STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
5350 Master's thesis in economics
Academic Year 2018-2019

The Impact of Climatic Disasters on Output and Prices

A Panel VAR-X Approach

Agnes Magnusson (23414)

Abstract

This paper sets out to study the short-term effects of climatic disasters on two macroeconomic variables: output and prices. The study makes use of a panel vector-autoregression model in the presence of endogenous variables and exogenous shocks (VAR-X), and applies it to a 1960–2017 cross-country panel. The findings suggest that the average mean response of GDP and CPI growth vary depending on the type of disaster shock, the severity of the disaster, and the level of country development. Overall, low and middle-income countries are more sensitive to climatic disasters, with moderate floods having a small but positive impact on GDP growth, severe storms having a negative impact on GDP growth, and droughts having a large and positive impact on CPI growth. When using an alternative, cost-based outcome measure of climatic disasters, low and middle-income countries also experience a negative impact on GDP growth and a positive impact on CPI growth following droughts. High income countries, on the other hand, are less impacted by climatic disasters. The study highlights large disparities across country groups, and moreover, suggests that emerging economies—which in many cases already struggle with economic and environmental challenges—are more exposed to negative supply shocks following droughts.

Keywords: Natural disasters, climate change, economic growth, inflation
JEL: E31, O11, O40, Q54
Supervisor: Pamela Campa
Date submitted: 12 May, 2019
Date examined: 27 May, 2019
Discussants: Karl Sundblad and Gustav Tillman
Examiner: Mark Sanctuary

Acknowledgements

First and foremost, I wish to thank Pamela Campa for her valuable guidance and feedback throughout this project. I also wish to thank Lisa Eichler, Willemijn Verdegaal, and Linda Knoester for their invaluable support. Finally, I would like to thank Selina Meyers for making me laugh along the way.

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1 Introduction

Natural disasters have the potential to cause major economic and social disruption (Cavallo and Noy 2011). Tropical cyclones and flooding can have large and negative effects on productive capital, while longer-lasting disasters, such as droughts, can have adverse effects on agriculture output. With rising global temperatures, it is likely that the frequency and magnitude of some natural disasters will increase. According to the Intergovernmental Panel on Climate Change (IPCC), rising temperatures could lead to an increased risk of droughts, a growing frequency of heatwaves, and an increased intensity of storms (Banholzer, Kossin, and Donner 2014).

At the same time, rising temperatures constitute a unique challenge for monetary policy makers and financial supervisors, and in the past six months there has been an increased focus on the adverse physical impacts of climate change among financial institutions (Cœuré 2018; Carney, Villeroy de Galhau, and Elderson 2019; Debelle 2019; Strašuna and Breman 2019). In a 2019 speech, Guy Debelle, Deputy Governor of the Reserve Bank of Australia, addressed the direct connection between climate change, natural disasters, and macroeconomic outcomes. Natural disasters such as droughts, Debell explains, can be characterized as negative supply shocks, meaning that they often lead to a reduction in output but an increase in prices. Since they cause output and prices to move in the opposite direction, negative supply shocks constitute a more complicated challenge for monetary policymakers. Still, Debell notes, if the natural disaster is temporary in nature, economic activity will return to what it was prior to the extreme weather event and the involvement of financial institutions will be limited. If natural disasters become more frequent as a result of climate change, however, the question of what monetary policy intervention to use will become less straight forward:

> "The recent IPCC report documents that climate change is a trend rather than cyclical, which makes the assessment much more complicated. What if droughts are more frequent, or cyclones happen more often? The supply shock is no longer temporary but close to permanent. That situation is more challenging to assess and respond to." (Debelle 2019)

As such, it is becoming increasingly important to understand the macroeconomic effects of climate-related natural disasters (from now on only referred to as 'climatic disasters'). Specifically, it is relevant for both monetary policy makers and financial supervisors to know the likely path of output and inflation following climatic disasters. This is since it provides decision makers with greater guidance on how to maneuver the macroeconomic landscape following a climatic disaster, and moreover, since it assists governments with calculating the future costs of aid and reconstruction programs following such disasters.

This paper sets out to study the short-term effects of different climatic disasters on two macroeconomic variables: output and prices. The study makes use of the methodological approach used in Fomby, Ikeda, and Loayza (2013), which consists of a fixed-effects vector auto-regression model in the presence of endogenous variables and exogenous shocks (VAR-X). Data on the main macroeconomic variables of interest are obtained from the World Bank, while data on climatic disasters are obtained from the Emergency Events Database (EM-DAT), provided by the Center for Research on the Epidemiology of Disasters (CRED). The full sample stretches from 1960 to 2017 and covers 30 low and middle-income counties and 27 high-income countries. To limit my analysis to larger and more costly disaster events, I construct three main composite indicators: two composite indicators that are based on the number of fatalities and people affected by the disaster event, and one composite indicator that is based on the damage (measured in current USD) caused by the disaster event.

I begin by studying the effect of aggregate climatic disasters, and then go on to study a number of climatic disasters separately in order to allow for heterogeneous effects across disaster types. Specifically, I focus on three types of climatic disasters—droughts, storms and floods—as these are believed to increase in frequency and/or magnitude as a result of climate change. Moreover, I differentiate between moderate and severe disasters, and split the country-sample based on low and middle-income economies, high-income economies, and countries vulnerable to natural disasters. This is as previous literature suggests heterogeneity in effects across emerging and developed countries, and moderate and severe climatic disasters.

The paper's findings suggest that the annual mean response of GDP and CPI growth vary depending on the type of disaster shock, the severity of the disaster, and the level of country development. Overall, low and middle-income countries are more sensitive to climatic disasters, with moderate floods having a small but positive impact on GDP growth, severe storms having a negative impact on GDP growth, and droughts having a large and positive impact on CPI growth. High income countries, on the other hand, are less impacted by climatic disasters. When using an alternative outcome measure for climatic disasters based on the total damage of the disaster, low and middle-income countries record small but positive effects on GDP growth following storms and floods, but small and negative effects on GDP growth following droughts. Similar to the findings in the main analysis, low and middle-income countries also record a large and positive impact on CPI growth following droughts. The findings highlight the large difference in the annual mean response of GDP and CPI growth across country samples. Low and middle-income countries (and notably, the countries more vulnerable to climate risk) are much more vulnerable to climatic disasters compared to high-income countries. The finding suggests that emerging economies, that in many cases already struggle with economic and environmental challenges, are more exposed to negative supply shocks following climatic disasters.

The study provides an extended analysis on the effects of climatic disasters on output and prices. Previous literature has focused on output and price inflation separately, and the literature on natural disaster shocks on inflation has until now not fully covered the impact of different types of climatic disasters by the severity of the disaster and the level of country development. Moreover, I make a further contribution to the literature by using a fixed effects panel VAR-X approach, which enables me to capture the time dynamics of both output and prices while studying a large selection of low and middle-income and high-income countries. Finally, the study makes use of natural disaster data on both the total number of people affected by the disaster and the total damages caused by the disaster event. By creating two types of composite indicators for climatic disasters—one based on the number of fatalities and people affected by the disaster and one based on the total damages caused by the disaster—I am able to capture the impact of various disaster types on a broader set of countries. Previous studies have mainly relied on composite indicators based on the total number of people affected by the disaster, and as such, failed to include costly disaster with limited impact on the local population.

The paper proceeds as follows: Section two provides a brief summary of the systemic effects of natural disasters and the literature connecting climatic disasters with warming temperatures. Section three reviews the empirical literature on the economic effects of natural disasters. Section four describes the macroeconomic data, the EM-DAT Database, and the construction of the composite indicators of climatic disasters used in this study. Section five explains the empirical approach and section six present the subsequent results. Section seven discusses the results in further detail, and section eight concludes.

2 Background

In the following section, I will first provide an overview of the channels through which natural disasters affect the economy. This will then be followed by a brief summary of the literature linking climate change to the occurrence of climatic disasters.

2.1 The Systemic Effects of Natural Disaster

Natural disasters have the potential to cause major economic and social disruption (Cavallo and Noy 2011). Still, the economic effects of droughts, floods and storms are not straightforward, and will often be contingent on the type and the magnitude of the natural disaster and the economic state of the affected country or region.

First, the economic consequences of a natural disaster will depend on the subsequent changes in prices. (Hallegatte and Przyluski 2010) If the price level changes following a natural disaster, this can either reduce or increase the output losses associated with the disaster. For instance, following Hurricane Harvey that hit the state of Texas in 2017, large numbers of personal vehicles were destroyed and had to be scrapped. This lead to a boost in car sales in the months following the disaster, which in turn pushed up prices for new and used vehicles. (Donnelly 2017) The new price level faced by consumers then had to be taken into consideration when estimating the direct costs of the natural disaster. As such, if changes in prices fail to be considered, the direct economic effects of the natural disaster will be underestimated. However, Hallegatte and Przyluski also explain that price inflation following natural disasters, sometimes referred to as "demand surges", may have positive economic effects:

> "[Post-disaster price inflation] helps attract qualified workers where they are most needed and creates an incentive for all workers to work longer hours, therefore compensating for damaged assets and accelerating reconstruction. [...] Demand surge, as a consequence, may also reduce the total economic cost of a disaster, even though it increases its burden on the affected population." (Hallegatte and Przyluski 2010, p.12)

Second, the longer the reconstruction phase, the larger are the final costs of the natural disaster. (Hallegatte and Przyluski 2010) This is made clear by a simple example: if a natural disaster destroys your home, then losing your home for one week will likely have a much smaller effect on output compared to if you lose your home for a full year. The reconstruction phase can be extended by constraints in the access to funding, physical resources and workers who can carry out the reconstruction work.

Third, natural disasters can have a stimulative effect on the economy due to the subsequent increase in demand for goods and services in the reconstruction sector. (Hallegatte and Przyluski 2010) Still, whether or not the stimulus will result in positive output effects will likely depend on the state of the economy and the phase of the business cycle. During a phase of economic expansion, the natural disaster will destroy or divert productive capital that is being used in the economy. As a consequence, the event will likely have adverse effects on the economy. During a economic recession, however, the existence of unused capital will likely compensate for lost production and dampen the negative effects of the natural disaster. (Hallegatte and Ghil 2008)

Fourth, the destruction of crucial infrastructure, such as transportation, water or energy infrastructure, can cause major disruption to the economic system. (Hallegatte and Przyluski 2010) If access to water, electricity or gas is restricted, businesses that are not directly hit by the natural disaster will likely suffer from production losses. For instance, Hurricane Katrina that hit the state of Florida and Louisiana in 2005, caused the region's oil production facilities and refineries to close down, leading to shortages in refined oil products and a subsequent spike in the oil price. (Mouawad and Romero 2005)

Finally, natural disasters can lead to an increase in the turn-over of capital, which in turn can have positive effects on output. (Hallegatte and Przyluski 2010) When a natural disaster destroys productive capital (such as buildings and transportation infrastructure), and that capital is replaced with newer and more productive technologies, there may be productivity gains. The productivity gain would then compensate for the productivity loss directly associated with the disaster. According to Hallegatte and Przyluski (2010), this "productivity effect" can therefore push economies to adopt new technologies, and by doing so, accelerate output growth. The authors note, however, that a productivity effect is not always present. "[W]hen a disaster occurs, producers have to restore their production as soon as possible. [...] Producers have thus a strong incentive to replace the destroyed capital by the same capital, in order to restore production as quickly as possible, even at the price of a lower productivity." (Hallegatte and Przyluski 2010, p.13)

It is also important to note that destructive natural disasters can foster so called "poverty traps". (Hallegatte and Przyluski 2010) A "poverty trap" is a mechanism were an individual (or a country) is unable to escape poverty since a significant amount of capital is needed to escape poverty. Thus, if a country has limited capacity to rebuild houses, roads and other necessary infrastructure following a natural disaster, and the country is regularly affected by extreme weather events, the country may find itself in a permanent state of reconstruction. As a result, much of the available resources will be used to rebuild—but not to improve or expand—infrastructure, and the country will end up in a state of disaster-related under-development.

2.2 Are Extreme Weather Events Becoming More Common?

As seen in Figure 1 and Figure 3, hydrological and meterological natural disasters appear to have become more common and more destructive over the past four decades [1]. Since 1980, there has been a steady increase in the number of meterological and hydrological natural disasters (as recorded by the EM-DAT Database[2]), while the number of climatological and geophysical natural disasters has remained steady. Moreover, climatological, hydrological and meterological disasters have become increasingly costly as measured in billions of US dollars. Still, the amount of total damage varies year per year, with the year 2005 recording costs of roughly 260 billion US dollars (mainly due to hurricane Katrina that hit the state of Florida and Louisiana) and the year 2006 only recording 30 billion US dollars. Despite this trend, climate researchers have historically been hesitant to attribute the increase in frequency and magnitude of natural disasters (let alone specific natural disaster events) to climate change. While it is possible that the increased frequency of extreme weather events is related to rising global temperatures, one could also argue that it could be due to improved reporting (Cavallo and Noy 2011) and larger settlements along coastal areas which are more exposed to natural disasters such as storms and flooding (Neumann et al. 2015).

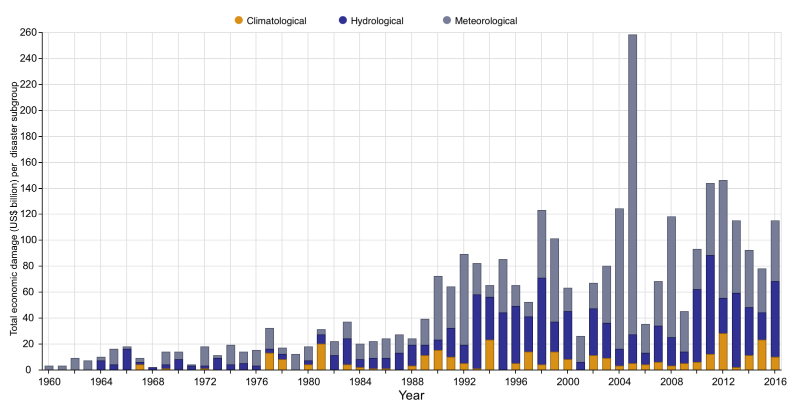

Figure 1: Total economic damage (USD billion) of natural disaster events, 1960-2016.
Source: EM-DAT Database (2019).

1. For associated maps, see Figure 15-17 in Appendix.

2. The EM-DAT Database categorizes natural disasters into four main categories: 1. Climatological disasters: drought, glacial lake outburst, and wildfire. 2. Hydrological disasters: flood, landslide, wave action. 3. Meterological: extreme temperatures, fog, storms. 4. Geophysical: earthquake, mass movement, and volcanic activity.

