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Abstract
This study investigates the average and median impact of large natural disasters on government debt. It includes 163 countries for the period 1971 to 2014. We apply a panel synthetic control method which constructs a counterfactual for the disaster country. This synthetic control group consists of nondisaster countries that closely resemble the macroeconomic, institutional, geographical and other characteristics of disaster country in the predisaster period. We investigate the difference in government debt between the disaster countries and their respective synthetic control groups. Our findings reveal a considerable increase in government debt for most damaging and deadliest disasters. This study also deals with possible endogeneity of the disaster identification method by using the disaster magnitude. Government debt, on average, increases by 11.3% of GDP compared to the synthetic control group. The median effect on government debt is 6.8% of GDP. Some natural disasters result in a debt increase over 20% of GDP. When we investigate only the 0.5% largest natural disasters, this study finds even larger effects on government debt.

Keywords: government debt, government finances, natural disasters, panel synthetic control method, disaster identification;

JEL classification: E62, Q51, Q54, Q58;

The views expressed here are solely those of the author and do not in any way represent the view of the institution to which he is affiliated.

1. Introduction

Large natural disasters, such as the Haiti earthquake, cyclone Nargis, hurricane Mitch or the Indian Ocean earthquake and tsunami, have caused tremendous human suffering and economic destruction. These natural disasters have an adverse impact on the macroeconomic situation, and consequently the government's fiscal position, in the impacted country. Several scientific sources suggest that anthropogenic climate change increases the frequency of extreme weather events and change the climate in certain regions tremendously (Raschky, 2008). Consequently, the macroeconomic costs are projected to increase over time. In the words of the Global Assessment Report on Disaster Risk Reduction (GAR) (2013, p. iii), "the worst is yet to come."

[Insert Figure 1, here]

Governments feel that disaster relief is their moral obligation. In addition, it is also of a politician's self-interest to respond in a decisive manner. Governments are typically held accountable for their response to disasters (Cavallo and Noy, 2010).[3] The fiscal impact of natural disaster results partly from the (immediate) provision of emergency aid and relief. Disaster reconstruction is a long-term effort because rebuilding houses, schools, hospitals and other infrastructure takes time. This effect will also influence the fiscal position in a medium- to long-term. There are also indirect effects on the government's financial position. These effects also include indirect costs, like production disruptions or additional government expenses. There are also effects on the revenue side because production disruptions, for example, lead to lower tax revenues. Furthermore, the current account position worsens as the exporting capacity is hampered, and imports for reconstruction surge (Borensztein *et al.*, 2009). The reconstruction efforts also can crowd-out the other productive expenditures, such as education or infrastructure, which might seriously hamper economic development. Another issue is how the natural disaster influences the country's debt sustainability. Higher interest rates can lead to higher budget deficits and, as a consequence, higher levels of government debt. Standard & Poor's (S&P) (2015) notes that direct- and indirect economic losses adversely affect the country's credit worthiness.

This study estimates the *ex-post* disaster costs, more specifically the effect on government debt. The aim of this study is to provide a better estimation of the impact on government debt when a large natural disaster strikes a country. There have been some attempts to investigate the macroeconomic effect of natural disasters on the developed and developing economies. These studies mostly concentrate on the

[3] The consequences of large natural disaster are also massive from a social welfare perspective. Calibrations indicate that society would willingly reduce GDP by around 20 percent each year to eliminate rare disasters (Barro, 2009).

effect on output (see amongst others, Albala-Bertrand, 1993; Skidmore and Toya, 2002; Noy, 2009; Strobl, 2012). These studies find mixed evidence on whether there is an adverse impact on output. These mixed findings are often attributed to different levels of income and development. There are a limited number of studies which quantify the effect of natural disasters on the government's fiscal position (see Rasmussen, 2004; Noy and Nualsri, 2011; Acevedo, 2014). Most of these studies only focus on a very limited selection of countries, especially Caribbean countries. Although these studies on the fiscal position have contributed to the understanding of the fiscal costs of natural disasters, more generalizable conclusions are necessary. Our analysis of government debt includes the effects on output, government revenue, government spending and inflation on the government's fiscal position in the aftermath of a natural disaster.

This study investigates the largest natural disasters in the period 1971 till 2014. Our study includes over 160 countries. We apply a panel synthetic control methodology which allows us to observe how the disaster affects government debt. The econometric analysis reveals the path of government debt as if no natural disaster has occurred. In this way, it is possible to assess the effect of the natural disaster on government debt. The disaster effect is investigated up to ten years after the natural disaster. Furthermore, this study applies different disaster identification strategies to deal with the possible endogeneity of these strategies. We define large disasters based on the total number of people affected over the country's population, the number of deaths over the country's population and damages as a percentage of GDP.[4] Besides the standard disaster identification strategy, we use the intensity of the impact in terms of land area which puts a greater emphasis on the benefits of geographical size. For example, large countries can diversify or limit the impact due to their geographical advantage. Moreover, this study also identifies the occurrence of natural disaster in an exogenous way by using the severity of the natural disaster (e.g. the Richter scale, wind speed etc.). This method deals with the possible endogeneity if disasters are defined according to disaster outcomes. For example, high incomes countries have higher damages in terms of GDP because there is a larger capital stock (e.g. machines, houses, infrastructure etc.), whereas low income countries are primarily impacted in terms of deaths and population affect. This study is only one of the few studies (except, for example, Klomp, 2016) which deal with this issue.

This study makes numerous contributions to the literature on macroeconomic costs of natural disasters. Firstly, this study is a comprehensive attempt to estimate the effect of natural disasters on the government debt. We employ all possible controls which can potentially influence the height of government debt (e.g. domestic and/or external sovereign default). Other studies on the macroeconomic

[4] We use the population of the previous year as the population in the disaster year is influenced by the disaster impact. For the same reason, this study uses GDP of the previous year.

impact of natural disasters focus on the output effects. Secondly, this study uses the panel synthetic control method. We employ this innovative econometric methodology which accounts for long-term underlying trends in the macroeconomic environment to estimate a counterfactual. This counterfactual allows us to isolate the effect of the natural disaster on the government debt. Third, most previous studies either estimate the short- or long-term effect of the natural disaster on macroeconomic indicators. Our economic methodology enables us to present the entire postdisaster trajectory up to 10-years after the natural disaster. In other words, we present the short-, medium and long-term effect on government finances. Fourth, we apply different disaster identification strategies. Different levels of development can determine whether a natural disaster is identified. For example, high income countries have more expensive assets which results in higher damages in terms of GDP. This study deals with this identification problem by applying an exogenous estimation of the occurrence of a natural disaster. Fifth, for cost-benefit analysis reasons, policymakers need an estimation of the (potential) fiscal costs of natural disaster. These costs' assessments are needed for, for example, the evaluation of prevention measures.

This study is structured as follows. The next section introduces the natural disaster literature on the macroeconomic impact of natural disasters. In section 3, we discuss our methodology and data, and section 4 highlights our results. Section 5 presents an exogenous disaster identification strategy and its results. We discuss our policy recommendation in section 6 and section 7 concludes.

