country panel data with a large sample from 2006 and 2015 to evaluate the extent to which floods and storms affect monthly export flows. To estimate the disaster impacts in both origin and destination countries on trade flows, this study considers the natural hazards that occurred in exporting and importing countries. Moreover, we conduct a series of analyses to explore whether the effects of natural hazards are heterogeneous among countries.

The main results show that climate-related disasters are significantly related to export flows. We find that flood events in exporting countries have a negative and significant effect on exports, with trade losses of 1.1% within a month of the onset of the disaster. The results of the lagged variables also reveal the negative effects of disasters persisting in the post-disaster period. The cumulative effects of exporters' floods in a given month reduce bilateral exports by 13.2% annually. Similarly, we find that importers' floods also negatively affect bilateral trade flows. The results show that 10.5% of total export losses are incurred as a result of flood events in importing countries. These findings suggest that floods affect both exporters and importers, resulting in a decline in trade flows.

We further examine the disaster impacts by splitting the sample into developing and developed countries. The estimation results demonstrate that developing countries, as exporters and importers, tend to suffer greater export losses than developed countries. Notably, a decline in bilateral trade is associated with flood events in developing countries, with annual losses of 13.3% from exporters' floods and 29.2% from importers' floods. These findings suggest that developing countries are more vulnerable to floods in the

context of international trade. In addition, this study finds a negative and significant impact of tropical storms in developed countries, where storms inflict trade losses on both exporters and importers. Another analysis using the breakdown of exports finds that agriculture is more vulnerable to disaster shocks than manufacturing. In particular, the results suggest that flood and storm events in the origin countries cause export flows to diminish. Although uncovering the causal mechanisms of disaster impacts is challenging, this study shows the heterogeneous disaster impacts that impede international trade.

The results of this study suggest that natural disasters negatively affect a country's economy through international trade. Our empirical findings offer important policy implications for better understanding disaster risks in countries, particularly where vulnerability to climate shocks is high. While poverty makes countries more vulnerable to natural disasters, the adverse effect of such disasters could further hinder economic development. Considering that trade serves as a channel through which the climate affects the aggregate economy, the results of this study provide suggestive evidence that mitigating disaster risks in trade could also reduce poverty. This requires further work to understand the mechanisms underlying the effects of natural disasters in more detail. Future research should thus focus on the interrelations among poverty, industrial structure, and the impact of natural disasters.

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CHAPTER 5

CONCLUDING REMARKS

This dissertation examined the effect of weather-related natural disasters on economic activities. Each chapter focused on a particular aspect of the economy to explore whether and to what extent extreme weather events affect economically relevant outcomes. The results of the empirical investigation in three studies revealed that natural disasters have statistically significant effects on these outcomes, highlighting them as channels through which climate may affect the aggregate economy.

To summarize these studies, the following conclusions can be drawn. First, the effect of climate shocks can be persistent as well as contemporaneous. In Chapter 2, the impact of climate variability was analyzed using drought response actions in Japanese river basins. This study found the intensity and duration of water restrictions during droughts are associated with climate variability: changes in precipitation and temperature affect not only the amount of water being curtailed but also the duration of water restrictions. The results regarding the duration suggest that variability in weather conditions may impose a long-term effect of weather shocks on water use. As a result of extreme dry spells or heat waves, water shortages could affect local communities for a longer period. Evidence of the long-term effect of climate shocks was also provided in Chapters 3 and 4. These chapters examined the effect of natural disasters on international trade and found that the occurrence of floods and storms causes a decline in bilateral export flows. The occurrence of disasters has an immediate effect on exports, leading to trade losses within a month of the onset of the events. Moreover, these studies applied lagged disaster variables to explore the dynamic impact of natural disasters. The results showed a statistically significant effect of these variables, suggesting that disaster impacts persist for several months after the events. The analysis also revealed the total damage from disaster events over the past 12 months. These findings imply that a disaster event that occurs in a given month cumulatively causes export losses in the post-disaster period.

Second, the three studies in this dissertation demonstrated that the impact of natural hazards and extreme weather are present in various dimensions of the economy. As shown in Chapter 2, variability in precipitation and temperature exacerbates water restrictions as more stringent restrictions are imposed. Since water is distributed for various purposes, for example, for drinking, agricultural use, and industrial production, more restrictions on water intakes as a result of droughts could cause a widespread impact on urban water supply in local communities. Moreover, the results of Chapters 3 and 4 indicated negative impacts of disasters on exports of agricultural and manufacturing products. This suggests that the agricultural and manufacturing sectors are affected by the occurrence of natural hazards through international trade. In line with many previous studies focusing on climate impacts on agricultural outputs, the studies in this dissertation also demonstrated the adverse effect of climate shocks on agriculture. In addition, Chapters 3 and 4 identified climate impacts on non-agricultural outcomes. These findings suggest empirical evidence that the effect of climate shocks is not limited to a particular sector but appears in the broader dimensions of the economy. Furthermore, this conclusion is strengthened by Chapter 4, in which the heterogeneous impacts of natural disasters were investigated. One highlight of this chapter was that developing countries are more vulnerable to disasters than developed countries. The results showed that floods in developing countries cause significant and larger export losses. This also supports the existing literature examining the macroeconomic impact of climate on countries with different economic levels, especially poor countries. Together with Chapter 3, these chapters suggest that the effect of natural disasters is heterogeneous among countries, as well as industrial sectors.