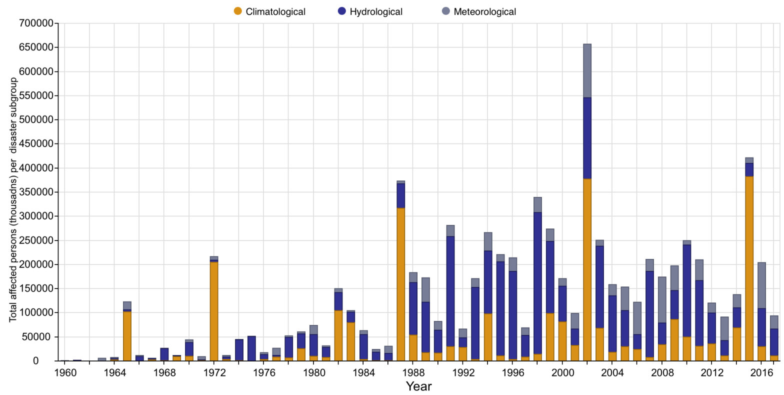

Figure 2: Total number of affected people (thousands) following natural disaster events, 1960-2017. Source: EM-DAT Database (2019).

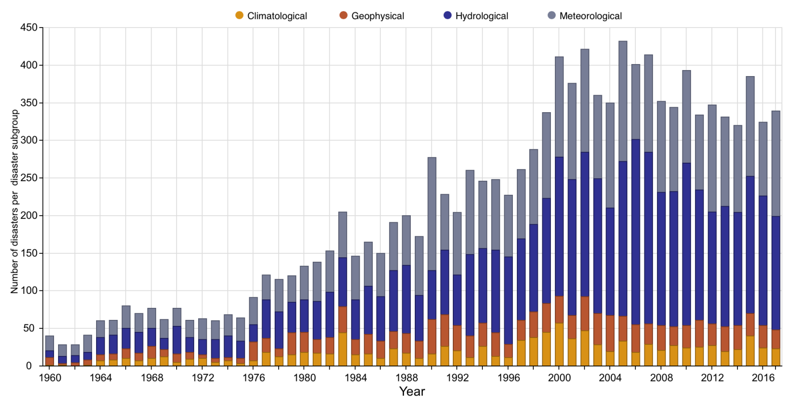

Figure 3: Total number of disasters per disaster group, 1960-2017. Source: EM-DAT Database (2019).

Still, there is a growing consensus that extreme weather is becoming more frequent as a result of climate change, and researchers are today able to determine the extent to which climate change contribute to specific natural disaster events. In 2018, Nature analyzed 170 papers on extreme weather events published between 2004 and mid-2018, and found that two-thirds of the studied extreme weather events had been made more likely by climate change. Extreme heat made up 43 percent, droughts made up 18 percent and flooding made up 17 percent of the studied events. (Schiermeier 2018) Moreover, in a report studying the extreme weather events of 2016 published by the American Meterological Society, 78 percent of the surveyed events (including heavy rainfalls in Southern China, droughts in Southern Africa, and marine heatwaves in North America and Europe) were shown to have been made more severe by climate change. (Herring et al. 2018) Researchers at the Potsdam Institute for Climate

Impact Research have also found that the impact of the tropical storm Harvey, which hit the state of Texas in 2017, was likely made more severe due to climate change ("Storm Harvey: impacts likely worsened due to global warming" 2017).

In short, the emerging literature on attribution science suggests that heatwaves, droughts, heavy rainfalls, flooding and storms are becoming more frequent or larger in magnitude as a result of climate change. As such, even in the unlikely scenario that the world successfully limits global warming to 1.5 degrees Celsius, extreme weather events will likely become more frequent and more severe, as compare to pre-industrial times.

3 Literature Review

In the last two decades, there has been an increased interest in the macroeconomic effects of natural disaster. A majority of the economic literature has made use of a fixed effects approach, and almost exclusively, focused on the effects on output growth. It should also be noted that the vast majority of papers use the EM-DAT Database for data on natural disaster events, and hence, are based on outcome data (i.e. the number of people affected or the estimated monetary damage).

In one of the first papers studying the macroeconomic effects of natural disasters, Noy (2009) uses a fixed effects regression approach to estimate the short-term effect of natural disasters on output growth. Noy uses the annual data on the period 1970-2003, and studies 109 countries with an average 15 annual observations per country. In line with previous empirical growth literature, Noy includes controls for a number of different country-specific growth determinants, including government surplus, inflation, credit growth and institutional quality. The main independent variable of interest is the disaster magnitude, measured as the number of people affected or the total amount of damages, with only the latter outcome measure generating significant results. Hence, the findings suggest that destruction of the physical capital stock (rather than the human capital stock) has a more significant short-term negative effect on output growth. The study finds that developing countries and smaller economies are more adversely affected by natural disasters. Moreover, it finds that countries with a higher literacy rate, better institutions, higher per capita income, higher degree of openness to trade, and higher levels of government spending are less affected by extreme weather shocks.

Similarly, Felbermayr and Gröschl (2014) use a fixed effects regression to study the short-term effects of different types of extreme weather events on output growth. The authors study a sample of 108 countries over the period 1979-2010, and include controls for a set of growth determinants as well as time fixed effects to account for common time trends across countries. To limit the selection bias that is present in the EM-DAT Database (see section 4.2 for extended discussion), the authors construct a new natural disaster data set, the GeoMet Database, based on physical disaster intensity. The authors find that all studied extreme weather events have a negative and statistically significant short-term effect on growth.

To further explore the different channels in which different types of natural disasters affect the economy in the medium-term, Loayza et al. (2012) disaggregate the effects of natural disasters by economic sectors (agriculture, industry, and services). Loayza et al. (2012) apply a dynamic Generalized Method of Moments panel estimator to a panel of 94 countries for the period 1961-2005, and analyze the data in 5-year periods. The authors find that different natural disaster events impact different sectors differently, with moderate (but not severe) floods having positive effects on the agriculture sector, and droughts having negative effects on the agriculture sector. Moreover, the authors point out that developing countries appear to be more sensitive to natural disasters, and that severe natural disasters (as opposed to moderate) only have adverse effects on economic growth.

In an effort to improve on the econometric approach and to provide a better picture of the short-run effects of natural disaster events, Raddatz (2009) uses a vector auto-regression framework to study the short-term mean effects of different types of natural disasters. Under the assumption that extreme weather events are exogenous to a country's short-run growth performance, the approach provides estimates of the average impact on output growth of different types of natural disasters. The analysis is performed using a panel auto-regressive distributed lags and a panel vector auto-regression model, and estimate the annual mean response of the various country samples studied in the paper. The author finds that developing countries are more sensitive to natural disaster shocks, and that droughts and extreme temperatures have negative effects on output growth, while storms and floods do not have any significant effect on output growth.

In a similar manner, Fomby, Ikeda, and Loayza (2013) uses a panel vector auto-regression model with exogenous shocks in the form of natural disaster events to study the short-term mean impact of different natural disasters on output growth (disaggregated into agriculture and non-agriculture growth). The authors apply a bootstrap bias-corrected (BSBC) estimator to a panel of 84 countries for the period 1960-2007, and include controls for various endogenous and exogenous growth determinants. Based on the previous evidence that developing countries are more sensitive to natural disaster events compared to developed economies, Fomby et al. split their sample into developed and developing countries. Much like previous studies, the authors find that developing countries are less able to withstand the effect of natural disaster events, and that severe natural disasters appear to have larger and more negative impacts on economic growth. Finally, different types of natural disasters are found to have different effects on growth, with droughts having overall negative effects on growth and moderate floods having positive effects on growth.

In one of the few empirical papers on natural disasters and prices, Parker (2018) uses a fixed effects regression model to study the short-term effects of different types of extreme weather events on price inflation. The analysis is performed on headline inflation as well as on four sub-indices: food, housing, energy, and CPIxFHE [3] price inflation. The author studies a sample of 212 countries over the period 1980-2012, but refrains from including controls for the standard growth determinants that are otherwise commonly included in the literature. The findings of the paper are in line with the studies that focuses on output growth. The effect on developed economies is negligible, while the effect on developing economies can be significant and last for several years. Moreover, the impact varies depending on the type of natural disaster, with storms and floods having a short-run positive impact on inflation and earthquakes having a negative impact on inflation (when excluding food, housing, and energy inflation).

To summarize, the current empirical literature suggest that natural disaster events have heterogeneous effects on the economy, depending on the economic development of the country and the type of economic disaster. Overall, moderate disasters—mainly in the form of floods—appear to have positive effects on output growth, while severe natural disaster events have more negative effects on the economy. Emerging countries, as opposed to developed countries, also appear to be less insulated from the effects of natural disasters.

4 Data

In the following sections, I will provide an overview of the macroeconomic data and the disaster data used in this study. I will first describe the macroeconomic data and then present the EM-DAT Database and describe the construction of the composite indicators of climatic disasters.

3. CPIxFHE is a consumer price index that excludes food, housing and energy price inflation.

4.1 Macroeconomic Data Series

The study includes 57 countries, out of which 30 countries are categorized as lower and middle-income economies and 27 countries are categorized as high-income economies [4]. The selection of countries is based on the availability of reliable data, and countries with less than 15 annual observations are excluded from the sample. Table 9 in the Appendix provides a full list of countries included in the study. The study covers the period 1960 to 2017. Since the data coverage varies across countries, the panel is unbalanced.

Data on macroeconomic variables are collected from a number of different sources. Annual data on real GDP, real GDP per capita, consumer price index, world real GDP per capita, value of agriculture, forestry, and fishing as a share of GDP, and population are taken from the World Bank World Development Indicator Data Catalogue (*World Development Indicators* 2018) [5] and annual data on terms of trade are taken from Data Market (*Data market> Data set> Terms of trade* 2019). For data on systemic banking crises, I use data from the Global Crisis data set compiled by Reinhart et al. (Reinhart et al. 2019) [6] Finally, for data on country-level vulnerability to natural disasters, I use the Germanwatch Global Climate Risk Index (Eckstein, Künzel, and Schäfer 2017). Table 1 and Table 10-12 in the Appendix provide a summary of the macroeconomic data used in the study. Table 1 shows that low and middle-income countries and the top half of the most climate vulnerable countries (CRI50) have higher median growth and inflation figures. However, terms of trade growth appears to be more volatile among the high-income countries.

Variable	Sample	N	Mean	Std. Dev	Min	Max	10%	25%	50%	75%	90%
GDP growth (%)	Low & Middle-Income	1244	2.60	3.76	-14.34	18.52	-1.88	0.76	2.80	4.82	6.85
GDP growth (%)	High-Income	1277	2.36	3.30	-25.61	24.37	-0.76	0.92	2.22	3.85	5.73
GDP growth (%)	CRI 50	1234	2.44	3.26	-14.34	17.92	-1.20	0.83	2.51	4.33	6.13
CPI growth (%)	Low & Middle-Income	1244	42.90	428.38	-7.63	11749.64	1.95	3.91	7.50	13.40	27.15
CPI growth (%)	High-Income	1277	6.92	24.53	-4.47	504.73	0.53	1.70	3.21	6.40	12.30
CPI growth (%)	CRI 50	1234	40.05	430.25	-7.63	11749.64	1.24	2.62	5.30	10.03	18.32
World GDP growth (%)	All	2521	1.69	2.00	-2.92	4.50	0.06	1.13	1.87	2.55	3.07
Terms of trade growth (%)	Low & Middle-Income	1244	11.03	69.06	-85.25	952.08	-29.32	-14.25	0.44	17.71	48.66
Terms of trade growth (%)	High-Income	1277	6.91	81.53	-93.44	1499.56	-28.61	-12.50	-.50	13.02	33.03
Terms of trade growth (%)	CRI 50	1234	12.36	74.03	-85.25	1394.00	-26.99	-12.35	1.46	18.91	46.19

Table 1: Overview of macroeconomic data.

4. Countries are categorized according to the World Bank Country and Lending Groups.

5. Data on Taiwan was taken from CEIC Data (*CEIC data> Home> Countries> Taiwan* 2019), as it is not covered by the WDI Database.

6. For the countries not included in the data set (Bangladesh, Cameroon, Jamaica, Mongolia, Tanzania, Uganda and Vietnam), I use supplementary data from the Systemic Banking Crisis data set compiled by Laeven and Valencia (Laeven and Valencia 2018).

4.2 EM-DAT Database

Data on climatic disasters are taken from the Emergency Events Database (EM-DAT) (Guha-Sapir 2019). The EM-DAT is provided by the Center for Research on the Epidemiology of Disasters (CRED), and is the only publicly available and frequently updated multi-country natural disasters database. The EM-DAT includes natural disaster events that fulfill one or several of the following criteria: the natural disaster has resulted in a call for international assistance, a declaration of a state of emergency, 100 or more people reported affected, or 10 or more fatalities. As such, the EM-DAT data does not include small natural disaster events.

The EM-DAT provide information on natural disaster events using three main variables: the total number of individuals affected, the total number of fatalities, and total damage (reported in thousand USD). The total number of individuals affected is the sum of individuals who have been injured as a direct result of the disaster, individuals whose house have been destroyed or damaged and need shelter following the disaster, and individuals who require immediate assistance (e.g require food, water or shelter) following the disaster. The total number of fatalities is the sum of individuals who died or went missing as a result of the disaster. Total damage equals the total amount of damage to buildings, crops, and livestock caused by the disaster. The estimated figure is reported in current USD for the year of the event.

The EM-DAT divide natural disaster events into 5 sub-groups, out of which I choose to study hydrological, climatological and meterological disaster events. This is since I am interest in studying the macroeconomic effects of natural disasters that are expected to increase in frequency and/or magnitude as global temperatures continue to rise.[7] Specifically, I am focusing on three types of climatic disasters: floods, droughts, and storms. The analysis also includes observations on landslides, extreme temperatures and wildfires, but given the limited number of observations for these types of events, they will mainly be included in the aggregated climatic disaster measure or serve as controls. The EM-DAT report the starting date and ending date of the climatic disaster events included in the database. Table 2 and Figure 4 provide an overview of the EM-DAT data used in the study.

As previously mentioned, the EM-DAT Database is the most commonly used data set among researchers studying the economic effects of climatic disasters. Still, it should be noted that previous

7. Some data suggests that earthquakes could become more common as ice-sheets shrink in size, but a direct link between geological disasters and rising global temperatures does not appear to be supported by the climate literature (Lunsford 2019).

Outcome variable	Disaster type	N	Mean	Std. Dev	Min	Max	25%	50%	75%
People affected	Storm	2536	360680	2984211	0	1.00e+08	0	300	20000
	Flood	2491	1260600	1.02e+07	0	2.39e+08	306	5200	75003
	Drought	243	8547210	3.83e+07	0	3.30e+08	0	128604	1900000
	Wildfire	271	18196	187799	0	3000000	0	200	1425
	Extreme temperature	332	295389	4236384	0	7.70e+07	0	0	57
	Landslide	418	20810	172918	0	2500000	0	9	593
Fatalities	Storm	2536	114	2795	0	138866	1	7	26
	Flood	2491	61	249	0	6054	1	10	35
	Drought	243	6225	96223	0	1500000	0	0	0
	Wildfire	271	6	21	0	240	0	0	4
	Extreme temperature	332	496	3547	0	55736	5	30	131
	Landslide	418	62	135	0	1765	13	25	58
Damages (USD)	Storm	2536	4.72e+08	3.71e+09	0	1.25e+11	0	3450000	1.31e+08
	Flood	2491	2.60e+08	1.50e+09	0	4.00e+10	0	0	4.32e+07
	Drought	243	5.92e+08	1.88e+09	0	2.00e+10	0	0	2.34e+08
	Wildfire	271	2.72e+08	1.07e+09	0	1.30e+10	0	0	9.80e+07
	Extreme temperature	332	1.81e+08	1.26e+09	0	2.11e+10	0	0	0
	Landslide	418	1.90e+07	1.04e+08	0	9.89e+08	0	0	0

Table 2: Overview of climatic disaster data.