2. Empirical literature

Most of the macroeconomic literature on the costs of natural disasters focusses on the consequences for output. Some studies find positive effect on economic growth (see Albala-Bertrand, 1993; Skidmore and Toya, 2002). These studies rely on a Schumpeterian creative destruction argument. A natural disaster can destroy the capital stock, and this will lead to growth in the reconstruction phase. However, most studies find a negative effect on output (see, for instance, Auffret, 2003; Rasmussen, 2004; Heger *et al.*, 2008; Noy, 2009; Hochrainer, 2009; Raddatz, 2009; Noy and Nualsri, 2011; Strobl, 2012; Fomby *et al.*, 2013; Acevedo, 2014).

The severity of the natural disaster and the state of development are deemed important for the output costs[5]. According to Cavallo and Noy (2010), including the severity of the disaster might bridge the seemingly contradicting findings on output growth above. Small disasters only result in small damage, and

[5] We only list the most important aspect. Other aspects might also matter. For example, the state of economy before the disaster could influence the disaster costs. Hallegate and Ghil (2007) show that the growth effect is larger during an expansion of economic activity because there is no excess production capacity left. There are many more potential influences (e.g. short- vs. long-term output effects) but these are beyond the scope of this paper as the focus is on the fiscal costs. For a comprehensive literature survey on the effects of natural disaster on output, see Cavallo and Noy (2010).

they allow for a quick recovery. Large natural disasters can strain a country's capabilities, which hamper the possibilities for a quick recovery. Another important aspect is the state of development of the country in question. There is consensus that the state of development matters for the costs of a natural disaster (see, amongst others, Anbarci *et al*., 2005; Kahn, 2005; Toya and Skidmore, 2007; Noy, 2009; Strobl, 2012). Whether this is a linear relationship remains a point for discussion. Kellenberg and Mobarak (2008), for example, identify a nonlinear relationship between per capita GDP and the costs of natural disasters. Although output is one of the channels by which a natural disaster could influence the height of government debt, it is not the focus of our research. The discussion of the output effect, however, gives some insights into the possible effects on government debt, and which aspects partly determine the costs of a natural disaster.

In methodological terms, our study follows Cavallo *et al*. (2013). They investigate the effect of a large natural disaster on output. They compute the counterfactual using synthetic controls. Cavallo *et al*. (2013) do not find a decline in output for large natural disaster when they control for political changes. However, they investigate only a very limited number of disasters. There are some natural disaster case studies which use the synthetic control methodology. Fujiki and Hsiao (2015) investigate the Great Hanshin-Awaji earthquake that took place on January 17, 1995. Their findings illustrate that there were no persistent earthquake effects. DuPont *et al*. (2015) investigate the same disaster using the synthetic control methodology. They find that the population size and the average income level in Kobe are lower 15 years later than without the earthquake. Thus, the earthquake has a permanent negative impact, especially in areas closer to the epicenter. Besides Japan, there are case studies on Hawaii. Coffman and Noy (2011) estimate the long-term impacts of hurricane Iniki on the Hawaiian island of Kauai in 1992. They find that Kauai's economy still should recover after 18 years. Their findings also show that the island's current population is 12 per cent smaller than without the occurrence of hurricane Iniki. In addition, aggregate income and the private sector jobs are proportionally lower. In another study on Hawaii, Lynham *et al*. (2017) investigate the consequences of a tsunami struck the city of Hilo on May 23, 1960. Their findings reveal that unemployment was still 32% higher and population was still 9% lower 15 years after the tsunami. In our study, we use the synthetic control method to determine the effect of a natural disaster on government's finances. To our knowledge, we are the first applying this method for the effects on the government's fiscal position.

There are studies, which quantify the impact of natural disasters on the government's fiscal position. These attempts focus mostly on the disaster-prone region of the Caribbean. Rasmussen (2004) investigates the macroeconomic implications of natural disasters in the Caribbean for the period 1970 to 2002. His analysis includes the effect on the fiscal balance. It should be noted that his study focusses on small island states which are member of the Eastern Caribbean Currency Union (ECCU). He stresses that there is a large variation in outcomes for the fiscal balance. However, he finds that the median public debt will increase by a cumulative 6.5 percentage points over three years. This results from a small reduction in revenue, and an increase in spending. Other findings are a median reduction in real GDP growth by 2.2 percentage points and a median increase of the current account deficit by 10.8 percent of GDP in the year of the disaster.[6]

Heger *et al*. (2008) also investigates the macroeconomic costs of a natural disaster for the Caribbean. They find a strong decline in GDP per capita in short-term but a subsequent recovery in the following years. Their findings reveal that external debt[7] decreases in the year following a natural disaster. This may, however, be explained though the flows of aid to countries and the subsequent relief of external debt that is granted in the course of reconstruction (Heger *et al*., 2008). External debt relief might be insufficient to lower the entire public debt. As a result, Rasmussen (2004) finds a median increase of 6.5 percentage points.

In a more recent paper, Acevedo (2014) investigates the effect of storms and floods on GDP per capita and public debt. He also focusses on the Caribbean[8]. His sample covers the period 1970 through 2009 using a panel vector autoregression (VAR) model. He finds a negative effect on GDP per capita growth for both types of disasters. However, the evidence on public debt is mixed. He finds that debt only increases with floods. Another notable finding is the effect of debt relief. He finds weak evidence that debt relief contributes to ease the negative effects of storms on debt (Acevedo, 2014).

Noy and Nualsri (2011) estimate the fiscal consequences of a natural disaster for a broader set of countries. They obtain their disaster data from the EM-DAT database and their dataset includes 22 developed and 20 developing countries. Contrary to most studies, they use quarterly data employing a panel VAR framework[9]. Their main finding is that developed economies behave counter-cyclical, whereas developing economies act counter-cyclically (reducing spending and increasing revenues). The effects on the fiscal consequences are also split along these lines. For developed countries, they find that the government outstanding debt increases following the shock (1.07% of GDP), accumulating more than 8% of GDP over a year and a half (Noy and Nualsri, 2011). This is the consequence of higher spending and lower revenue which translates into an increase in borrowing. In contrast, developing economies pursue pro-cyclical policies. As a result, government outstanding debt decreases.

[6] These very large same-year effects are all the more striking when one considers that all the events occurred in the second half of the year (Rasmussen, 2004).
[7] Raddatz (2009) focusses on the growth effects of natural disasters but it also touches briefly on the external debt position. He finds that the debt position before the disaster does not affect the output loss.
[8] Antigua and Barbuda, The Bahamas, Barbados, Dominica, Dominican Republic, Grenada, Haiti, Jamaica, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines and Trinidad and Tobago.
[9] Their panel VAR framework also controls for the business cycle.

Melecky and Raddatz (2011) investigate the economic and fiscal consequences of a natural disaster for middle and high-income countries over the period 1975 through 2008. They divide the disasters in three broad categories: geological disasters, climate disasters and a residual group (*e.g.* famines, industrial accidents etc.). The authors find that, on average budget, deficits increase only after climatic disasters, but for lower-middle-income countries, the increase in deficits is widespread across all events (Melecky and Raddatz, 2011). They confirm the finding by Raddatz (2009) that higher initial government debt has no effect on the size of the deficit and the development of output. They also find that financial development shields an economy from the consequences of disasters. However, these lower costs go together with expanding budget deficits. Melecky and Raddatz (2011) also find that insurance penetration influences the costs of a natural disaster, as high insurance penetration lowers the output and deficit consequences of a disaster.