The studies in this dissertation have illustrated the economic costs of climate change incurred by the onset of weather-related disasters. The results draw attention to the importance of addressing disaster risks and reducing vulnerability to climate change. For example, the findings from Chapter 2 imply that strengthening the role of coordination councils may facilitate drought response actions in Japanese river basins. At the local level, a coordination body, such as drought councils in Japan, may help mitigate potential conflicts among stakeholders and enhance the institutional capacity to adapt to climate change. The results of Chapters 3 and 4 suggest that disaster risk reduction is important, particularly in emerging countries where exports play a key role in boosting economic development. Considering the persistent effect of natural disasters found in the studies, investment in more disaster-resilient infrastructure is urgent to alleviate the long-term impact of disasters and accelerate post-disaster recovery and rehabilitation. In private and public sectors, the integration of risk reduction measures into business strategies or urban

planning may also be called for. As we can expect more frequent and extensive weather events in the coming decades, which will become more likely under climate change, efforts for disaster risk reduction will become more crucial for building disaster-resilient societies while achieving economic growth and development.

APPENDIX

I Appendix for Chapter 3

Table 3.A List of importers used in the analysis

Afghanistan	Gambia	Norway
Algeria	Georgia	Oman
Andorra	Germany	Pakistan
Angola	Ghana	Palau
Antigua and Barbuda	Greece	Panama
Argentina	Grenada	Papua New Guinea
Armenia	Guatemala	Paraguay
Aruba	Haiti	Peru
Australia	Honduras	Poland
Austria	Hong Kong, China	Portugal
Azerbaijan	Hungary	Qatar
Bahamas	Iceland	Romania
Bahrain	India	Russian Federation
Bangladesh	Iran	Rwanda
Barbados	Iraq	Samoa
Belarus	Ireland	Saudi Arabia
Belgium	Italy	Senegal
Belize	Jamaica	Seychelles
Benin	Japan	Sierra Leone
Bermuda	Jordan	Singapore
Bolivia	Kazakhstan	Slovakia
Botswana	Kenya	Slovenia
Brazil	Kiribati	Solomon Islands
British Virgin Islands	Korea	Somalia
Brunei Darussalam	Kuwait	South Africa
Bulgaria	Kyrgyzstan	Spain
Burundi	Lao People's Democratic Republic	Sri Lanka
Cambodia	Latvia	Sudan
Cameroon	Lebanon	Suriname
Canada	Liberia	Swaziland
Cayman Islands	Libya	Sweden
Central African Republic	Lithuania	Switzerland
Chile	Luxembourg	Syrian Arab Republic
China	Macao, China	Taipei, Chinese
Colombia	Macedonia	Tajikistan
Congo	Madagascar	Tanzania
Cook Islands	Malawi	Timor-Leste
Costa Rica	Maldives	Togo
Croatia	Mali	Tonga
Cuba	Malta	Trinidad and Tobago
Cyprus	Marshall Islands	Tunisia
Czech Republic	Mauritius	Turkey
Côte d'Ivoire	Mexico	Turkmenistan
Denmark	Micronesia	Uganda
Djibouti	Moldova	Ukraine
Dominica	Mongolia	United Arab Emirates
Dominican Republic	Morocco	United Kingdom
Ecuador	Mozambique	U.S. Minor Outlying Islands
Egypt	Myanmar	United States
El Salvador	Nepal	Uruguay
Estonia	Netherlands	Uzbekistan
Ethiopia	Netherlands Antilles	Vanuatu
Fiji	New Caledonia	Venezuela
Finland	New Zealand	Viet Nam
France	Nicaragua	Yemen
French Polynesia	Niger	Zambia
Gabon	Nigeria	Zimbabwe

II Appendix for Chapter 4

Table 4.A List of countries used in the analysis

Developed country		Developing country	
Australia	Norway	Argentina	Lebanon
Austria	Poland	Bolivia	Madagascar
Belgium	Portugal	Botswana	Malawi
Bulgaria	Russian Federation	Brazil	Malaysia
Canada	Serbia	Burkina Faso	Mauritius
Croatia	Slovakia	Burundi	Mexico
Cyprus	Slovenia	Cameroon	Morocco
Czechia	Spain	Chile	Mozambique
Denmark	Sweden	Colombia	Nicaragua
Estonia	Switzerland	Congo	Niger
Finland	United Kingdom	Costa Rica	Nigeria
France	United States	Dominican Republic	Pakistan
Germany		Ecuador	Paraguay
Greece		Egypt	Peru
Hungary		El Salvador	Philippines
Iceland		Ethiopia	Republic of Korea
Ireland		Georgia	Rwanda
Israel		Guatemala	South Africa
Italy		Honduras	Thailand
Japan		India	Turkey
Latvia		Indonesia	Uganda
Lithuania		Jordan	Uruguay
Luxembourg		Kazakhstan	Venezuela
Netherlands		Kenya	Zambia
New Zealand		Kuwait	