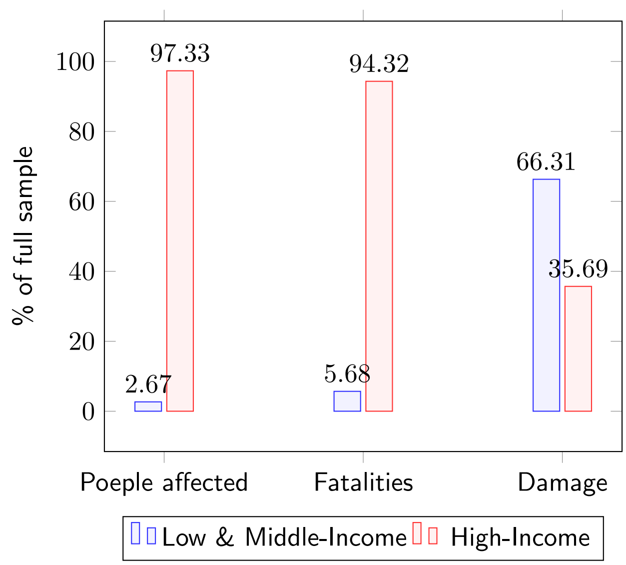

Figure 4: Share of people affected, fatalities, and damage by level of country development. Note: Author's rendering of EM-DAT data (2019).

research has highlighted a number of issues associated with the EM-DAT database (Felbermayr and Gröschl 2014; Kousky 2014). First, the database does not include smaller events that do not fulfill one or more of the previously listed criteria. This is even as frequent low-impact disasters can cause major economic damage. Second, the main focus of EM-DAT is to "aid humanitarian response" (Carolyn Kousky 2013, p.580). As a result, large natural disasters in developed economies that have little or no impact on the local population and do not call for international assistance may not be included in the database. Third, the database is a compilation of third party data. As such, the quality and precision of the EM-DAT data can only be as high as its data sources. Sources include various United Nation Agencies, the World Bank, national governments, insurance companies, research institutes and the media. (*Guidelines: EM-DAT* 2019) Finally, the inclusion of climatic disasters has increased over time, especially in the 1960s and the 1970s. Nevertheless, according to Cavallo and Noy (2011), the increase in the number of included events mainly applies to smaller climatic disasters with limited effects on the macro-economy.

4.3 Composite Indicator

As stated in Section 4.2, the EM-DAT Database has several selection criteria for including climatic disaster events. Even so, the EM-DAT Database includes a large number of comparatively small climatic disasters with (presumably) limited impacts on the economy. I have therefore decided to only consider moderate and severe extreme weather events in this analysis. For the main analysis of this paper, the climatic disaster variable, $CD_{i,t} = (flood_{i,t}, drought_{i,t},\ storm_{i,t}, wildfire_{i,t}, temperature_{i,t}, landslide_{i,t})$, is given by:

$$CD_{i,t}(k) = \sum_{j=1}^{J} frequency^{k}_{i,t,j} \tag{1}$$

where

$$\begin{aligned} frequency^{k}_{i,t,j} &= 1 \text{ if } \frac{fatalities^{k}_{i,t,j} + 0.3 \cdot total\ affected^{k}_{i,t,j}}{population_{i,t}} > 0.0001 \\ &= 0 \text{ otherwise} \end{aligned} \tag{2}$$

where k corresponds to one of the six climatic disasters and J is equal to the total number of type-k climatic disaster events that took place in country i in year t. The $CD_{i,t}$ measure is equal to the number of type-k climatic disaster events in country i in year t where the sum of the total number of fatalities, $fatalities^{k}_{i,t,j}$, and 30% of the total number of affected individuals, $total\ affected^{k}_{i,t,j}$, make out more than 0.01% of the population in country i.

Based on the six separate climatic disaster indicators, I also create a composite indicator that equals the sum of all hydrological, climatological and meterological disaster events:

$$CD_{i,t} = \sum_{j=1}^{J} frequency_{i,t,j} \tag{3}$$

where J is equal to the total number of climatic disaster events that took place in country i in year t.

Previous literature has found that more severe climatic disaster events tend to have larger effects on the economic system (Parker (2018), Loayza et al. (2012), Fomby, Ikeda, and Loayza (2013)). In line with Fomby et al., I therefore create a second climatic disaster measure to capture the dynamics of severe climatic disasters. The measure of severe climatic disasters, $sevCD_{i,t} = (sev\ flood_{i,t}, sev\ drought_{i,t}$, $sev\ storm_{i,t}$, $sev\ wildfire_{i,t}, sev\ temperature_{i,t}, sev\ landslide_{i,t})$, is given by:

$$sevCD_{i,t}(k) = \sum_{j=1}^{J} frequency^{k}_{i,t,j} \tag{4}$$

where

$$\begin{aligned} frequency^{k}_{i,t,j} &= 1 \;\text{ if }\; \frac{fatalities^{k}_{i,t,j} + 0.3 \cdot total\ affected^{k}_{i,t,j}}{population_{i,t}} > 0.01 \\ &= 0 \;\text{ otherwise} \end{aligned} \tag{5}$$

where k corresponds to one of the six climatic disasters and J is equal to the total number of type-k climatic disaster events that took place in country i in year t. The $CD_{i,t}$ measure is the same as in (2), but is now the sum of all climatic disaster events where the total number of fatalities, $fatalities^{k}_{i,t,j}$, and 30% of the total number of affected individuals, $total\ affected^{k}_{i,t,j}$, make out more than 1.0% of the population in country i. Similar to before, I create a composite indicator that equals the sum of all hydrological, climatological and meterological disaster events. The measure is constructed in line with Equation (3).

The frequency measures, as seen in Equation (2) and (5), are similar to the ones used by Fomby, Ikeda, and Loayza (2013) and Parker (2018), and are designed to give more weight to disaster events that result in a higher number of fatalities. This is since climatic disasters that result in a high number of fatalities (as opposed to disasters that have a small impact on a large number of individuals, such as disasters that result in short but wide-spread power outages) are more likely to have a lasting effect on the economy. It should also be noted that the type of composite indicator used here equals the sum of the *number* of events that result in a fraction larger than 0.01 percent (or 1 percent), meaning that it does not differentiate between disaster events as long as they pass the aforementioned threshold. This can be compared to the composite indicator that is used in Parker (2018), which sum up the total value of fractions larger than 0.01 percent (or 1 percent). As always, each construction method has its own strengths and weaknesses. The first construction method puts its weight on the number of moderate (or severe) natural disaster events that occurred in a country i in year t. The second construction method, on the other hand, puts its weight on the total intensity of all moderate (or severe) disasters that occurred in country i in year t. To use the latter method, it is therefore necessary to specify some internal reference point(s), for instance by calculating the 75th and/or the 90th percentile of all included disaster events. While both computation methods likely render similar results [8], I proceed by using the first method since it better captures the effect of intensive disaster years as measured in the number of moderate (or severe) climatic disaster events.

In my benchmark model, I measure the intensity of the climatic disaster by studying the effect on human capital (i.e. the number of fatalities and people affected), as opposed to physical capital (i.e. the total damage). Previous research, however, has found that climatic disasters that affect the physical capital stock of a country have more significant effects on short-term output growth (Noy 2009). Many climatic disasters, especially in developed economies, may be destructive in nature without causing widespread harm to settlement or directly impacting the lives of citizens. For instance, the severe drought that affected the state of California between the years 2014-2015 did not have any major direct effect on the individuals living in the state [9]. However, according to the EM-DAT Database, the estimated costs associated with the drought surpassed 4 billion US dollars. I therefore proceed by constructing an alternative composite indicator that is based on the total damage caused by climatic disaster events. The cost-based composite indicator, $damCD_{i,t} = (flood_{i,t}, drought_{i,t}, storm_{i,t}, wildfire_{i,t}, temperature_{i,t}, landslide_{i,t})$, is given by:

$$damCD_{i,t}(k) = \sum_{j=1}^{J} frequency_{i,t,j}^{k} \tag{6}$$

where

8. For a comparison between the result of binary and continuous intensity measures, see for instance Noy (2009).
9. The EM-DAT has no registered fatalities or people affected for the droughts in 2014 and 2015.

$$frequency^k_{i,t,j} = 1 \ \text{ if } \ \frac{damages^k_{i,t,j}}{GDP_{i,t}} > 0.0001$$
$$= 0 \ \text{ otherwise} \tag{7}$$

where k corresponds to one of the six climatic disasters and J is equal to the total number of type-k climatic disaster events that took place in country i in year t. The $damCD_{i,t}(k)$ measure is similar to 2, but is now the sum of all climatic disaster events where the total damage (measured in current USD), $damages^k_{i,t,j}$ make out more than 0.01% of the GDP (current USD) in country i. Similar to before, I create a composite indicator that equals the sum of all hydrological, climatological and meterological disaster events. The measure is constructed in line with Equation (3).

As highlighted by Felbermayr and Gröschl (2014) and Kousky (2014), GDP per capita is an important predictor for whether or not a natural disaster event is included in the EM-DAT Database. Storms and floods that occur in high-income countries are more likely to be included in the database. Moreover, economic losses are often under-reported in low and middle-income economies, and according to a UN study, total economic losses can be up to 50 percent higher than recorder in the EM-DAT Database. Still, it should also be noted that for all climatic disaster events the probability of inclusion is higher the stronger the physical intensity of the climatic disaster. Since more intensive climatic disaster events can be assumed to be more destructive (in terms of the number of affected people and the total amount of damages), the composite indicator constructed here will likely suffer less from the above mentioned selection bias.

Table 3 provides an overview of the number of observations for each outcome variable, by climatic disaster type and country sample. Storms, floods and droughts have the most number of observations, while wildfires, extreme temperatures and landslides are less commonly recorded. The number of observations also vary depending on the outcome variable and the level of country development. Low and middle-income countries have more observations recorded when using the outcome variable based on the total number of people affected. High-income countries, on the other hand, have more observations recorded when using the outcome variable based on total damage. This can also be seen in Figure 4, which shows that the vast majority of people affected by climatic disasters live in emerging countries, while the largest disaster-related damages are recorded in developed countries. The difference between the two country samples highlight the unequal ability of low and high-income countries to protect the local population from the adverse effects of climatic disasters. Moreover, it suggests that the cost-based outcome measure does not adequately capture extreme weather events in low and middle-income countries, as it partly excludes disasters that cause major disruption to the local population. It also becomes clear that when studying slow-onset disasters, such as droughts and wildfires, it is often necessary to use cost-based outcome measures as opposed to an outcome measure based on the number of people affected by the disaster.

	Full Sample		Low & Middle-Income Countries		High-Income Countries	
Disaster Type	People Affected	Damage	People Affected	Damage	People Affected	Damage
All Climatic Disasters	1592	1586	1378	879	214	707
Storm	536	784	457	372	79	412
Flood	831	599	732	398	99	201
Drought	137	90	132	60	5	30
Wildfire	20	52	6	12	14	40
Extreme Temperatures	44	36	29	25	15	11
Landslides	24	25	22	12	2	13

Table 3: Observations per outcome variable by climatic disaster type and by country sample.

5 Empirical Approach

In the following sections, I outline my empirical approach. I begin by describing my econometric model, and then go on and perform various diagnostic tests. I end by discussing some of the limitations with my chosen empirical approach.

5.1 Econometric Model

To study the dynamic effects of natural disaster on output and prices, I use a panel vector auto-regression model with exogenous variables (VAR-X). By using a panel VAR-X approach, I am able to capture the time dynamics of both output and prices at the same time, and moreover, study how exogenous shocks affect a large sample of emerging and developed economies. A VAR-X model includes a K-dimensional vector of endogenous variables and an M-dimensional vector of exogenous variables. Endogenous variables are determined within the system of interest, while exogenous or "unmodelled" variables are determined outside of the system of interest. As such, exogenous variables can be used to condition the analysis without influencing the results of the system. (Lütkepohl 2005) A panel VAR-X model has the same structure as a VAR-X model, in the sense that it builds on both endogenous and exogenous variables, but also includes a cross sectional dimension (Canova and Ciccarelli 2013).

My benchmark model is given by:

$$y_{i,t} = \alpha_i + \beta_1 y_{i,t-1} + \beta_2 y_{i,t-2} + \gamma_0 x_{i,t} + \gamma_1 x_{i,t-1} + \gamma_2 x_{i,t-2} + \epsilon_{i,t} \tag{8}$$

where countries are indexed by $i = 1, 2, ..., N$ and the time index for each country *i* is $t = 1, 2, ..., T_i$. $y_{i,t}$ is a vector of endogenous variables, $x_{i,t}$ is a vector of exogenous variables, $\alpha_{i,t}$ represents the country fixed effects, and $\epsilon_{i,t}$ is a vector of system errors. The country fixed effect coefficient, $\alpha_{i,t}$, captures the unobserved and time-invariant heterogenities of the countries covered by the data. The model includes two endogenous variables: (1) real GDP per capita growth and (2) CPI inflation:

$$y_{i,t} = \begin{bmatrix} GDP_{i,t} \\ CPI_{i,t} \end{bmatrix}$$

Moreover, the benchmark model [10] includes four exogenous variables: (1) floods, (2) storms, (3) droughts, (4) wildfires, (5) extreme temperatures, (6) landslides, and (7) world real GDP per capita growth:

$$x_{i,t} = \begin{bmatrix} Storms_{i,t} \\ Floods_{i,t} \\ Droughts_{i,t} \\ Wildfires_{i,t} \\ Extreme\ temperatures_{i,t} \\ Landslides_{i,t} \\ World\ GDP_{i,t} \end{bmatrix}$$

In equation (5) I assume a homogeneous error structure $E(\epsilon_{i,t}\epsilon'_{i,t}) = \Omega$ for all i and t where $\epsilon_{i,t}$ is a vector of errors. Furthermore, I assume independence of the errors within equations, $E(\epsilon_{i,t}\epsilon'_{i,t}) = 0, s \neq t$, and across equations, $E(\epsilon_{i,t}\epsilon'_{i,t}) = 0$, for any s and t where $i \neq j$.

The identifying assumption that is central to my empirical strategy is that climatic disasters are exogenous, meaning that climatic disasters are uncorrelated to any past or present values of the depen-

10. In Section 6.2.3 I run additional specifications to test the robustness of my benchmark model.

dent variables of interest. In much of the previous literature on the macroeconomic effects of natural disasters, models include a large set of controls, such as financial depth, capital formation, and institutional quality, in order to eliminate omitted variable bias. However, as pointed out by Dell, Jones, and Olken (2014) and Parker (2018), the inclusion of additional control variables will not necessarily produce estimates that are closer to their true values:

> "Yet as Dell et al. (2014) note in their review of the literature, this can lead to a problem of 'overcontrolling' if part of the impact of disasters works precisely through these controls, which would result in an underestimate of the impact of disasters. Dell et al. (2014) instead recommend using the system of country and time fixed effects and dispensing with other controls." (Parker 2018, p. 30)

In my benchmark model, I therefore follow the recommendations of Dell et al. (2014) and control for country fixed effects but do not include any additional endogenous controls. This is since climatic disasters, and in my case, different types of climatic disasters, will likely affect output and prices through multiple channels, including the quality of institutions and the level of government consumption.