Klomp (2015) focusses on the sovereign default premium and natural disasters. He obtained a dataset which includes more than 380 large-scale natural disasters for about forty emerging market countries in the period 1999–2010. He finds that the sovereign default premium increases significantly after a natural disaster. In other words, investors perceive natural disasters as an adverse shock that makes the government debt less sustainable and eventually triggers a sovereign default (Klomp, 2015)[10]. This increase in sovereign default premium will translate into higher government bond rates. In other words, borrowing becomes more expensive when it is needed most.

Klomp (2017) also investigates whether natural disasters can trigger a sovereign debt default. He finds evidence that a natural disaster increases the onset probability of a sovereign debt default by about three percentage points. The probability of a sovereign debt default also depends on the frequency of the occurrence of a large-scale natural disaster. Since the median country in our sample is projected to be hit approximately three times by a large-scale event in the next twenty years, the average default risk in our sample would then be about ten-percentage points (Klomp, 2017). Klomp (2017) distinguishes the effects between different disaster types. He finds that particularly major earthquakes and storms increase the likelihood of sovereign default.

Another motivation to estimate the fiscal cost is to better enable governments to directly insure against disaster losses, indirectly through the issuance of catastrophic bonds (cat bonds), or through precautionary saving (Borensztein *et al*., 2009). Borensztein *et al*. (2009) use the example of Belize's public finances to demonstrate the virtues of insurance. Their main finding is that cat bonds can improve debt sustainability. The methodology employed makes it possible to estimate the appropriate level of

[10] He finds heterogeneous results for different type of disaster. It turns out that geophysical and meteorological disasters increase the credit default premium in both the long run as well as in the short run, while hydrological disasters have only a temporary effect (Klomp, 2015).

insurance, which for the case of Belize is a maximum coverage of US$120 million per year (Borensztein *et al*., 2009). Whether these results apply to a wider range of countries remains an open question.

In summary, there is some evidence that indicates that government debt increases after a natural disaster. However, whether the evidence is generalizable beyond the Caribbean region, or holds for both developing and developed countries remains open for discussion.

3. Methodology and data

3.1. Data

We investigate the impact of natural disasters on government. In total, we include 163 countries which consist of disaster countries as well as nondisaster countries. Table 1 shows the list of the countries included in this study, whereas Figure 2 shows a map of the included countries. It is clear from this figure that the countries are spread equally across the globe. This allows us to study different types of natural disasters, such as climatological and seismological disasters. Furthermore, the geographical distribution makes our results more generalizable than when a region is under- or overrepresented in our sample.

[Insert Figure 2 and Table 1 here]

We obtain the disaster data from the EM-DAT dataset.[11] Our sample includes extreme temperature, storm, wildfire, drought, mass movement (dry), volcanic activity, earthquake, landslide and flood events from 1971 to 2014. The EM-DAT database uses some criteria before a natural hazard qualifies as a natural disaster. One of these criteria must be met before the natural hazard is defined as a natural disaster: 10 or more deaths; 100 or more people affected, injured or homeless; or a declaration of a state of emergency or an appeal for international assistance.[12] The EM-Data database includes the type of disaster, the frequency of occurrence, total deaths, injured, homeless and affected, and the total damage per country-year. The reported damage is direct damage, whereas this study mostly investigates the secondary effects of the disaster, especially its effect on government debt. Consequently, we use direct damages as disaster identification strategy because direct damages approximate the severity of the natural disaster. The macroeconomic data are obtained from different sources amongst others, UNSTAT and the World Bank (see for more details, Table 31).

This study uses the EM-DAT database because it is the most comprehensive disaster dataset available. We are aware that it has some notable drawbacks. The first drawback is that the dataset is

[11] EM-DAT (2016a). The CRED/OFDA International Disaster Database, D. Guha-Sapir, R. Below, P. Hoyois, Université Catholique de Louvain, Brussels. www.emdat.be.
[12] EM-DAT (2016b). EM-DAT guidelines. Accessed 30 March 2016 at http://www.emdat.be/guidelines.

compiled from government reports and insurance statements with no common methodology and little transparency in their calculation (Pelling *et al*., 2002). Consequently, the credibility of the estimates might differ between the different sources. A possible reason for this is put forward by Albala-Bertrand (1993). He notes developing country governments might overestimate the amount of damages with the intention to receive more disaster aid. It can even be the case that governments try to conceal the occurrence of a natural disaster. Our study investigates only the largest natural disasters which make it more difficult to conceal the occurrence. Furthermore, the largest disasters are recorded by multiple sources which enable a better estimation of the disaster consequences. The second drawback is the potential underestimation of the natural disaster costs. Many impacts, such as loss of human lives, cultural heritage, and ecosystem services, are difficult to value and monetize, and are thus poorly reflected in estimates of losses (IPCC, 2012). Our study will not monetize the nonmonetary consequences of the impact of a natural disaster. Our focus is on the consequences of the impact of a natural disaster on government debt which only has a monetary value. A third potential drawback is rooted in the improvements in telecommunications and the invention of the internet which might lead to improvements in the reporting of natural disasters. This can bias reporting over time. Even though this could be true, it is unlikely to influence our results because our study only uses the largest natural disasters which would have been reported anyway. A fourth drawback is the occurrence of specific climate even in a specific period of the year, like hurricanes. Our data does not report the date of occurrence; thus, we are unable to correct for this. However, our study investigates up to ten years after the occurrence of the natural disaster. Consequently, this has only a limited influence on our estimates. This is an issue for studies that only investigate the short-term effects of the impact of natural disasters.

This study defines a natural disaster in a different way than the EM-DAT database. Our panel synthetic control methodology requires a mix of disaster and nondisaster countries. Thus, we warrant large natural disasters, whereas the EM-DAT database includes many small natural disasters. The perception of the public of a natural disaster is a large catastrophic event, resulting in destruction, deaths and human suffering. Most importantly, we study the impact on government debt which requires a large natural disaster. The EM-DAT database provides the total number of deaths, the total number of affected and the direct damages. This study uses nine disaster identification strategies for robustness reasons. First, we use the standard natural disaster identification strategy in natural disaster literature. We adjust the EM-DAT indicators to reflect the size of the population or the economy: the total number of deaths over population, the total number of affected over population and damages over GDP.[13] Second, we apply a more

[13] The reader should note that we take the population of the previous year to prevent to account for possible endogeneity. The same holds for GDP which is used to calculated the damages as a percentage of GDP.

exogenous disaster indicator which relates to the land area. This captures the intensity of the natural disaster by dividing deaths, total affected population and damage over squared kilometers. Third, we identify natural disasters exogenously by using the severity of a disaster (e.g. Richter scale, wind speed, temperature, precipitation etc.). This study uses the composition of the disaster identified by the standard natural disaster identification strategy.[14] Table 2 reveals that if we use the standard identification strategy the different indicators identify different types of natural disasters.