Finally, my dependent variables of interest are likely affected by global shocks, such as financial crises or fluctuations in energy or commodity prices. This means that if a natural disaster event has occurred in the same year as a financial crisis, such as the 2008 financial crisis or the 1973 oil shock, the estimated AR(p) process will be incorrect. To control for exogenous shocks, I therefore control for world real GDP per capita growth. World real GDP per capita growth is the same for all countries in the sample, and hence, captures the impact of global events and trends that are common across all countries. The variable is assumed to be exogenous, meaning that none of the countries included in the sample is assumed to have a direct effect on world output.

5.2 Model Estimations

In line with Fomby, Ikeda, and Loayza (2013), I proceed by estimating the fixed effects or least square dummy variable (LSDV) estimator, as it is suitable with panels with large T and small N. [11] [12] I begin by stacking the observations over time and across countries, and arrive at

11. Other estimation methods include the first-differenced Generalised Method of Moments (GMM) estimator and the system GMM estimator. Such GMM estimators are typically employed on micoeconomic panels where N $\rightarrow \infty$ (Everaert and Pozzi 2004)

12. The model is estimated using the MatLab code written by Y. Ikeda (2011), with some modifications made to fit the specified model.

$$
\begin{aligned}
y &= D\alpha' + \beta_1' y_{-1} + \beta_2' y_{-2} + \gamma_0' x + \gamma_1' x_{-1} + \gamma_2' x_{-2} + \epsilon_t \\
&= D\alpha' + Z\delta' + \epsilon_t
\end{aligned} \tag{9}
$$

where

$$
D = \begin{pmatrix} i_{T_1} & 0 & \dots & 0 \\ 0 & i_{T_2} & \dots & 0 \\ \vdots & 0 & \ddots & 0 \\ 0 & 0 & \dots & i_{T_N} \end{pmatrix} \tag{10}
$$

is a $T \times N$ matrix and i is a $T_i \times 1$ column of ones. The vector of fixed effects is defined as $\alpha = (\alpha_1 \ \alpha_2 \ \alpha_N)'$ and the vector of endogenous variables are defined as $y_i = (y_{i,1} \ y_{i,2} \ \dots \ y_{i,T_i})'$, $y_{i(-1)} = (y_{i,0} \ y_{i,1} \ \dots \ y_{i,T_i-1})'$, $y_{i(-2)} = (y_{i,-1} \ y_{i,0} \ \dots \ y_{i,T_i-2})'$, $y = (y_1' \ y_2' \ \dots \ y_N')'$, $y_{-1} = (y_{1(-1)}' \ y_{2(-1)}' \ \dots \ y_{N(-1)}')'$, and $y_{-2} = (y_{1(-2)}' \ y_{2(-2)}' \ \dots \ y_{N(-2)}')'$. The vector for exogenous variables is constructed in a similar manner. The LSDV estimator $\hat{\delta}$ for δ is given by

$$
\hat{\delta} = inv(Z'AZ)Z'Ay_t \tag{11}
$$

where the matrix Z is defined as $Z = (y_{-1} \ y_{-2} \ y_{-3} \ y_{-4} \ x \ x_{-1} \ x_{-2})$, the matrix $\hat{\delta}$ is defined as $\hat{\delta} = (\beta_1 \ \beta_2 \ \gamma_0 \ \gamma_1 \ \gamma_2)$, and A is defined as a $T \times T$ matrix of the form

$$
A = \begin{pmatrix} A_1 & 0 & \dots & 0 \\ 0 & A_2 & \dots & 0 \\ \vdots & 0 & \ddots & 0 \\ 0 & 0 & \dots & A_N \end{pmatrix} \tag{12}
$$

with $A_i = I_{T_i} - \frac{1}{T_i} i_{T_i} i_{T_i}'$ where i is defined as a $T_i \times 1$ vector of ones. I am interested in estimating the mean response of output and prices to natural disasters. To obtain the mean response, I will estimate the generalized impulse response function. The generalized response function measures the direct effect of the natural disaster event on each of the dependent variables. In other words, at time zero, the generalized impulse response function captures the direct impact from the imposed shock, and not the secondary effects from the other dependent variable. The generalized impulse response function is different from the orthogonal impulse response function as it is invariant to the ordering of the variables in the VAR. (Pesaran and Shin 1998)

After controlling for the country fixed effects, the multiplier form of equation (8) can be written as

$$y_{i,t} = \beta(L)^{-1}\gamma(L)x_{i,t} + \beta(L)^{-1}\epsilon_{i,t} \tag{13}$$

where L is the lag operator. As such, the mean response of either of the dependent variables of interest to a type-k natural disaster is given by the lag polynomial

$$\Phi(L) = \beta(L)^{-1}\gamma(L) \tag{14}$$

Standard error bands are calculated using Monte-Carlo simulations. Simulations are repeated 30,000 times, and used to calculate the 90% confidence interval for the mean response of the estimated variables.

For dynamic models that uses panel data and individual fixed effects, and where T is small and constant, the LSDV estimator will be inconsistent. The bias will remain as N $\rightarrow \infty$, but decrease as T $\rightarrow \infty$. (Nickell 1981) It is possible to correct the bias by using a bootstrap algorithm (see for instance Pesaran and Zhao (1999)). However, as pointed out by Fomby, Ikeda, and Loayza (2013), the LSDV estimator produces good approximations for series with T as small as 35 years per country. Since the average time period covered in my sample is 48 years, with low and middle-income countries averaging 46 years and high-income countries averaging 50 years, I will proceed by using the LSDV estimator.

5.3 Diagnostic Tests

5.3.1 Tests of Stationarity

I begin by testing for the stationarity of my series by performing individual and panel unit root tests. A series is rendered stationary if its statistical properties, such as the mean, variance, and autocorrelations, are all constant over time. If a series is non-stationary, it might lead to inaccurate results or so called spurious regressions. A spurious regression appear to be statistically significant (with a high R^2 and t-statistics that indicate statistical significance) without there actually being any economic meaning behind the results. (Lütkepohl 2005)

As is common, I use the log transformation of the included variables. The log transformation is used since it stabilizes the variance of the data, and since it allows for easier interpretation of the results in the case when a unit root is detected in the data and the series is first-differenced. (Lütkepohl 2005)

The individual and the panel unit root tests are dependent on the presence of deterministic elements in the series. In order to obtain valid results when testing for the presence of a unit root, it is therefore necessary to correctly specify the deterministic elements of the data. I therefore test for the significance of the trend in all four series by testing the significance of the intercept in the AR(2) process of each variable and for each country:

$$\Delta z_{i,t} = \alpha_i + \phi_i z_{i,t-1} + \psi_i \Delta z_{i,t-1} + \epsilon_{i,t} \tag{15}$$

where $z_{i,t}$ is the logged variable of interest for country i, and Δ is the first-difference operator. As recommended by Fomby, Ikeda, and Loayza (2013), I specify an AR(2) process to ensure that the residuals of the equation are white noise processes. If the null hypothesis $H_0 : \alpha_i = 0$ is rejected, I conclude that a trend is present in the series. Table 4 provides an overview of the number of countries with significant trend (on a 5% significance level) for each series.

	No. countries with significant trend
GDP per capita	22/57
CPI	37/57
Terms of trade	18/56
World GDP per capita	P-value: 0.000

Table 4: Overview of number of series with trend. All tests are reported on a 5% significance level.

As seen in Table 4, CPI and world real GDP per capita appear to have a significant trend present in the series. For real GDP per capita and terms of trade, however, a trend does not appear to be present.

After testing for the deterministic elements of the data, I perform the individual and panel unit root tests. I begin by performing the individual unit root tests, for which I use the augmented Dickey–Fuller (ADF) test. The test is performed series-by-series for each country. I then perform the Im–Pesaran–Shin

(IPS) panel unit root test, which is a panel unit root test that allows for unbalanced panels. The test is performed series-by-series. Depending on whether or not a trend is present in the series, the autoregressive processes are given by:

$$\Delta z_{i,t} = \phi z_{i,t-1} + \sum_{j=1}^{p_i} \psi_{i,j} \Delta z_{i,t-j} + \epsilon_{i,t} \tag{16}$$

$$\Delta z_{i,t} = \alpha_i + \phi z_{i,t-1} + \sum_{j=1}^{p_i} \psi_{i,j} \Delta z_{i,t-j} + \epsilon_{i,t} \tag{17}$$

For the individual unit root tests, the null hypothesis is that the series contains a unit root, and the alternative hypothesis is that the series is generated by a stationary process. In the case of the panel unit root test, the null hypothesis is that the series contains a unit root *for all countries*. Specifically, the null hypothesis is $H_0 : \phi_i = 0$ for the individual unit root tests, and $H_0 : \phi_i = 0$ for all i for the panel unit root test. The main advantage of using the panel root test is that the power of the test is higher compared to the standard country-by-country unit root test. As is the case with statistical tests, the power of the unit root test is dependent on the variation in the data—both in terms of the number of observations and the variation of those observations. Pooling the country-level data therefore adds significant variation across time, which in turn improves the precision of the parameter estimates. (Taylor and Sarno 1998). The test results from all three unit root tests can be seen in Table 5.

Transformation	Unit root test	GDP per capita	CPI	Terms of trade	World GDP per capita
Logged series	ADF-test: No. of countries where H_0 is rejected.	11/57	35/57	18/57	
	ADF-test: P-value				0.0871
	IPS-test: P-value	0.9997	0.8678	0.6254	
Differenced series	ADF-test: No. of countries where H_0 is rejected.	33/57	39/57	57/57	
	ADF-test: P-value				0.0007
	IPS-test: P-value	0.0000	0.0000	0.0000	

Table 5: Overview of individual and panel unit root tests. Note: All tests are reported on a 5% significance level.

From Table 5 it can be read that the logged series of real GDP per capita, CPI, terms of trade and world real GDP per capita does not appear to be stationary. The ADF test suggests that the logged series of CPI could be rendered stationary, while the IPS test suggest that it contains a unit root. For the logged series of real GDP per capita, terms of trade, and world real GDP per capita, the result from the ADF test as well as the results from the IPS test suggest that the series contain a unit root. For the differenced series, all series appear to be stationary. I therefore proceed by using the log differenced series of real GDP per capita, CPI, terms of trade, and world real GDP per capita.

5.3.2 Lag Structure

The next important step in the specification of my panel VAR-X model is the determination of the appropriate lag length. If a VAR model is estimated with a shorter lag length than its true lag length, the generated impulse response functions will be inconsistent. Similarly, if a VAR model is overfitted, i.e. estimated with a longer lag length than its true lag length, it will result in larger mean-square forecast errors. A higher lag order will also be costly in terms of power, which in the case of macroeconomic studies (where T usually is small) is especially relevant to consider.

I proceed by selecting the lag length using two different criterions: the Akaike's information criterion (AIC) and the Schwarz's Bayesian information criterion (SBC). The test is performed on p=q=1, p=q=2, and p=q=3 on the different country samples studied in the paper. The AIC and SBC test statistics can be seen in Table 6. For the low and middle-income economies and for the top half of the most climate vulnerable countries (CRI 50), AIC suggest p=q=3 while SBC suggest p=q=1, and for the high-income economies AIC suggest p=q=3 while SBC suggest p=q=2. A more parsimonious specification will fail to fully capture the dynamics of the mean responses of the dependent variables of interest to exogenous shocks. At the same time, including a longer lag length will reduce the power of the statistical tests. Given this and the results of the two selection criteria, I use a model with the lag length of two (p=q=2). In a majority of cases, VAR-models are estimated using symmetric lags, meaning that the same number of lags is used for all variables and all equations in the system. (Ozcicek and Douglas Mcmillin 1999) I therefore estimate my VAR-X model using symmetric lags, since it is standard in the literature and simplifies the interpretation of my results.

Country Sample	Lags	Low and Middle-Income Economies	High-Income Economies	CRI 50
AIC	p,q=1	-4.4410	-7.8372	-4.8924
	p,q=2	-4.4697	-8.0432	-4.9283
	p,q=3	-4.4784	-8.0838	-4.9447
SBC	p,q=1	-4.3586	-7.7571	-4.8094
	p,q=2	-4.3379	-7.9141	-4.7955
	p,q=3	-4.2971	-7.9063	-4.7623

Table 6: Overview of selection criteria for optimal lag length.

5.4 Limitations of Empirical Approach

The analysis in this paper is performed on different country samples, as opposed to individual countries. As such, the main limitation of my empirical approach is that it builds on the assumption that the response to different types of climatic disasters is homogeneous within country samples. It is possible that the experience following climatic disasters vary across countries, and that the effects on output and prices are very different in large countries such as China and smaller island nations such as Fiji. In line with previous research (see for instance Noy (2009) and Fomby, Ikeda, and Loayza (2013)), this study has divided the full country sample into smaller, and likely less diverse, country samples. Still, one should be careful to assign any of the paper's findings to a specific country included in the analysis, since it is possible (and in some cases likely) that the annual mean response of a specific country sample is an inaccurate estimation of the annual response of a specific country.

In addition, it should be noted that when the disaster hits (year 0) my model only captures the direct effect of the climatic disaster event on the dependent variables, and not the secondary effects from the other dependent variable. In the case that there are secondary effects, the results should be seen as a lower or an upper bound for the effect of climatic disasters on output and prices.

6 Results

In the following sections, I will analyze the effects of different climatic disasters on output and prices. The analysis is performed on emerging and developed economies, as well as on countries that are more exposed to climate risks. I begin by studying the effect of all climatic disasters together (from now on referred to only as climatic disasters), and then go on to study each type of disaster separately in order to allow for heterogeneous effects across disaster types. The analysis covers two types of outcome measures of climatic disasters: fatalities and number of people affected by the disaster, and the total damage of the disaster. As a robustness test, I also include controls for country-specific exogenous shocks in the form of banking crises and shocks to terms of trade.

6.1 Benchmark Model

My benchmark model studies the effect of different climatic disaster events on output and prices, and includes controls for country-fixed effects and the development of world GDP. In the main analysis, the outcome variable for climatic disasters is the total number of fatalities and number of people affected by the disaster.

6.1.1 Moderate Climatic Disasters

As previously stated, moderate climatic disasters have previously been shown to have less, and sometime positive, impacts on the economy. This also appears to be case here, with overall positive impacts on GDP growth and limited effects on CPI growth. The results can be seen in Table 7 and in Figure 5-8.