For the disaster indicators, we use six parts of the disaster severity distributions. We classify the 0.5%, 1%, 1.5%, 2%, 2.5% and 5% largest natural disasters. Our study defines a country-year observation a disaster when the country experiences a natural disaster in the top 2.5% of most severe natural disasters in our sample. We define the country-year observations between the 2.5% and 5% of the largest natural disasters as nonclassified. We qualify all other country-year observations as nondisasters. Tables 3 and 4 show the summary statistics of the disaster impact. Disaster country-year observations result in the death of 0.05% of the population, 36.6% of the population is affected and the damage amounts to 19.9% of GDP. It is noteworthy that the most severe disasters have an even larger impact. In contrast, nondisaster country-year observations reveal 0% deaths of the population, 0.24% of the population affected and a damage of 0.03% of GDP. From these disasters, we classify the disaster countries.

[Insert Table 3 and Table 4 here]

The disaster classification is the basis of our country classification. We classify the countries into three categories (nondisaster countries, disaster countries and nonclassified countries) based on the disaster severity distribution. The synthetic control group which is used for the estimation of the counterfactual consists of nondisaster countries. This study adds the category nonclassified to the categories used by Cavallo *et al*. (2013). This inclusion prevents that a country just above the disaster threshold is qualified as a disaster country and just below as a nondisaster country. The nonclassified countries are not used in our analysis because they might potentially influence our results. Although this additional category lowers the number of nondisaster countries, we deem the possible contamination as much more important. Especially, since Abadie *et al*. (2010) reveals that the synthetic control method requires no large number of comparison units in the donor pool.

Figure 3 and Figure 4 give a graphical representation of the approach used to classify the countries in disaster, nondisaster or nonclassified. These figures present the nondisaster countries to the left of the dashed line, whereas the nonclassified countries are between the dashed lines. All country-year

[14] The fixed composition is necessary because the disaster severity indicators, such as temperature and Richter scale, are not comparable.

observations to the right of the right dashed line are classified as disaster countries. When one or more country-year observations are in the natural disaster part of the graph (the largest 2.5% of natural disasters), the country is classified as a disaster country. If the country is not classified as a disaster country, we classify a country as a nonclassified country if one or more of the country-year observations are in the nonclassified part. Those are the countries which experience at least one disaster between 2.5% and 5% largest natural disasters in the disaster severity distribution, and no disaster which qualifies for the 2.5% largest disasters. When the country is not classified as a disaster or a nonclassified country, it is classified as nondisaster countries. Nondisaster countries have not experienced one of the 5% largest natural disasters.

[Insert Figure 3 and Figure 4 here]

3.2. Methodology

Our study does not directly test for the alternative theories of natural disaster costs. We focus on the impact on government debt up to ten years after the natural disaster. In other words, this study shows the development of government debt compared to the case when no disaster would have occurred. We use the synthetic control method developed by Abadie and Gardeazabal (2003) and Abadie *et al*. (2010). This methodology produces a counterfactual for the disaster country. This counterfactual consists of a mix of nondisaster countries. The selection and weighting of nondisaster counties is based on the resemblance of these countries with the disaster country based on several characteristics. The synthetic control method makes explicit the contribution of each comparison unit to the counterfactual of interest (Abadie *et al*, 2015). The advantage for disaster research is that predisaster resemblance leads the selection of countries in the counterfactual. Furthermore, it prevents other issues which occur if we simply extrapolate the government debt path of the disaster countries. By design, the synthetic control estimations cannot fall outside the minimum and maximum values observed for the nondisaster control group.[15]

Following Abadie and Gardeazabal (2003), Abadie *et al*. (2010) and Cavallo *et al*. (2013), we estimate the synthetic control case-studies. The starting point is equation (1).

$$\alpha_{1t} = DEBT_{1t}^{I} - DEBT_{1t}^{N} = DEBT_{1t} - DEBT_{1t}^{N} \quad (1)$$

[15] The synthetic control method constructs a counterfactual from a pool of nondisaster countries. The weights of the selected countries lay between zero and one and taken together sum to one. This means that the counterfactual does not lay outside the observed observations for the variable of interest. Therefore, the method does not suffer from extrapolation bias. This is especially important as extrapolating predisaster trend might give unreasonable estimates of the counterfactual, considering the other countries in the sample.

$DEBT_{it}^{N}$ denotes government debt for country i at time t without the occurrence of a natural disaster, for countries $i = 1, \dots, J + 1$, and time periods $t = T_0 - 10, \dots, T_0 + 10$. $J + 1$ is the number of countries and T denotes time. The number of predisaster periods is defined as $T_0 - 10 < T_0$, and the postdisaster period is from period T_0 to $T + 10$. We use $DEBT_{it}^{I}$ to denote the government debt in postdisaster period. In other words, it is the government debt that is observed for country i at time t if a natural disaster has occurred. In accordance with Cavallo *et al*. (2013), we also deem that the occurrence of a natural disaster is unpredictable.[16] In paragraph 5, we relax this assumption. Therefore, the government debt is not influenced before the occurrence of the disaster itself, resulting for $t \in \{T_0 - 10, \dots, T_0 - 1\}$ and all $i \in \{1, \dots, N\}$ in $DEBT_{it}^{I} = DEBT_{it}^{N}$.

Notice that we are interest in the difference between the country i subject to a natural disaster and the country i subject to the 'what-if'-scenario of no natural disaster. Thus, we are interested in the disaster effect, $\alpha_{it} = DEBT_{it}^{I} - DEBT_{it}^{N}$, for country i at time t in the postdisaster periods $T_0, T_0 + 1, T_0 + 2, \dots, T_0 + 10$. The effect of the natural disaster on government debt is given by calculating the alphas for the postdisaster period $(\alpha_{1,T_0}, \dots, \alpha_{1,T_0+10})$. Notice that the size of the disaster effect can change over the postdisaster period. Therefore, the estimates allow for a study of the postdisaster trajectory. In this way, this study captures the potential short-, medium- and long-run effect of the disaster. For the postdisaster period, $t \geq T_0$,

The 'what-if' scenario of no natural disaster is not observed. The synthetic control method allows us to come up with an approximation of this effect, $DEBT_{1t}^{N}$. An important pre-condition to estimate $DEBT_{1t}^{N}$ is that it is not affected by the same or another natural disaster. This can be problematic because the synthetic control countries also suffer from the consequences of a natural disaster. We solve this by imposing a strict natural disaster threshold to the nondisaster countries (also called, donor countries) and the exclusion of countries that experience large idiosyncratic shocks.[17] The synthetic control group $(DEBT_{1t}^{N})$ is composed of multiple nondisaster countries with specific weights which add up to one. The weight falls in the interval $[0, 1]$. The countries with positive weights are used to construct a counterfactual for country i. A selection of controls is used to determine the resemblance of the donor pool countries. These controls consist of macroeconomic, institutional, geographical and other country

[16] This assumption holds for certain aspects of the occurrence of a natural disaster. For example, the specific timing of occurrence is unpredictable (Cavallo *et al*., 2013).