		Low & Middle-Income				High-Income	
		Moderate Disasters		Severe Disasters		Moderate Disasters	
Natural Disaster Type	Year	GDP growth	CPI growth	GDP growth	CPI growth	GDP growth	CPI growth
All Natural Disasters	0	0.0001	-0.0008	-0,0047**	0.0030	0.0008	-0.0026
	1	0.0021**	0.0021	0.0005	0.0039	0.0020	-0.0035
	2	0.0007	-0.0002	0.0014	0.0243	0.0000	-0.0049
	3	0.0003**	-0.0007	0.0001	0.0203	0.0003	-0.0043
	4	0.0001	-0.0007	0.0000	0.0137	0.0000	-0.0033
	5	0.0000	-0.0005	0.0000	0.0085	0.0000	-0.0022
	Cum.	0.0033**	-0.0009	-0.0027	0.0739	0.0033	-0.0210
Storms	0	-0.0006	-0.0017	-0,0115**	0.0030	0.0036	-0.0018
	1	0.0014	-0.0051	0.0040	0.0039	0.0022	-0.0027
	2	-0.0010	-0.0045	0.0013	0.0243	0.0009	-0.0047
	3	0.0000	-0.0025	0.0010	0.0203	0.0006	-0.0043
	4	0.0000	-0.0014	0.0005	0.0137	0.0002	-0.0032
	5	0.0000	-0.0008	0.0003	0.0085	0.0001	-0.0021
	Cum.	-0.0002	-0.0160	0.0044	0.0737	0.0076	-0.0188
Floods	0	0.0013	-0.0061	0.0019	-0,0501**	-0.0002	-0.0010
	1	0.0034**	0.0050	-0.0027	-0,0508*	0.0030	0.0000
	2	0.0021**	-0.0003	0.0033	-0.0410	0.0011	0.0003
	3	0.0007**	-0.0016	0.0007	-0.0286	0.0007	0.0007
	4	0.0003**	-0.0014	0.0006	-0.0178	0.0003	0.0009
	5	0.0001	-0.0010	0.0002	-0.0106	0.0002	0.0008
	Cum.	0.0079**	-0.0054	0.0040	-0,1989*	0.0051	0.0017
Droughts	0	-0.0021	0.0229	-0.0043	0.0384		
	1	-0.0021	0.0251	0.0007	0.065**		
	2	-0.0028	0.055**	0.0003	0.1262**		
	3	-0,0012*	0.0451**	-0.0010	0.0998**		
	4	-0,0007*	0.0301**	-0.0008	0.0657**		
	5	-0,0003*	0.0186**	-0.0005	0.04**		
	Cum.	-0.0095	0.1971**	-0.0056	0.4353**		
Number of Observations		1244	1244	1244	1244	1277	1277
Number of Countries		30	30	30	30	27	27

Note: **p<0.05. *p<0.10. significance tests are one-tail tests. Endogenous variales include GDP growth and CPI growth. Exogenous variables include storms, floods, droughts, landslides, extreme temperatures, wildfires, and world GDP growth.

Table 7: Results from benchmark model. Note: The outcome variable for climatic disasters is the total number of people affected by the disaster.

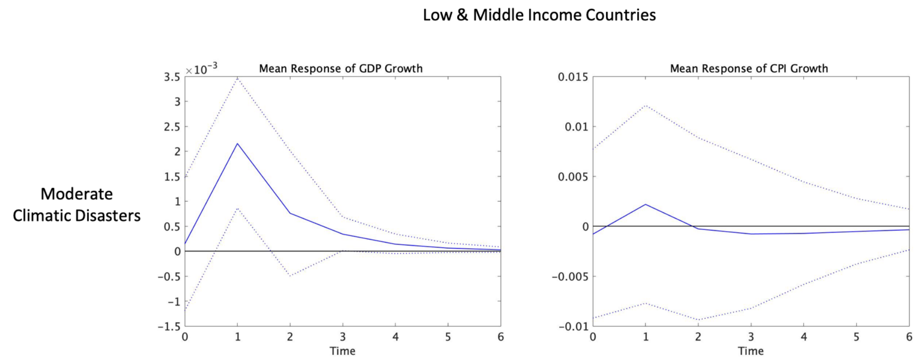

Figure 5: Annual mean responses of low & medium-income economies to moderate climatological, hydrological, and meterological disasters.

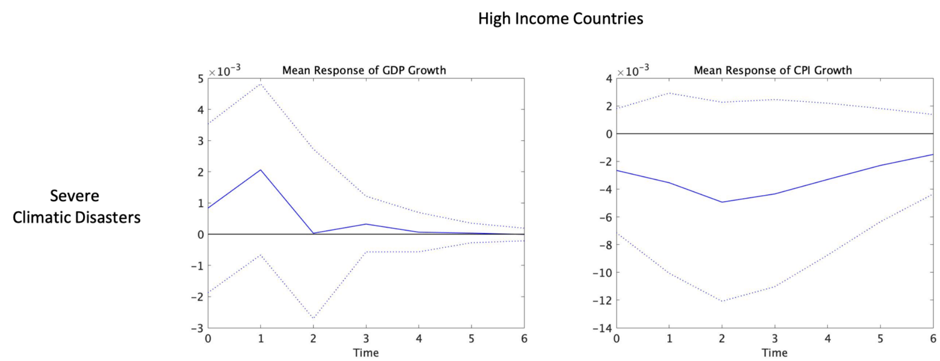

Figure 6: Annual mean responses of high-income economies to moderate climatological, hydrological, and meterological disasters.

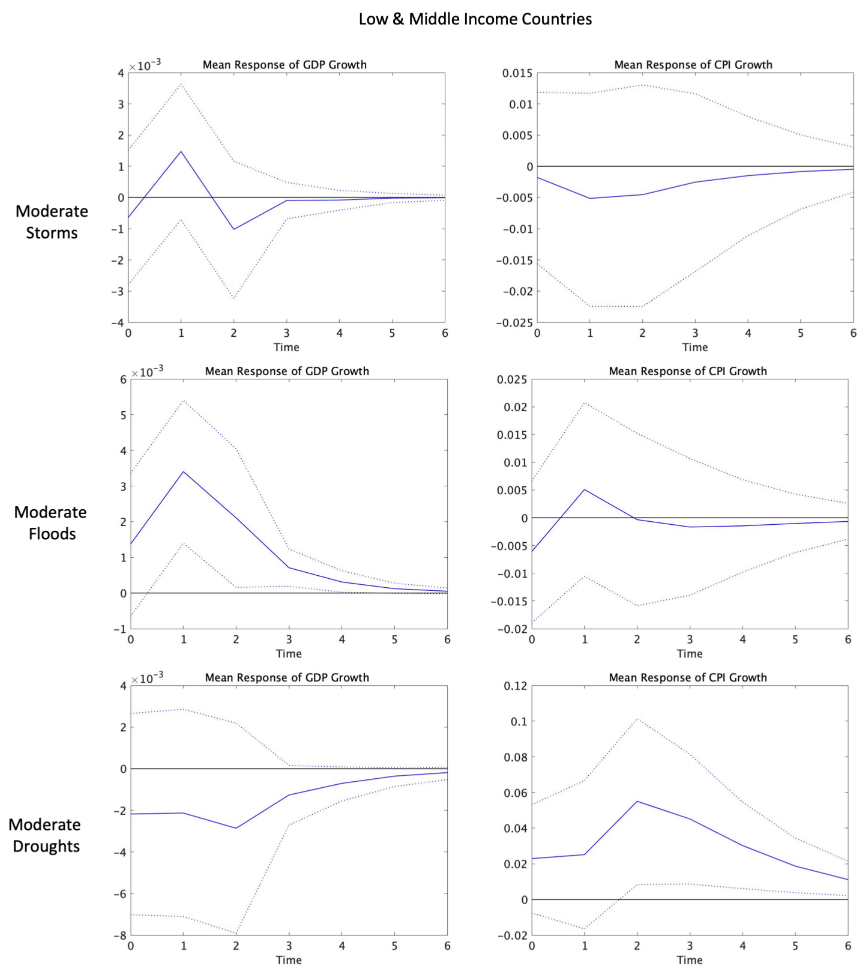

Figure 7: Annual mean responses of low & medium-income economies to moderate climatic disasters.

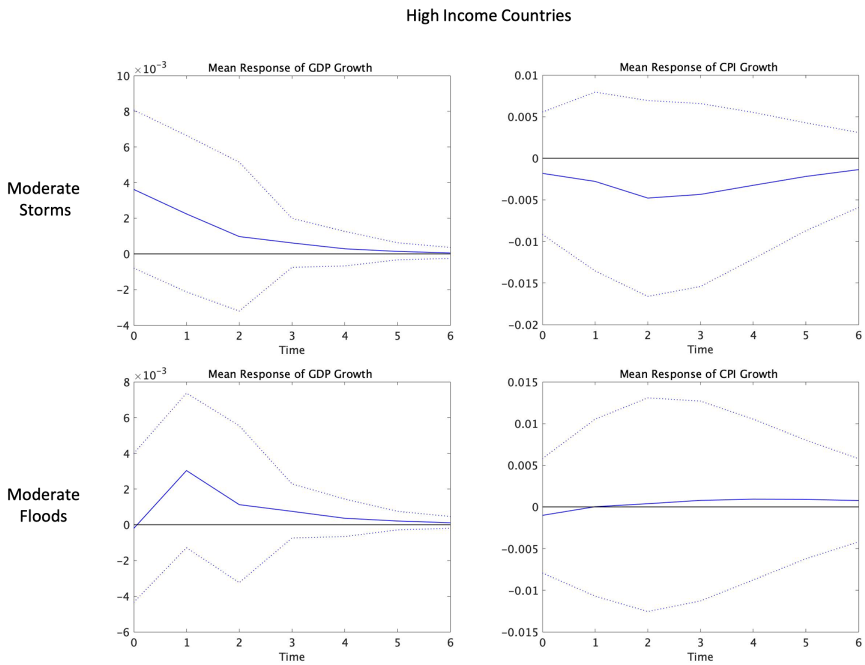

Figure 8: Annual mean responses of high-income economies to moderate climatic disasters.

For the climatic disaster measure, the immediate impacts on GDP growth appear to positive only for low and middle-income countries. In year 1 following the climatic disaster, GDP growth experience a small but statistically significant increase for low and middle-income countries. Specifically, GDP growth increases by 0.21 percentage points (pp), and over the studied time period (year 0-5), the cumulative impact on GDP growth amounts to 0.33 pp. For CPI growth, the overall impacts are insignificant for both low and middle-income countries and high-income countries.

For moderate disaster shocks in the form of storms, floods and droughts, the impacts vary depending on the disaster type and the level of country development. For low and middle-income countries, storms have a small and positive but statistically insignificant effect on GDP growth in year 1 following the disaster. Floods have an immediate positive effect on GDP growth, and a small, positive and statistically significant effect on GDP growth in year 1 following the shock. Over the observed time period, the cumulative impact of moderate floods on GDP growth amounts to 0.79 pp. However, storms and floods do not have any significant impact on CPI growth. Finally, droughts have a negative but insignificant effect on GDP growth in year 2-3 following the shock, and a positive and significant effect on CPI growth in year 2-5 following the shock. Over the observed time period, the total cumulative impact of moderate droughts on CPI growth amounts to 19.71 pp. For high-income countries, storms have an immediate small and positive but statistically insignificant impact on GDP growth, while floods have a small and positive but statistically insignificant impact on GDP growth year 1 following the shock. [13] None of the disaster types have any major impact on CPI growth for high-income countries.

6.1.2 Severe Climatic Disasters

As opposed to moderate disasters, more severe climatic disaster events appear to have an overall negative effect on the economy. The results can be seen in Table 7 and in Figure 9-10. Due to a low number of observations, high-income economies have been leaved out from the analysis.

For the climatic disaster measure, low and middle-income economies experience an immediate, small, negative and statistically significant effect on GDP growth, and a large and positive but statistically insignificant effect on CPI growth in year 2-4 following the shock.

As in the previous case, the impacts of severe disaster vary depending on the type of climatic disaster. For low and middle-income countries, storms have an immediate, negative and statistically significant effect on GDP growth. In the year of the disaster, the negative impact on GDP growth equals 1.15 pp. The impacts on CPI growth, however, remain insignificant. For floods, the impact on GDP growth is insignificant while the impact on CPI growth is small, negative and statistically significant on the year of the disaster. The cumulative effect (which is statistically significant only on a 10 percent level) for year 0-5 amounts to a negative 19.89 pp. Finally, droughts have no significant effects on GDP growth but a significant, large and long-lasting positive effects on CPI growth. Only in year 2 following the disaster, the estimated impact equals 12.62 pp, and the overall cumulative effects amount to as much as 43.53 pp.

13. Since there is only a limited number of observations for moderate droughts (as measured by number pf people directly affected) for high-income countries, views are not included here.

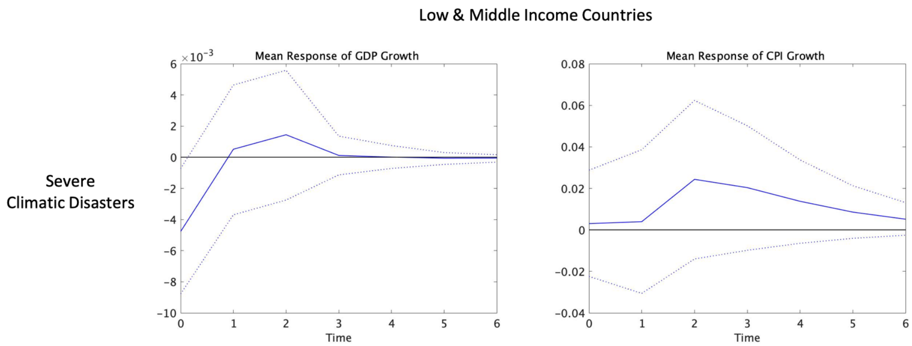

Figure 9: Annual mean responses of low & medium-income economies to severe climatological, hydrological, and meterological disasters.

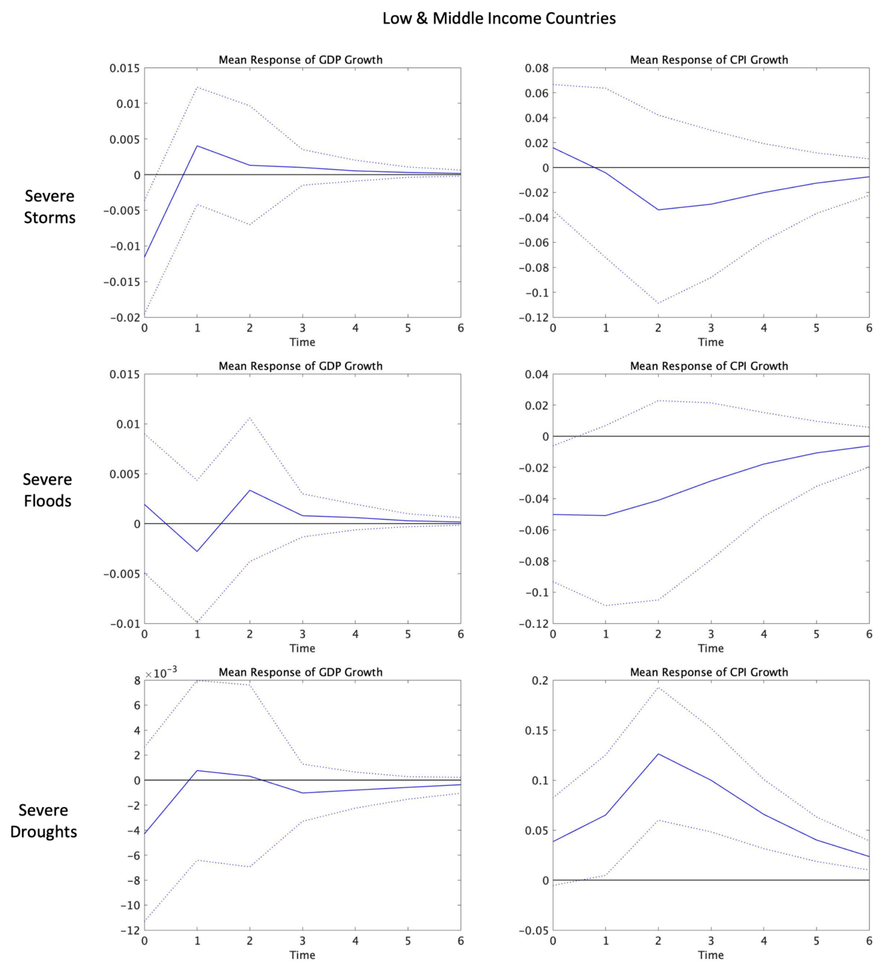

Figure 10: Annual mean responses of low & medium-income economies to severe climatic disasters.