[17] This study excludes nondisaster countries from the synthetic control pool if they experience a change of government debt in 0.5% or 99.5% of the distribution. In other words, we exclude these nondisaster countries experience an extreme positive or negative shock to their debt stock in the postdisaster period.

characteristics and circumstances. The resemblance between the disaster countries and the nondisaster countries is determined in the predisaster period $(T_0 - 10, \ldots, T_0 - 1)$. This study choses a ten years' predisaster period which assures an accurate estimation of the synthetic control group. Thus, the resemblance of the disaster country characteristics is not taken for a short period, which might be influenced by unique macroeconomic, financial market or political circumstances. This study also presents the postdisaster period trajectory over ten years after the occurrence of the natural disaster $(T_0, \ldots, T_0 + 10)$. Abadie *et al*. (2015, p. 500), for example, state that "a sizable number of post-intervention periods may also be required in cases when the effect of the intervention emerges gradually after the intervention or changes over time." This can potentially hold for the effect of a natural disaster. However, most studies focusing on the macroeconomic impact of natural disaster focus on the short- to medium term effect.

We present a synthetic control case-study approach for simplicity reasons. The panel synthetic control analysis will be discussed later on. In this case, only one country experiences a natural disaster. The donor pool of nondisaster countries consists of J countries, all countries except the disaster country (which is $j = 1$).[18] The estimation process considers a $(J \times 1)$ vector of weights $W = (\omega_2, \ldots, \omega_{J+1})'$. These weights are conditioned to $\omega_j \geq 0$ for the nondisaster countries, $j = 2, \ldots, J + 1$, and their respective weights add up to one, $\omega_2 + \omega_3 + \ldots + \omega_{J+1} = 1$. The separate weights sum up to the synthetic control group. This procedure allows us to estimate equation (2):

$$\hat{\alpha}_{1t} = DEBT_{1t} - \sum_{j=2}^{J+1} \omega_j DEBT_{jt} \qquad (2)$$

The reader should note that an exact match of the synthetic control group and the disaster country is often unattainable. Therefore, the method selects the weights based on the best possible match between the predisaster trajectory of the disaster country and the donor pool. The procedure minimizes the Root Mean Square Percentage Error (RMSPE)[19] in the predisaster period. Figure 5 shows an example of a synthetic control case-study for Belize. In the figure, the trajectory of disaster country and the synthetic control group closely match in the predisaster period. A good match in the predisaster period increases the credibility of the postdisaster estimation.

[Insert Figure 5 here]

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[18] The reader should note that, in our study, our donor pool is smaller because of the inclusion of multiple natural disasters, the identification of nonclassified countries and the exclusion of nondisaster countries which experience a large idiosyncratic shock in the postdisaster period.

[19] The RMSPE is calculated as, $RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2}$.

Our goal is to provide generalizable conclusions of the effect on the government's fiscal position after a natural disaster. The estimates above are for one country $(\hat{\alpha}_{1,T_0}, \dots, \hat{\alpha}_{1,T_0+10})$. We estimate the country-level disaster effect for multiple natural disasters (G). In other words, G is the number of natural disasters in our sample. Equation (3) gives the average or median effect of natural disasters on government debt.[20]

$$\bar{\alpha} = \left(\bar{\alpha}_{T_0}, \dots, \bar{\alpha}_{T_0+10}\right) = \frac{1}{G}\sum_{g=1}^{G}(\hat{\alpha}_{g,T_0}, \dots, \hat{\alpha}_{g,T_0+10}) \qquad (3)$$

The synthetic control studies are estimated using several country characteristics. The selection of controls is obtained from the economic growth literature (see Islam, 1995; Barro and Sala-i-Martin, 2003) and the literature on macroeconomic effects of natural disasters (see Noy, 2009; Cavallo *et al*., 2013). Our study uses GDP growth, current account (% of GDP), openness (% of GDP), population density, population growth, GDP per capita, GDP share of agriculture, hunting and minerals[21], general government consumption (% of GDP) and gross capital formation (% of GDP). In some specifications, we include additional controls, namely the average latitude[22], years of schooling and the total societal and interstate major episodes of political violence. These indicators are identified in the literature as important determining factors for the costs of natural disasters. For example, the state of the business cycle can potentially influence the *ex post* disaster costs according to Hallegate and Ghil (2007). Other indicators focus on the sensitivity of the economy for such events. Sectors that are closely related to climate, such as agriculture, tourism, and water, are facing a great burden by extreme events (IPCC, 2012). Numerous studies also stress the importance of development. Consequently, we include GDP per capita to capture the level of development. Following Abadie *et al*. (2010), we also include pre-intervention outcomes of our variable of interest[23] in some specifications. This means, for example, that we include the predisaster government debt path $(DEBT_{T_0-10}, \dots, DEBT_{T_0-6})$ as input for the synthetic control group[24]. Table 5

[20] Contrary to other nonpanel synthetic control studies, this study does not utilize in space placebo estimations. We can construct a confidence interval due to panel approach whereas nonpanel synthetic control studies need to rely on the p-values found with the placebo analysis.

[21] Sectors that are closely related to climate, such as agriculture, tourism, and water, are facing a great burden by extreme events (IPCC, 2012).

[22] We include the average latitude to account for climatological circumstances.

[23] If the number of pre-intervention periods in the data is large, matching on pre-intervention outcomes helps control for unobserved factors and for the heterogeneity of the effect of the observed and unobserved factors on the outcome of interest (Abadie *et al*., 2015).

[24] Following Kaul *et al*. (2016), we do not include the entire predisaster period of the outcome variable in our specification. Furthermore, we estimate a couple of specifications where the outcome variable is not included as a predictor.

presents summary statistics of the variables included in the synthetic control analysis. It reveals that the government debt, on average, is equal to 61.6% of GDP. Furthermore, the Table 5 shows the different specifications of our five models. It specifies which variables are included in the different models. The number of observations is lower for the additional variables because these variables are not available for our entire sample. Table 6 reveals the pair-wise correlations between the indicators, which are relatively low.

[Insert Table 5 and Table 6 here]

4. Results

The results that are presented in this section are the outcomes of the panel synthetic control estimations. This equation enables us to present the difference in government debt between the disaster country and its synthetic control group in a percentage of GDP. A positive value indicates higher government debt for the disaster county than for the synthetic control group, and *vice versa*. For convenience reasons, we normalize the data by setting the outcome of the year preceding the disaster year $(T_0 - 1)$ equal to zero. This makes the interpretation of the disaster effect easier. We often discuss the maximum impact of the natural disaster on government debt because it captures the debt sustainability issue.

We first estimate the five model specifications without controlling for any additional country specific characteristics. The outcomes depend on the strategy that is chosen to identify the natural disaster (see Table 7). We find evidence that there is a negative effect on government debt when we use the total affected as our disaster identification strategy. This is a somewhat surprising result. However, notice that these results do not control for possible sovereign default. The other identification strategies, damage as a percent of GDP and deaths over population, show a positive and significant effect on the government debt for the disaster country. For damage, our findings reveal a maximum increase in government debt by 9.8% of GDP compared to the synthetic control group. The largest effect is found between two and four years after the occurrence of the natural disaster. The other significant maximum average disaster effects range from 5.1% to 7.3% of GDP. However, we find even larger insignificant effects, these, for example, equal 14.8% and 16.2% of GDP. For deaths, we also find evidence of an increase in government debt. Models (1)-(4) indicate an increase of government debt compared to the synthetic control group. These models consistently show that the level of government debt tops after between two and four years after the natural disaster. The government debt increases between 3.8% and 6.6% of GDP, these increases are at least significant at the 5%-significance level. Model (5) reveals no increase of the government debt. Our results are in line with the findings of Noy and Nualsri (2011). Their findings reveal a debt increase of 8% of GDP for developed countries after one and a half years of a natural disaster.[25]

This study also utilizes the median disaster effect as these estimates are more stable when outliers exist. The disasters identified by using total affected again reveal a negative effect on the government debt compared to the synthetic control group. The findings for damages reveal a smaller increase than the average disaster effect. The median effect ranges from 3.7% to 5.6% of GDP for the models (1)-(4), whereas we find an ambiguous effect in model (5). If we utilize all models, we find an increase of government debt equal to 4.1% of GDP. This finding is significant at the 1%-level. The deadliest disasters indicate larger median disaster effects than average disaster effects. These disasters have a positive effect on government debt ranging from 4.3% to 8.7% of GDP. These estimates also top between two and four years after the natural disaster. Our estimates are comparable to the findings of Rasmussen (2004). He finds a median increase of public debt of 6.5% of GDP after three years, whereas our finding reveals an increase of 5.2% of GDP for the combination of all models.

[Insert Table 7 here]

As a robustness check, we estimate the panel synthetic control models using the land area in squared kilometers in Table 8. The utilization of land area puts more emphasize on the geographical factors because it accounts for possible benefits of country size. The average disaster effect for the total affect over land area reveals an ambiguous effect on government debt. For damage over land area, we estimate a large positive effect on government debt compared to the counterfactual. The debt increases between 17.6% and 23.6% of GDP, all results are significant at the 1%-level. The debt is increasing over the entire postdisaster period. If the disaster is identified using deaths over land area, we find a positive effect on government debt. Although this effect is considerably smaller than for damages, it ranges from 4.6% to 7.6% of GDP. Furthermore, this study also estimates the median disaster effect for the disaster identification strategy using land area. Contrary to the average disaster effect, the median disaster effect for the total affected over land area gives a modest positive effect on government debt. The government debt increases around 4.7% of GDP compared to the synthetic control group. We find a much larger median disaster effect when we use damage over land area. Like the average disaster effect, we find increasing government debt over the entire postdisaster period. For most models, the government debt increases until the last post disaster period. Thus, the disaster country still feels the consequences of the natural disaster, even after eight to ten years. The level of government debt increases between 12.3% and

[25] Note that our estimates also include developing countries. Later, we distinguish between developed and developing countries.

16.0% of GDP, these findings are highly economically and statistically significant. For the deaths over land area, we find a somewhat larger median disaster effect than the average disaster effect. The estimates show an increase of government debt ranging from 5.3% to 9.9% of GDP compared to the counterfactual.

[Insert Table 8 here]

This study identifies whether countries are in external or domestic default. Sovereign default is option to lower the level of government debt, and more importantly the obligations that are a consequence of government debt.[26] The previous estimates include countries which default and countries that do not default on their debt obligations. As a consequence, sovereign default can potentially influence our results and bias our estimates downward because sovereign default seems more likely for a country which suffers from a severe natural disaster. In addition, sovereign default might lead to different paths of government debt in the postdisaster period due to more limited access to the financial markets. Our expectation is that countries with a default history are unable to increase their government debt in the same manner as countries without a default history.[27] There is also empirical evidence that investors do worry about debt sustainability after a natural disaster. Klomp (2015) uses the credit default swap (CDS) spread to investigate how a natural disaster affects debt sustainability. He reveals that CDS spreads increase significantly after a disaster. We control for the possibility of sovereign default in two ways. First, this study uses data on external and domestic default from Reinhart and Rogoff (2009). We do not distinguish between domestic and external default, so both are given a one for default in our dummy variable approach.[28] In other words, a country-year observation is either defined in default or not. Second, this study presents the stricter definition of sovereign default. Investors' behavior might be influenced by the country's default history. Therefore, we establish whether a country is in default in the pre- or postdisaster period. If the country is in domestic or external default in the pre- or postdisaster period, we define a country as default country. For our dummy approach, we define a default country as one and a nondefault country as zero.[29]

We present the results for the stricter default country's approach in Table 9. For all the standard identification strategies, our findings reveal a considerable drop in the number of natural disasters. This

[26] Disaster might create situations whereby debt service must compete with unexpected disaster expenses (Cassimon *et al*., 2008).
[27] We do not consider whether a country has a default history before 10-years preceding the natural disaster. It is indeed possible that previous defaults impede the access to the sovereign markets for countries.
[28] For reasons of space, we do not present the results of sovereign default dummies. These results show very similar results compared to the results for the default countries.
[29] We do not distinguish between the extents of the haircut.

indicates that a substantial part of our sample experiences a sovereign default in the pre- or postdisaster period. More precisely, over 70% of the sample countries experience a sovereign default in the pre- or postdisaster period. Nevertheless, the expectation was that this strict definition will increase the disaster effect on government debt. Our findings reveal no evidence of a higher impact on government debt. For damages, our findings reveal only a modest increase between 1.7% and 3.7% of GDP compared to the synthetic control group. The median disaster impact equals around 3% of GDP. For deaths over population, we do find a positive effect on government debt. The estimates reveal an increase between 5.4% and 15.7% of GDP with a minimal significance level of 5%. The median disaster effect gives relatively similar results compared to the results without controlling for sovereign default. The maximum increase of government debt equals 6.3% of GDP. These outcomes reveal that countries that default on their debt obligations are unable to lower their level of government debt, which indicates that the usage of the default option after a natural disaster is ineffective.

[Insert Table 9 here]

When we estimate the impact of natural disaster for land area disaster identification strategy, Table 10 shows a far lower number of default countries compared to our previous estimates. Our results are almost solely positive which indicates an increase in the level of government debt compared to the synthetic control group. For the total affected over land area, our average results reveal a modest positive effect on debt. The maximum government debt effect ranges from 2.3% to 20.4% of GDP. For the damage over land area, there is a large average disaster effect on government debt. The increase is between 20.8% and 30.5% of GDP at 1%-significance level. The average government debt for our entire sample is equal to 61.6% of GDP. Thus, the maximum increase of government debt amounts to 43% for the 'average' country in our sample. Similarly, we find an increase in government debt for deaths over land area. The models reveal a maximum average disaster effect which ranges from 5.1% to 20.8% of GDP. Our findings seem in accordance with numerous other studies which claim that the sustainability of the sovereign debt is reduced, mainly through the deterioration of the public finances of a country (Borensztein *et al*., 2009; Melecky and Raddatz, 2015; Noy and Nualsri, 2011).

The estimations of the median disaster effect reveal higher levels of government debt for the disaster countries than for the synthetic control group. The median effect for the total affected over land area reveal a maximum increase within the range of 3.2% and 22.0% of GDP. In similar vein as the previous estimates, the results for damages reveal the largest positive effect on government debt. The median effect ranges between 11.0% and 16.1% percent of GDP at the 1%-significance level. For deaths over land area, we find evidence of an increase in government debt between 8.5% and 19.2% of GDP compared to the synthetic control group. In general, we find convincing evidence of a positive effect on government when we use the land area in the disaster identification strategy. However, there is only mixed evidence when we use the standard disaster identification strategy.