6.2 Robustness Tests

In the following sections, I test for the robustness of my results by running a set of different robustness tests. I begin by restricting my sample of countries to countries that are more vulnerable to climate risks. I then go on by including controls for country-specific exogenous shocks in the form of systemic banking crises and shocks to terms of trade. Finally, I construct an alternative output measure of climatic disasters based on the total damage of the disaster in order to better capture the dynamics of the more physically destructive climatic disasters.

6.2.1 Exposure to Climate Risks

It is possible that countries that are more affected by climatic disasters systemically differ from countries that are less exposed to extreme weather events. For instance, one could imagine that countries with higher mean temperatures or countries located closer to the equator are not only more often hit by extreme weather events, but also exhibit different trends for GDP and CPI growth [14]. To control for the cross-country differences in exposure to climate risks, I use the Germanwatch Global Climate Risk Index (CRI) to group countries into two groups: countries that are more affected by natural disasters and countries that are less affected by natural disasters. Countries that have a CRI score that is below the group mean are categorized into the first group, and the remaining countries are categorized into the second group. Table 10 in the Appendix show the CRI score of all included countries.

The Germanwatch Global Climate Risk Index is based on data on natural disaster events and associated socio-economic indicators. The index reflects to what extent a specific country has been (adversely) affected by extreme weather events such as floods, storms and droughts. As such, it is a backward-looking index, and it does not take other climate-related impacts into account (i.e. it ignores the future impact of sea-level rise). Given that the focus of this study is climatic disaster events, the approach of the Global Climate Risk Index is preferable over similar but more inclusive indicators.

Overall, the index shows that there is a strong link between the level of economic development and the exposure to climate risk. Out of the 28 countries in the sample that are categorized as lower and middle-income economies, 19 countries have a CRI score that is lower than the group mean. Still, developed economies such as the United States also score low compared to the group mean, mainly due to the high frequency of extreme weather events and the high absolute costs of those events.

14. See for instance Hall and Jones (1996) and Sachs and Warner (1997).

As seen in Table 13 in the Appendix, the estimated annual mean responses of climate vulnerable countries are similar to the estimated annual mean responses of low and middle-income countries. Hence, it suggests that the results are mainly driven by low and middle-income countries that are highly exposed to extreme weather events. When I split the analysis on climate vulnerable countries between low and middle-income economies and high-income economies, I find that it indeed appears to be the case.

6.2.2 Exogenous Shocks

My benchmark model does not control for country-specific macroeconomic disturbances, including financial crises that are specific to certain countries or regions. To control for possible heterogeneities across countries, I therefore include two different types of country-specific controls: terms of trade and a dummy variable for the occurrence of systemic banking crises. In my first model specification I include terms of trade, which is used by Raddatz (2009) and Fomby, Ikeda, and Loayza (2013). Terms of trade varies across countries, and hence, captures how country-specific characteristics (such as whether a country is a net exporter or importer of oil) determine how global shocks affect output, prices and interest rates in each country. However, it is possible that by including terms of trade, I also capture some of the country-specific variations that are indeed caused by extreme weather events. I therefore specify a second model where I include a dummy variable that is equal to one if a banking crisis took place in country i during year t. The results can be seen in Table 14-15 in the Appendix. The results are very similar to those of the benchmark model, suggesting that indeed that the climatic disasters events are exogenous and not systemically occurring at the same time as other country-specific shocks. Similarly, the impact on inflation in low and middle-income countries does not appear to be driven by currency crises and subsequent periods of hyperinflation.

6.2.3 Composite Indicator Based on Total Damages

The EM-DAT uses two types of indicators to measure the outcome of natural disaster events: the number of people that have been affected by the disaster, and the total amount of direct damages that the disaster has caused. Until now, I have only studied the prior outcome measure, as this has been the dominating measure in the economic literature on natural disasters. However, there are a number of reasons as to why it could be useful to use total damages to estimate the effect of climatic disaster events on the economy. Mainly, Noy (2009) findings suggest that the destruction of the physical capital stock (rather than the human capital stock) has a more significant short-term negative effect on output growth. It is therefore relevant to limit the analysis on the events that have caused the most direct economic damage in order to fully capture the effects of extreme weather events on the economy. I proceed by using an alternative composite indicator that is based on the total damages (measured in current USD) associated with a specific disaster. When using the cost-based composite indicator, the number of included observations for climatic disasters increases for high-income countries. This is likely due to the fact that climatic disasters in developed economies can have limited or no impact on the local population, but still lead to large direct damages. Given the higher number of observations, I am now able to generate results for all three climatic disasters for both country samples. The results can be seen in Table 8 and Figure 11-14.

A slightly different picture emerges when using the cost-based composite indicator. For low and middle-income countries, climatic disasters have a small, positive and statistically significant effect on GDP growth in year 1 following the disaster, but no statistically significant effect on CPI growth. For high-income countries, climatic disasters only have a small, negative and statistically significant (still, only on a 10 percent level) impact on CPI growth.

When splitting the analysis on the different types of climatic disasters, it becomes clear that the impacts vary depending on disaster type and level of country development. For low and middle-income countries, storms have a small, positive and significant effect on GDP growth in year 1 following the disaster. Similarly, floods have a small and positive impact on GDP growth in year 0-3 following the shock. Neither storms nor floods appear to have any major impact on CPI growth. For droughts, however, the impact appears to be overall negative. Droughts have an immediate, small, negative and statistically significant impact on GDP growth. In the year of the disaster, GDP growth decreases by 1.01 pp and the cumulative effect for year 0-5 amounts to a negative 2.2 pp. Droughts also have a large and statistically significant impact on CPI growth. In year 3 following the disaster, CPI growth increases by 11.07 pp and the cumulative effect for year 0-5 amounts to 39.35 pp. For high-income countries, none of the climatic disasters appear to have any major impact on neither GDP nor CPI growth. Still, droughts have a small, positive and statistically significant (still, only on a 10 percent level) impact on GDP growth in year 1 following the disaster.

		Low & Middle-Income		High-Income	
		Total damage		Total damage	
Natural Disaster Type	Year	GDP growth	CPI growth	GDP growth	CPI growth
All Natural Disasters	0	-0.0004	0.0041	0.0002	-0.0006
	1	0.0028**	-0.0017	0.0008	-0.0019*
	2	0.0016*	0.0069	-0.0009	-0.0032*
	3	0.0005*	0.0060	-0.0002	-0.0031*
	4	0.0002	0.0040	-0.0002	-0.0026*
	5	0.0001	0.0025	-0.0001	-0.0019*
	Cum.	0.0048	0.0216	-0.0005	-0.0131*
Storms	0	-0.0012	0.0072	-0.0001	0.0003
	1	0.003*	-0.0040	0.0002	-0.0003
	2	0.0009	-0.0064	-0.0010	-0.0016
	3	0.0005	-0.0050	-0.0003	-0.0018
	4	0.0002	-0.0034	-0.0002	-0.0016
	5	0.0001	-0.0022	-0.0001	-0.0013
	Cum.	0.0035	-0.0135	-0.0014	-0.0062
Floods	0	0.0025*	-0.0057	0.0003	-0.0020
	1	0.0045**	-0.0060	0.0012	-0.0041
	2	0.0037**	0.0050	-0.0020	-0.0049
	3	0.0011**	0.0046	-0.0004	-0.0044
	4	0.0005*	0.0032	-0.0004	-0.0035
	5	0.0002	0.0019	-0.0002	-0.0026
	Cum.	0.0121	0.0030	-0.0015	-0.0213
Droughts	0	-0.0101**	0.0473**	0.0036	-0.0023
	1	-0.0038	0.0426	0.0076*	-0.0048
	2	-0.0038	0.1107**	0.0022	-0.0067
	3	-0.0022**	0.092**	0.0017	-0.0053
	4	-0.0014**	0.0622**	0.0008	-0.0035
	5	-0.0009**	0.039**	0.0005	-0.0020
	Cum.	-0.022**	0.3935**	0.0162	-0.0242
Number of Observations		1244	1244	1277	1277
Number of Countries		30	30	27	27

Note: **p<0.05. *p<0.10. significance tests are one-tail tests. Endogenous variables includes GDP growth and CPI growth. Exogenous variables includes storms, floods, droughts, landslides, extreme temperatures, wildfires, and world GDP growth.

Table 8: Results from benchmark model, using alternative cost-based composite indicator. Note: The outcome variable is total damage (in current USD).

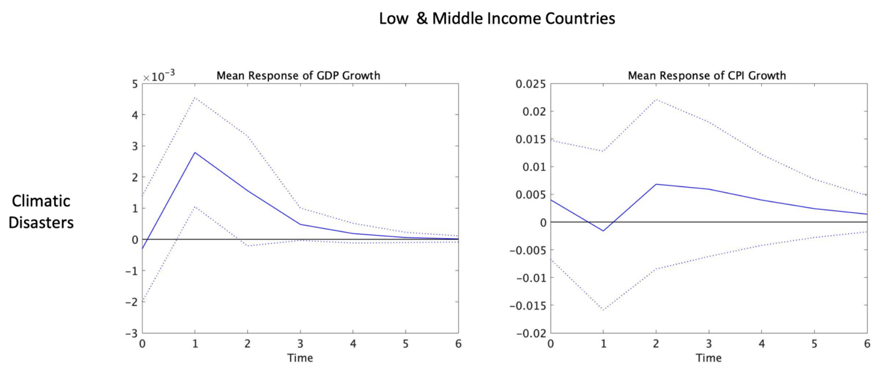

Figure 11: Annual mean responses of low & medium-income economies to climatological, hydrological, and meterological disasters, using alternative cost-based composite indicator.

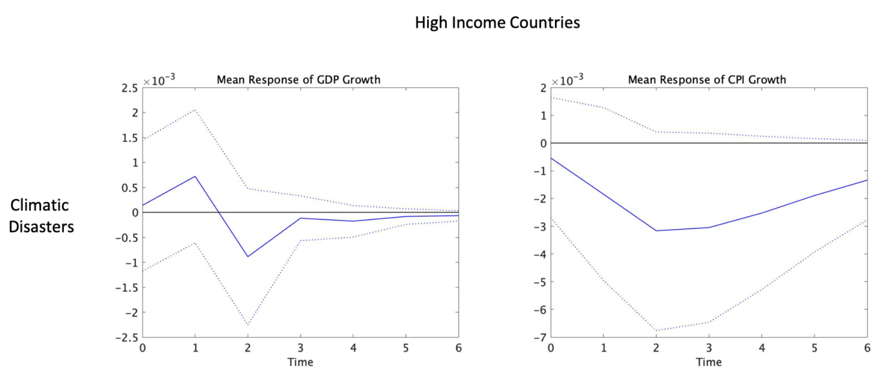

Figure 12: Annual mean responses of high-income economies to climatological, hydrological, and meterological disasters. Note: Output generated using alternative cost-based composite indicator.

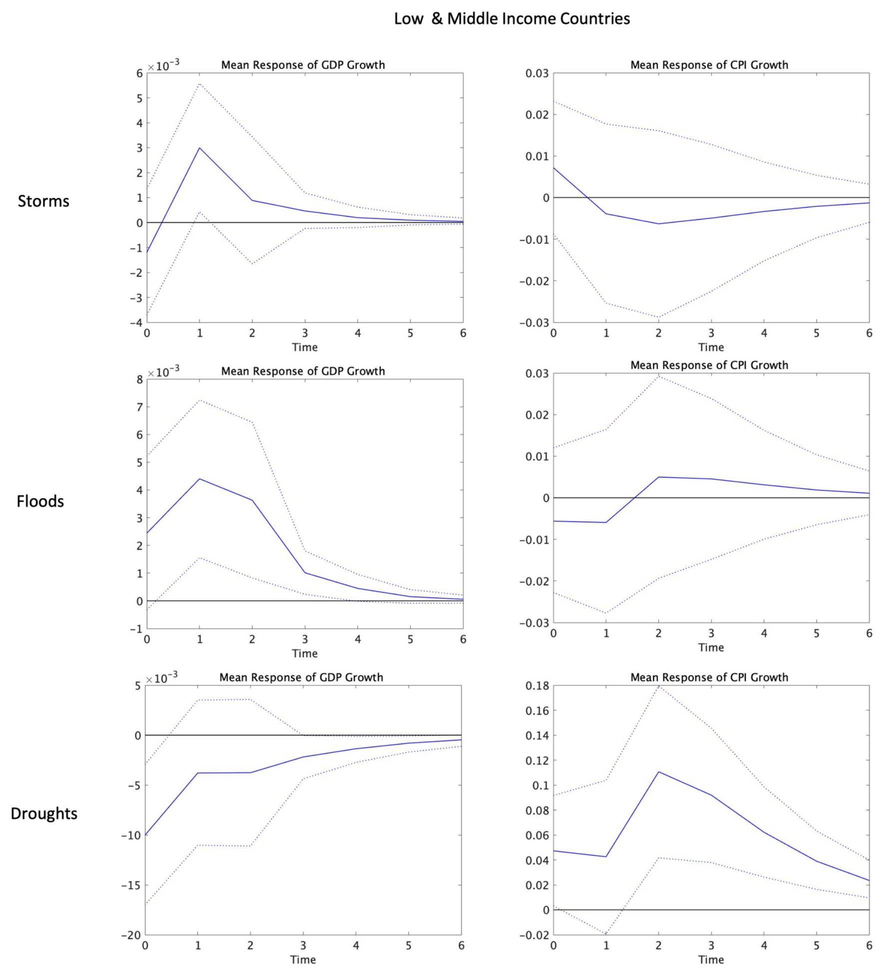

Figure 13: Annual mean responses of low & medium-income economies to climatic disasters. Note: Output generated using alternative cost-based composite indicator.