[Insert Table 10 here]

4.1. The predisaster fit of the synthetic control group

The credibility of our case study synthetic control estimates depends on the predisaster period match of the disaster country and its synthetic control. Thus, we review the case study estimates and use the accuracy of their predisaster match to indicate their credibility. The RMSPE gives the goodness of fit for the constructed synthetic control group in the predisaster period ($T_0 - 10, \ldots, T_0 - 1$). Following Abadie *et al*. (2010), we use equation (4) to estimate the fit of our case-study synthetic control estimates.

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{DEBT_i - \widehat{DEBT}_i}{DEBT_i}\right)^2} \qquad (4)$$

A lower RMSPE indicates a better fit of the estimated synthetic control group. A better predisaster fit of the synthetic control group will result in a more accurate approximation of the postdisaster trajectory. We introduce a weighting and ranking scheme.[30] The weights increase with synthetic control groups with a high predictive value in the predisaster period (a low RMSPE). This approach has a clear merit over the dummy approach because it does not impose an arbitrary threshold. In addition, it includes all synthetic control case studies. A drawback is the possibility that one case study has some exceptional fit which results in a very high weight. This can potentially render the other case studies as unimportant. The ranking scheme deals with this issue. It distributes the weights more equally over the synthetic cast studies. Another drawback is that the weighted median effects do not allow for an estimation of the confidence interval. Thus, we do not report the median disaster effects as no confidence intervals are obtained.

This study uses the RMSPE to weight the case study estimations in our panel estimation (see Table 11). The average disaster effect using total affected over population shows a negative effect on government debt. When applying the other standard natural disaster strategies, we find a positive effect on government debt. For damages over GDP, we find evidence of an increase of government debt between 3.9% and 7.4% of GDP whereas, for deaths over population, the increase of government debt ranges between 5.2% and 7.7% of GDP. Figure 6 presents the mean disaster effects for the different standard

[30] We normalize the total weights to equal 100.

disaster identification strategies. The effect on government debt identified by damages as percentage of GDP and deaths over population is clearly different at the 10%-significance level.

[Insert Figure 6 and Table 11 here]

As a robustness check, the land area disaster identification strategy is used. Table 12 reveals that median and average disaster effects have a positive effect on government debt. The disaster identified using total affected over land area shows a positive effect on government debt. This effect materializes only after a few years. There seems some indication that official development assistance is supplied because there is some decline in the disaster effect.[31] The maximum positive effect ranges from 5.1% to 7.7% of GDP compared to the counterfactual. The government debt effect is much larger if we identify disaster based on damages. The maximum average disaster effect ranges between 14.6% and 24.0% of GDP. For deaths over land area, our findings reveal a positive effect of government debt. The maximum effect on government debt ranges between 9.1% and 13.8% of GDP compared to the synthetic control group. Figure 7 shows that all land area identification strategies result in a positive and significant mean effect on government debt for a 90% confidence interval.

[Insert Figure 7 and Table 12 here]

The weighting of the RMSPE potentially puts a lot of weight on a limited number of synthetic case studies. Therefore, we also rank the case studies. This makes more equitable use of the case studies in Table 13 and Table 14. The standard disaster identification strategy again reveals a negative effect on government debt when we use total affected over population. For damages, the average disaster effect reveals a positive effect on government debt ranging from 4.5% to 7.6% of GDP compared to the synthetic control group. When we consider the deaths over population, our findings show consistent evidence of a positive effect on government debt. The effect ranges between 4.6% and 6.5% of GDP.

[Insert Table 13 here]

The land area disaster identification strategy reveals consistent positive effects on government debt after a natural disaster. On average, the government debt increases between 4.8% and 9.0% of GDP compared to the synthetic control group, when we use total affected over land area to identify natural disasters. For

[31] For example, Yang (2008) finds that after a hurricane official development assistance increases with a lag of one year.

damage over land area, the average disaster effect is quite substantial. The average disaster effect ranges between 15.2% and 21.7% of GDP. Our results reveal a continuous increasing impact of natural disasters. When we identify disaster using deaths over land area, the average disaster effect reveals a maximum increase of government debt between 10.0% and 12.5% of GDP.

[Insert Table 14 here]

4.2. The level of development

We conduct some additional sensitively analyses. There is consensus that the macroeconomic costs of a natural disaster are affected by the level of development (Anbarci *et al*., 2005; Kahn, 2005; Toya and Skidmore 2007; Noy, 2009; Strobl, 2012). Therefore, we also assess whether the level of development matters for the disaster impact on the level of government debt. The definitions are taken from the United Nations (2017) World Economic Situation and Prospects. This study defines high income countries as high- and higher-middle income countries. We find mixed evidence for high income countries if we use the standard identifications strategy (see Table 15). Only the panel synthetic control studies using deaths over population reveal a modest positive effect on government debt. The government debt increases between 4.2% and 9.5% of GDP in models (1)-(4). The median disaster effect shows an increase in government debt between 4.1% and 6.8% of GDP. The disaster identified by total affected over land area mostly reveals an insignificant effect on government debt. These findings are consistent for the median disaster effects. We find a positive average and median disaster effect for damage over land area. The average increase of government debt ranges between 21.6% and 31.2% compared to the synthetic control group, whereas the median increase of government debt is between 13.4% and 19.4% of GDP. These disaster effects are all highly statistically and economically significant. The average effect on government debt for deaths over land area shows a positive effect between 4.9% and 7.2% of GDP. The median effect is even somewhat larger, equaling around 9.4% of GDP. The reader should note that the increase of the level of government debt can be the consequence of anticyclical fiscal policies. This reasoning is in line with the arguments by Melecky and Raddatz (2015, p. 131): "Although deficits increase relatively more in financially developed countries (by 75%, compared to 10% in less financially developed countries), the resources that an efficient debt market can mobilize may help in dealing more effectively with the economic consequences of disasters."

[Insert Table 15 and Table 16 here]

This study defines low- income countries as low and lower-middle income countries following the United Nations (2017) World Economic Situation and Prospects. The total affected over population disaster indicator does reveal a negative effect on government debt after a natural disaster. The median disaster effects also show a decline of government debt in the aftermath of a disaster. For damage over GDP, we find convincing evidence of a positive effect on government debt. The maximum increase for models ranges between 11.7% and 28.6% of GDP. For all models, the disaster effect equals an increase of 17.2% of GDP at the 1%-significance level. The median disaster effects reveal considerably lower increase of government debt compared to the synthetic control group. The increases range from 4.9% to 12.8% of GDP. When we use deaths over population to identify natural disasters, we find mixed evidence on the level of government debt. Initially, there is an increase of government debt which continues in a decline of government debt. For the land area identification strategies, we find mixed evidence for the average disaster effects for all indicators, whereas this study also finds consistent evidence of a positive median effect on government debt. The large fluctuations of postdisaster outcomes can potentially be attributed to the domestic and external debt financing. Countries hit by an extreme disaster usually face a liquidity constraint to finance these increases since there is an outflow of foreign capital immediately following the disaster (Klomp, 2017). These concerns are especially of importance for many least developed countries as they rely on foreign capital to finance their budgetary needs (Cassimon *et al*., 2008). Thus, the least developed countries might be unable to use debt financing for relief- and reconstruction efforts.