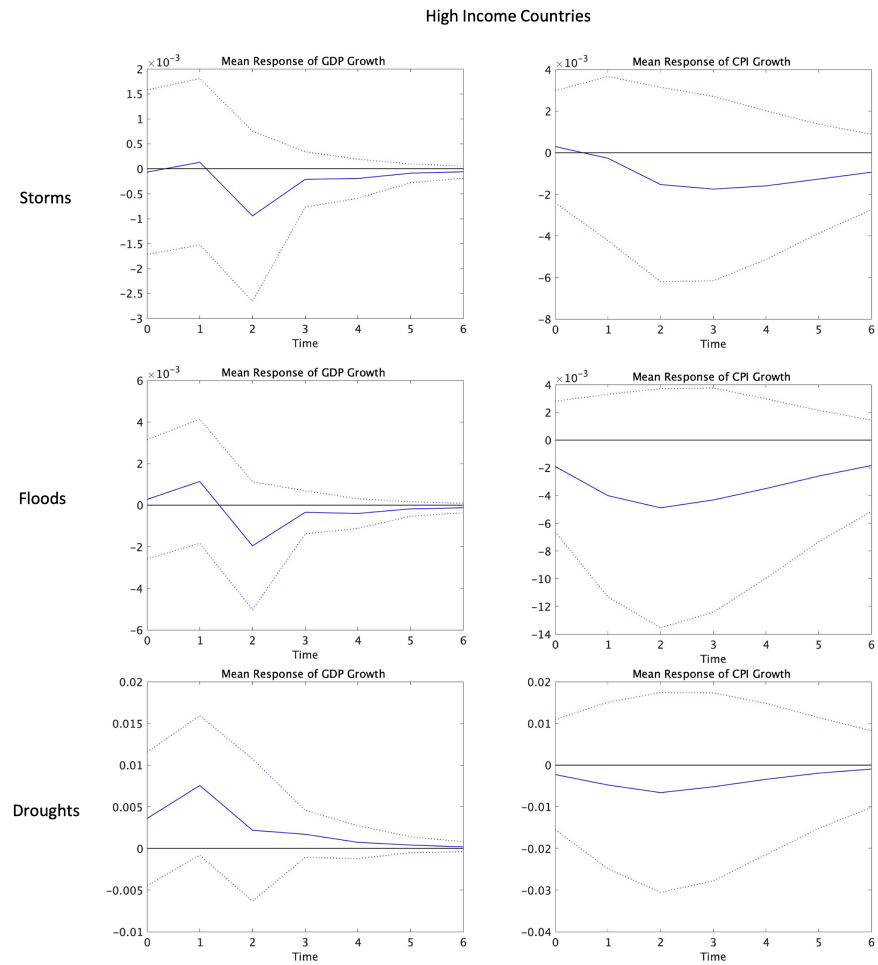

Figure 14: Annual mean responses of high-income economies to climatic disasters. Note: Output generated using alternative cost-based composite indicator.

7 Discussion

In this section, I will provide some candidate explanations for the various results presented in the previous sections. I will also briefly discuss some possible avenues for future research.

7.1 Key Results and Insights

The paper's findings suggest that the impact of different climatic disasters on GDP and CPI growth vary depending on the type of disaster shock, the severity of the disaster, and the level of country development. This is also in line with much of the previous literature studying the effects on climatic disasters on output and prices.

7.1.1 Climatic Disasters

Overall, the impact of climatic disasters is contingent on the severity of the disaster. Moderate climatic disasters have a small but positive impact on output, while severe climatic disasters have a contemporaneous negative impact on output. Similarly, when using the alternative cost-based composite indicator, climatic disasters have a positive impact on output in low and middle-income countries. The impacts on inflation, however, appear to be limited. Still, in order to gain additional insights it is necessary to split the analysis on the different types of climatic disasters.

7.1.2 Storms

Storms appear to have a limited impact on both low and middle-income countries and high-income countries, including countries with a higher exposure to climatic disasters. For low and middle-income countries, storms do not have any impact on output or inflation, while only severe storms have a negative impact on output. However, when using the alternative cost-based composite indicator, storms are found to have a small but positive impact on output. For high-income countries, there appear to be no significant impact on output and prices. The findings are somewhat surprising, given that storms have the potential to cause major damage to buildings and other types of productive infrastructure. Still, there are a number of factors that could explain these findings. First, storms mainly impact the economy through the destruction of productive capital. The impacts on buildings and infrastructure can be large, especially in developing countries, with recent examples including tropical cyclone Fani in India and tropical cyclone Idai and Kenneth in Mozambique. (*EM-DAT: Disasters of the week* 2019) At the same time, storms usually last only for a number of days, and less severe storms will likely not lead to extended business disruptions. As a result, storms that cause large damages likely stimulate the economy due to the subsequent increase in demand for goods and services in the reconstruction sector, while only the most severe storms have a negative impact on the economy. Second, as suggested by the existing literature (Noy 2009; Loayza et al. 2012), high-income countries are more successful at insulating their economies from extreme weather shocks, compared to low and middle-income countries.

7.1.3 Floods

Floods have a larger impact on output and prices, and similar to storms, mainly appear to affect emerging economies. For low and middle-income countries, moderate floods have a small but positive impact on output, while severe floods have a negative impact on prices. The cost-based composite indicator also finds a positive impact on output following floods. For high-income countries, the impacts appear to be limited. The findings clearly show how a specific type of climatic disaster can have markedly different effects on the economy, depending on the level of country development. The different effects likely depend on a number of factors. First, one can imagine that heavy rainfall and flooding have a positive impact on agriculture output (for instance, Loayza et al. (2012) finds that moderate floods have a positive effect on the agriculture sector). That would then suggest that moderate floods will have a more positive impact on output in countries that are more dependent on agriculture production. Among the studied countries, the top half of the countries with the highest share of agriculture production (as a share of GDP) are low and middle-income countries (see Table 11 in the Appendix), suggesting that it is indeed the case. Second, floods appear to cause a downward pressure on prices in low and middle-income countries. It is possible that even the more damaging floods have a small but positive impact on agriculture production. Assuming that prices are more sensitive to changes in agriculture production than output, this would then explain the drop in inflation following floods.

7.1.4 Droughts

Droughts have a large impact on low and middle-income countries but no apparent impact on high-income countries. In low and middle-income countries, moderate and severe droughts both lead to a sharp and prolonged increase in inflation. Moreover, when using the cost-based composite indicator, droughts are shown to have a large and negative impact on output and a large, positive and prolonged impact on inflation. High-income countries, on the other hand, appear to remain unaffected by droughts. The findings once again highlight how low and middle-income countries are more vulnerable to climatic disasters. The large and persistent impact on emerging economies likely depend on a number of factors. First, droughts have a negative impact on agriculture production, and given the higher reliance on the agricultural sector among the sample of low and middle-income countries (see previous section), emerging countries will be more adversely affected by droughts. Moreover, droughts can also have a negative effect on food production through killing livestock. In this case, the negative impact on output appears to translate into a sharp increase in inflation. This is likely due to the fact that a drop in food production creates a shortage of food in the market, which in turn drive up food prices. The effect is likely more made more pronounced in low income countries since these markets lack well-developed linkages to global supply chains. Moreover, compared to other climatic disasters, droughts are long-lasting events and can go on for several years and affect large geographical areas and even countries. At the same time, droughts leave crucial infrastructure, such as buildings, transportation and energy infrastructure, intact. As a result, droughts are not expected to have any stimulative effects on the economy. Instead, they appear to have a negative and relatively more persistent impact on the economy, and in this case, mainly in the form of inflated prices. Another interesting finding is the clear difference between the two composite indicators, with only the cost-based composite indicator finding that output is negatively impacted by droughts. One explanation to these diverse findings could be that droughts that affect large parts of the population do not necessarily affect the most productive share of the population. Instead, it is possible that these events mainly affect poor communities with limited access to irrigation systems and other types of infrastructure that can limit the adverse impacts of droughts. The droughts that have recorded large amount of direct damages, however, are events (perhaps longer lasting droughts) that also impact larger producers who contribute more to national output. It should also be noted that inflation is found to increase, independent of what composite indicator is used in the analysis. Similar to the result on floods, this suggests that inflation is sensitive to negative shocks to agriculture production. Finally, it is important to highlight the large difference in the average mean response of GDP and CPI growth across country samples. Low and middle-income countries (and notably, the countries more vulnerable to climate risk) are much more vulnerable to climatic disasters compared to high-income countries. The finding suggests that emerging economies, that in many cases already struggle with economic and environmental challenges, are more exposed to negative supply shocks following droughts. This should also be taken into consideration by low and middle-income and high-income countries in their strategies to limit carbon emissions and mitigate global warming and the occurrence of climate-related natural disasters. For instance, if an energy transition entails a higher dependency on biofuels derived from food crops, this could limit food production and push up food prices. Hence, countries should be aware that certain climate change mitigation strategies, such as a higher reliance on biofuels or plantation forestry, could lead to substantial increases in food prices in emerging economies and further limit their ability to withstand droughts.

7.2 Limitations and Avenues for Future Research

Climate change is an imminent threat to the global economy, and it is of paramount importance to establish the linkages between climate change and various macroeconomic variables. The findings in this paper suggest that droughts can have major effects on the economies in low and middle-income countries, mainly through the large and long-lasting impact on inflation. Still, this paper relies on historic data, and while this analysis has produced useful insights, it does not capture the future impacts of climate change on output or inflation. If climate change is altering the historic trend (as Guy Debell proposed in his speech on monetary policy and climate change), it is necessary to use estimation strategies that do not build on historic assumptions. Future research should therefore focus on the future effects of climatic disasters on various macroeconomic variables, for instance by building on the modelling work by Mercure et al. (2018). This would be particularly interesting for developed economies, since these countries have been historically less exposed to the adverse impacts of climate change. In addition, this paper highlights the need to not only focus on the impacts on output, but also study the links between climate change, climatic disasters and other macroeconomic variables.

8 Final Remarks

This paper set out to map how different climatic disasters affect output and prices. In line with the existing literature on the macroeconomic effects of extreme weather events, the findings suggest that the average mean response of GDP and CPI growth vary depending on a number of factors, including the type of disaster, the level of development and the severity of the disaster. Most notably, the paper's findings suggest that low and middle-income countries, as opposed to high-income countries, are exposed to negative supply shocks following droughts. While this paper has provided useful insights, it has also highlighted the need to further explore the economic effects of climate change and climatic disasters. To successfully capture the future economic impacts of climate-related natural disasters, it will likely be necessary to dispense from historic assumptions.

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Appendix

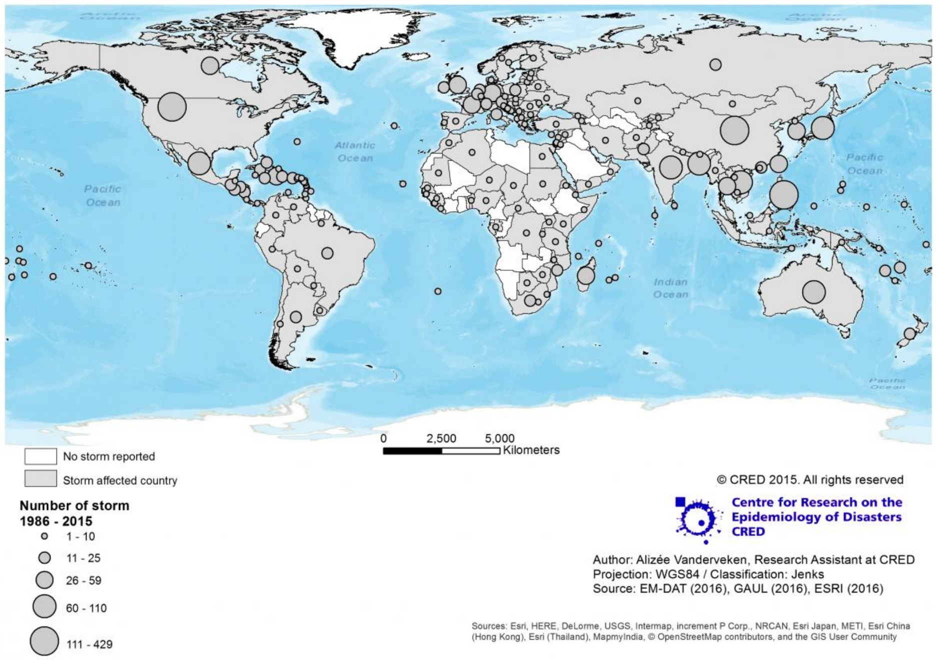

Figure 15: Map over number of storm events per country, 1986-2015. Source: EM-DAT Database (2019).

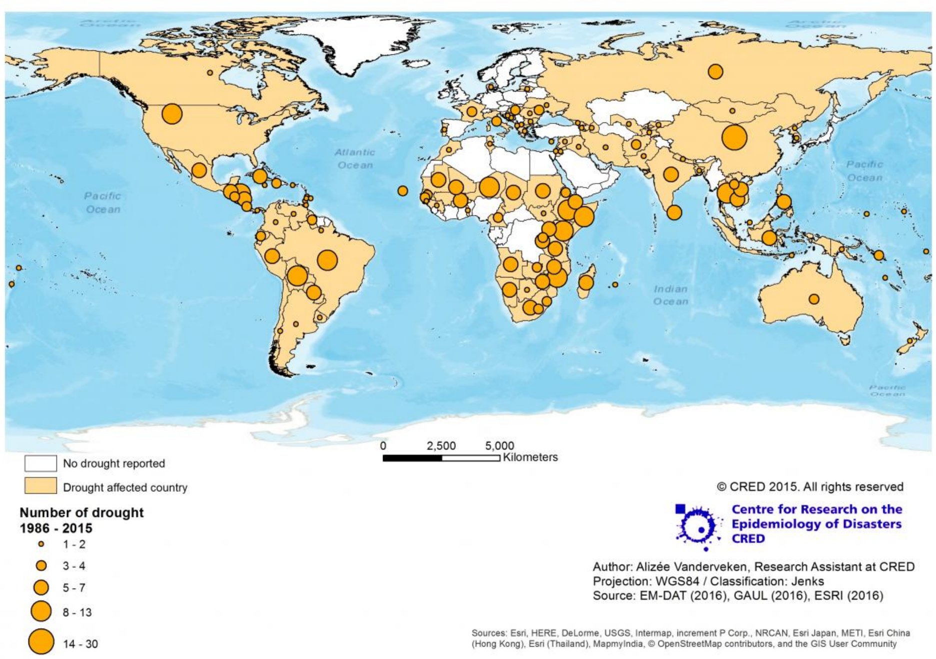

Figure 16: Map over number of drought events per country, 1986-2015. Source: EM-DAT Database (2019).

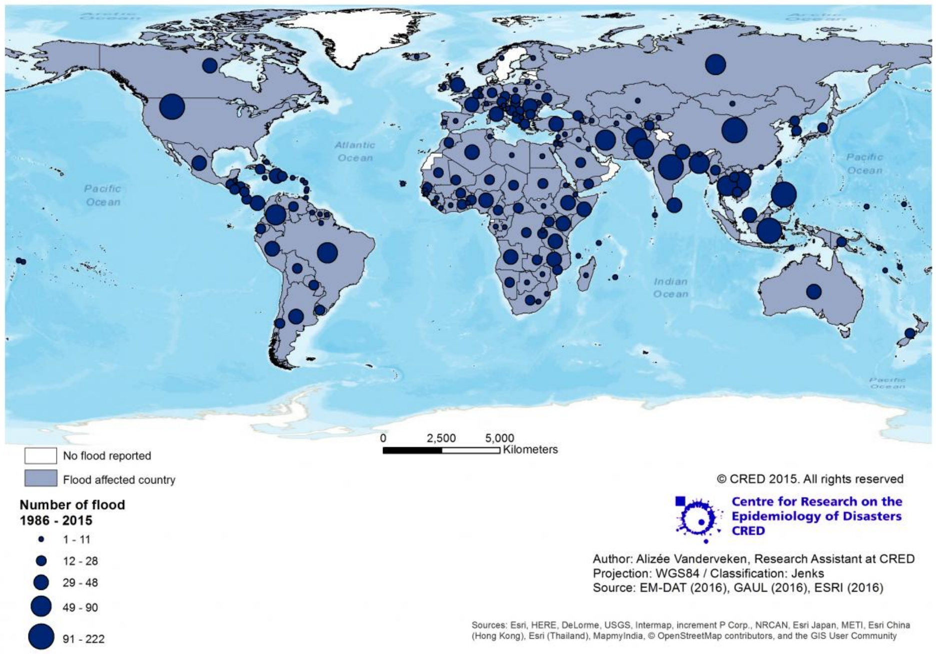

Figure 17: Map over number of flood events per country, 1986-2015. Source: EM-DAT Database (2019).

High-Income Economies	Low & Middle Income Economies
Australia	Bangladesh
Austria	Bolivia
Belgium	Botswana
Canada	Brazil
Chile	Cambodia
Denmark	Cameroon
Finland	China
France	Colombia
Germany	Costa Rica
Hungary	Egypt
Iceland	Fiji
Ireland	India
Israel	Indonesia
Italy	Jamaica
Japan	Kenya
Korea	Malaysia
The Netherlands	Mexico
New Zealand	Mongolia
Norway	Morocco
Poland	Namibia
Saudi Arabia	Peru
Spain	Phillipines
Sweden	Russia
Switzerland	South Africa
Taiwan	Tanzania
United Kingdom	Thailand
United States	Turkey
	Uganda
	Vietnam
	Zambia

Table 9: Overview of countries and country groups.

Country	CRI Score	Country	CRI Score
Australia	42.17	Kenya	52.33
Austria	59.15	Korea	60.83
Bangladesh	27.00	Malaysia	65.50
Belgium	68.00	Mexico	46.67
Bolivia	19.33	Mongolia	109.50
Botswana	109.50	Morocco	93.17
Brazil	54.50	Namibia	40.83
Cambodia	95.17	Netherlands	60.83
Cameroon	97.83	New Zealand	78.17
Canada	51.67	Norway	77.17
Chile	62.00	Peru	47.67
China	23.83	Phillipines	31.33
Colombia	69.33	Poland	64.17
Costa Rica	40.17	Russia	60.67
Denmark	90.33	Saudi Arabia	69.67
Egypt	73.33	South Africa	42.33
Finland	109.50	Spain	51.83
Fiji	10.17	Sweden	93.50
France	56.33	Switzerland	78.83
Germany	51.50	Taiwan	23.83
Hungary	109.50	Tanzania	68.00
Iceland	109.50	Thailand	37.50
India	46.17	Turkey	92.83
Indonesia	18.33	Uganda	51.00
Ireland	101.50	United Kingdom	66.83
Israel	62.17	United States	23.17
Italy	76.50	Vietnam	15.33
Jamaica	82.83	Zambia	40.33
Japan	57.50		

Table 10: Overview of CRI score by country.

Country	% of GDP	Country	% of GDP
Australia	2.8790	Kenya	28.9963
Austria	2.3667	Korea	13.9893
Bangladesh	34.5967	Malaysia	19.8582
Belgium	0.9145	Mexico	6.4134
Bolivia	15.0234	Mongolia	19.4763
Botswana	14.3603	Morocco	15.4002
Brazil	8.5598	Namibia	8.5467
Cambodia	34.7679	Netherlands	3.0521
Cameroon	22.0338	New Zealand	8.5284
Canada	1.5144	Norway	2.6651
Chile	6.5578	Peru	11.3284
China	23.6146	Phillipines	21.163
Colombia	15.5018	Poland	3.1108
Costa Rica	15.5317	Russia	5.9603
Denmark	2.8634	Saudi Arabia	3.5726
Egypt	18.7193	South Africa	5.1430
Finland	4.5307	Spain	3.0143
Fiji	17.9853	Sweden	2.2766
France	3.8861	Switzerland	1.0869
Germany	0.8214	Taiwan	n/a
Hungary	4.3466	Tanzania	33.8052
Iceland	6.2206	Thailand	17.7911
India	28.5575	Turkey	22.8249
Indonesia	17.2763	Uganda	43.8730
Ireland	1.8919	United Kingdom	0.8311
Israel	1.4338	United States	1.1514
Italy	2.3847	Vietnam	26.1349
Jamaica	6.2322	Zambia	13.3710
Japan	1.3107		

Table 11: Average value of agriculture, forestry, and fishing, as a share of GDP, 1990-2017.

Country	No. of years	Country	No. of years
Australia	8	Kenya	11
Austria	7	Korea	9
Bangladesh	3	Malaysia	10
Belgium	10	Mexico	10
Bolivia	10	Mongolia	4
Botswana	4	Morocco	6
Brazil	11	Namibia	1
Cambodia	2	Netherlands	10
Cameroon	10	New Zealand	7
Canada	7	Norway	10
Chile	10	Peru	12
China	4	Phillipines	14
Colombia	12	Poland	5
Costa Rica	11	Russia	9
Denmark	15	Saudi Arabia	4
Egypt	13	South Africa	7
Finland	12	Spain	19
Fiji	4	Sweden	10
France	12	Switzerland	10
Germany	9	Taiwan	6
Hungary	3	Tanzania	3
Iceland	8	Thailand	13
India	8	Turkey	12
Indonesia	10	Uganda	3
Ireland	4	United Kingdom	17
Israel	4	United States	14
Italy	16	Vietnam	1
Jamaica	5	Zambia	5
Japan	12		

Table 12: Overview of crisis years by country.

		Climate Vulnerable			
		Moderate Disasters		Severe Disasters	
Natural Disaster Type	Year	GDP growth	CPI growth	GDP growth	CPI growth
All Natural Disasters	0	0.0004	-0.0001	-0.0047**	0.0034
	1	0.0024**	0.0023	0.0016	0.0066
	2	0.0007	0.0003	0.0004	0.0338**
	3	0.0003**	-0.0004	-0.0002	0.029**
	4	0.0002	-0.0005	-0.0002	0.0195**
	5	0.0001	-0.0004	-0.0002	0.012**
	Cum.	0.0039**	0.0014	-0.0033	0.1040
Storms	0	0.0002	1.00E-04	-0.0113**	0.02870
	1	0.0016	-0.0035	0.00440	0.01660
	2	-1.40E-03	-0.0032	-0.00050	-0.01610
	3	-3.00E-04	-0.0011	0.00040	-0.01650
	4	-2.00E-04	-0.0004	0.00020	-0.01190
	5	-1.00E-04	-1.00E-04	0.00020	-0.00750
	Cum.	-1.0E-04	-8.1E-03	-0.0067	-0.0067
Floods	0	0.0013	-0.0054	0.0023	-0.0645**
	1	0.0033**	0.0055	-0.0028	-0.0714**
	2	0.0027**	0.0009	0.0024	-0.0463
	3	0.0009**	-0.0015	0.0007	-0.0294
	4	0.0004**	-0.0016	5.00E-04	-0.0172
	5	0.0002**	-0.0012	2.00E-04	-0.0097
	Cumulative	0.0086**	-0.0033	0.0032	-0.2382
Droughts	0	-0.0007	0.0242	-0.0042	0.0412**
	1	0.0008*	0.0292	0.0026	0.0763**
	2	-0.004*	0.0647**	-0.0009	0.1491**
	3	-0.0016**	0.0546**	-0.0013	0.1191**
	4	-0.0009**	0.0366**	-0.0010	0.0778**
	5	-0.0004	0.0225**	-0.0006	0.0465**
	Cum.	-0.0067	0.2316**	-0.0052	0.5096**
Number of Observations		1234	1234	1234	1234
Number of Countries		28	28	28	28

Note: **p<0.05. *p<0.10. significance tests are one-tail tests. Endogenous variables include GDP growth and CPI growth. Exogenous variables include storms, floods, droughts, landslides, extreme temperatures, wildfires, and world GDP growth.

Table 13: Results from benchmark model on CRI50 country sample. Note: The outcome variable for climatic disasters is the total number of people affected by the disaster.

		Low Income				High-Income	
		Moderate Disasters		Severe Disasters		Moderate Disasters	
Natural Disaster Type	Year	GDP growth	CPI growth	GDP growth	CPI growth	GDP growth	CPI growth
All Natural Disasters	0	0.0001	-0.0010	-0.0049**	0.0023	0.0008	-0.0028
	1	0.0021**	0.0022	0.0004	0.0036	0.0020	-0.0036
	2	0.0008	-0.0002	0.0012	0.0239	0.0001	-0.0049
	3	0.0004	-0.0006	0.0001	0.0202	0.0004	-0.0043
	4	0.0002	-0.0006	0.0001	0.0137	0.0001	-0.0033
	5	0.0001	-0.0004	-0.0001	0.0086	0.0001	-0.0023
	Cum.	0.0033*	-0.0005	-0.0033	0.0720	0.0033	-0.0209
Storms	0	-1.00E-04	-0.0020	-0.0108**	0.01520	0.0037	-0.0019
	1	0.0016	-0.0058	0.00430	-0.00510	0.0021	-0.0028
	2	-1.30E-03	-0.0059	0.00090	-0.03670	0.0011	-0.0045
	3	-2.00E-04	-0.0036	0.00100	-0.03130	0.0007	-0.004
	4	-2.00E-04	-0.0022	0.00040	-0.02120	0.0004	-0.0029
	5	-1.00E-04	-0.0013	0.00030	-0.01310	0.0002	-0.002
	Cum.	-1.0E-04	-0.0206	-0.0041	-0.0921	0.0079	-0.0178
Floods	0	0.001	-0.0058	0.002	-0.0513**	-0.0002	-0.0011
	1	0.0031**	0.006	-0.0036	-0.0529*	0.0032	6.00E-04
	2	0.0022**	0.0011	0.0041	-0.0422	1.30E-03	0.0008
	3	0.0007**	-0.0006	0.0008	-0.0297	0.0008	0.0011
	4	0.0003**	-0.0006	6.00E-04	-0.0182	4.00E-04	0.0012
	5	0.0002*	-0.0005	3.00E-04	-0.0108	3.00E-04	0.0011
	Cum.	0.0074	-0.0004	0.0040	-0.2048*	0.0057	0.0036
Droughts	0	-0.0029	0.0220	-0.0054	0.0378*		
	1	-0.0024	0.0247	0.0005	0.0665**		
	2	-0.0035	0.0557**	-0.0011	0.1286**		
	3	-0.0014*	0.0459**	-0.0013	0.1022**		
	4	-0.0007*	0.0305**	-0.0008	0.0671**		
	5	-0.0003	0.0187**	-0.0004	0.0407**		
	Cum.	-0.0109	0.1972**	-0.0083	0.4426**		
Number of Observations		1244	1244	1244	1244	1277	1277
Number of Countries		30	30	30	30	27	27

Note: **p<0.05. *p<0.10. significance tests are one-tail tests. Endogenous variables include GDP growth and CPI growth. Exogenous variables include storms, floods, droughts, landslides, extreme temperatures, wildfires, world GDP growth, and systemic banking crises.

Table 14: Results from alternative specification, including control for banking crises. Note: The outcome variable for climatic disasters is the total number of people affected by the disaster.

		Low Income				High-Income	
		Moderate Disasters		Severe Disasters		Moderate Disasters	
Natural Disaster Type	Year	GDP growth	CPI growth	GDP growth	CPI growth	GDP growth	CPI growth
All Natural Disasters	0	0.0003	-0.0013	-0.0045**	0.0012	-0.0038	-0.0029
	1	0.0020**	0.0015	0.0004	0.0016	0.0019	-0.0037
	2	0.0009	-0.0004	0.0036	0.0266	0.0013	-0.0050
	3	0.0004	-0.0009	0.0006	0.0216	0.0001	-0.0045
	4	0.0002	-0.0008	0.0003	0.0142	0.0003	-0.0036
	5	0.0001	-0.0006	-0.0001	0.0085	0.0002	-0.0026
	Cum.	0.0036*	-0.0024	-0.0005	0.0735	0.0013	-0.0221
Storms	0	-0.0008	-0.0018	-0.0091**	0.01360	0.0037	-0.0024
	1	0.0013	-0.0048	0.0005	-0.0092	0.0026	-0.0031
	2	-0.0005	-0.0045	0.0076	-0.0474	-0.0001	-0.0050
	3	-0.0001	-0.0028	0.0024	-0.0431	0.0004	-0.0045
	4	-0.0001	-0.0017	0.0014	-0.0294	0.0001	-0.0035
	5	-0.0001	-0.0010	0.0007	-0.0182	-0.0001	-0.0024
	Cum.	-0.0001	-0.0165	-0.0034	-0.1335	0.0066	-0.0207
Floods	0	0.0014	-0.0068	0.0013	-0.0539**	-0.0002	-0.0014
	1	0.0033**	0.0044	-0.0008	-0.0584*	0.0020	-0.0006
	2	0.0016**	-0.0002	0.0022	-0.0502	-0.0009	0.0001
	3	0.0006**	-0.0013	0.0009	-0.0341	0.0001	0.0004
	4	0.0003**	-0.0012	0.0006	-0.0208	-0.0002	0.0004
	5	0.0001*	-0.0009	0.0003	-0.0120	-0.0001	0.0003
	Cum.	0.0072	-0.0058	0.0043	-0.2291*	0.0010	-0.0009
Droughts	0	-0.0017	0.0218	-0.0051	0.0440*		
	1	-0.0032	0.0207	0.0009	0.0766**		
	2	-0.0022	0.0581**	-0.0029	0.1540**		
	3	-0.0012*	0.0480**	-0.0008	0.1197**		
	4	-0.0007*	0.0318**	-0.0008	0.0769**		
	5	-0.0004	0.0193**	-0.0007	0.0454**		
	Cum.	-0.0109	0.1994**	-0.0053	0.5164**		
Number of Observations		1141	1141	1141	1141	1223	1223
Number of Countries		29	29	29	29	27	27

Note: **p<0.05. *p<0.10. significance tests are one-tail tests. Endogenous variables include GDP growth and CPI growth. Exogenous variables include storms, floods, droughts, landslides, extreme temperatures, wildfires, world GDP growth, and terms of trade.

Table 15: Results from alternative specification, including control for banking crises. Note: The outcome variable for climatic disasters is the total number of people affected by the disaster.