[Insert Table 17 and Table 18 here]

The sample is split in two parts between the highest and the lowest GDP per capita in the year preceding the natural disaster $(T_0 - 1)$.[32] In contrast with the distinction between low- and high-income countries, this measure changes over time. The disaster indicator, damage over GDP, reveals a modest increase of government debt. It, on average, equals 4.2% of GDP. The deaths over population reveal a large positive effect on government debt if countries have a high GDP per capita in the year preceding the natural disaster. On average, we find a maximum effect on government debt ranging from 6.6% to 14.3% of GDP compared to the synthetic control group, whereas the median disaster effect for the different models ranges from 6.5% and 13.5% of GDP. The total affected over population disasters indicators show mixed evidence. If we use the land area disaster identifications strategy, this study finds even stronger evidence for an increase of government debt in high GDP per capita countries. Although the average disaster effect for total affected over population reveals an ambiguous effect, the median disaster effect is a positive effect equaling 2.9% of GDP. The evidence for the damage over land area models is even more sizeable.

[32] The reader should note that, for example, financial market access is intertwined with GDP per capita.

All estimates of the postdisaster period reveal a positive effect. For the average disaster effect, the maximum increase of government debt ranges from 24.9% to 39.2% of GDP. These sizeable effects cannot be attributed to extreme cases because the median disaster effect ranges from 14.8% to 27.4% of GDP. These findings are also all significant at the 1%-level. The disaster identified using deaths over land area also positively impacts government debt for all postdisaster observations. The median disaster effect is more sizeable than the average disaster effect, and ranges from 7.1% to 12.4% of GDP.

For countries with a low GDP per capita preceding the natural disaster, we find evidence of a negative effect on government debt for the total affected over population. In contrast, damage over GDP reveals a substantial increase in government debt in the postdisaster period. When we combine all models, the average increase of government debt equals 14.9% of GDP. For deaths over population, we find evidence of negative impact on government debt. For the land area disaster identification strategy, we only find some mixed evidence on government debt when we investigate the average disaster effect. The other indicators generally reveal an increase of government debt *versus* the synthetic control group. The median effect using the total affected over land area reveals a debt increase equaling 6.4% of GDP. For damages over land area, we find maximal increases of government debt between 8.0% and 12.6% of GDP for the average disaster effect in models (1)-(3) and (5); and between 5.5% and 12.6% of GDP for the median disaster effect. For deaths over land area, we find relatively similar results. The average disaster effect has a maximal positive effect on government equaling 7.4% of GDP compared to the synthetic control group. The median effect on government debt equals 5.5% of GDP.

4.3. Country characteristics

Economies dependent on agriculture can be impacted more severely by a natural disaster. The production in upper-middle income countries takes more place in the industrial sector that is rather capital intensive (Klomp, 2017). Developed economies often rely less on agriculture than developing economies. We split our sample based on the dependency of an economy on agricultural production in the year preceding the natural disaster. In other words, we take the share of GDP produced by agriculture and split the sample based on this share. For the countries with a low dependency on agriculture, there are clear increases of government debt when the disaster is identified using damages and deaths. For damages, the mean government debt increases are between 3.5% and 8.4% of GDP, whereas the median disaster effect reveals an increase of government debt between 2.8% and 12.4% of GDP. In the postdisaster period, government debt, on average, increases between 5.5% and 12.5% of GDP when we identify disasters using deaths. Furthermore, the median disaster effect ranges from 5.9% to 13.3% of GDP. The findings of the land area disaster identification strategy also show an increase of government debt when damages and deaths are used to identify disasters. For damages over land area, the disaster impact on government debt is amongst the largest effects, we have observed in our study. On average, the disaster increases the government debt with 30.3% to 43.4% of GDP compared to the synthetic control group. Furthermore, the government debt is constantly increasing for the entire postdisaster period in all models. A tentative explanation for this effect is that the long-term effects on government spending might be large (for example, investments in reconstruction) (Melecky and Raddatz, 2015; Noy and Nualsri, 2011). Another reason might be that these investments crowd-out other productive investments, such as education and infrastructure investments. The median disaster effect also reveals a very substantial increase of government debt. We observe an increase of government debt between 16.8% and 33.0% of GDP compared to the synthetic control group. When we use deaths over land area, this study also reveals increasing government debt compared to the counterfactual. The average disaster effect ranges from 6.6% to 10.4% of GDP, whereas the median disaster effect ranges from 7.4% to 10.6% of GDP.

Our study also investigates the impact on government debt for countries with a high dependency on the agricultural sector. Our evidence reveals a mixed effect on government debt. The disaster indicator, total affected over population, shows a negative effect on government debt. For damages over GDP, we find that government debt increases by 12.9% of GDP at the 5%-significance level. If we identify disaster using deaths over population, we find somewhat mixed results on government debt. For all land area disaster identification strategies, we find an increase of government debt compared to the synthetic control group in the postdisaster period. If we combine the models, there is consistent evidence that we observe an increase of government debt. For the total affected over land area, the average disaster effect shows an increase of government debt equaling 6.1% of GDP. The median disaster effect increases government debt by approximately 8.9% of GDP. The most damaging disasters, on average, lead to an increase of government debt by 6.6% of GDP, whereas the median disaster effect equals an increase of 7.1% of GDP. For the deadliest disasters, our estimates are of a relatively similar magnitude. The average disaster effect leads to an increase of government debt of 7.9% of GDP, whereas the median disaster effect reveals an increase of government debt by 6.1% of GDP.

Small island states are extremely vulnerable because of the higher frequency of natural disasters that have a disproportionately large impact on their economy (Skidmore and Toya, 2002; Pelling *et al*., 2002; Rasmussen, 2004). Therefore, we investigate the impact of a natural disaster on Small Island Developing States (SIDS). Our results reveal some mixed evidence on this issue. For the damages, we find, on average, an increase of government debt equaling 9.4% of GDP at the 1%-significance level. For deaths over population, we reveal a substantial average disaster effect of 8.6%. Using the land area disaster identification strategy, we only find a clear positive impact on government debt for damages over land area. Our findings reveal an average increase in government debt equal to 13.6% of GDP. The median disaster effects reveal relatively similar results.

4.4. Additional sensitivity analyses

We conduct several additional sensitivity analyses. First, we divide the natural disaster based on their severity. In previous estimates, we investigate the 2.5% largest disasters. This paragraph also presents the 0.5%, 1%, 1.5% and 2% largest natural disaster. Our expectations are that the more severe disaster will result in a higher government debt. Generally, the impact on government debt is largest for the more severe disasters if we identify disasters using standard identification strategy. However, the 0.5% natural disasters do not always present the highest debt impact. This can be the result from sovereign default due to the extreme high impact of the natural disaster. For the total affected over population and damages, we observe a clear decline in the debt impact from the 0.5%-1% largest disaster to the 2.5% largest disasters. These patterns can also be observed for median disaster effects. When we use the land area identification strategy, we find convincing evidence for total affected and damage that the impact on government debt is even more pronounced for the 0.5% largest disaster than for the 2.5% largest disasters. For total affected over land area, the impact of the natural disaster declines from 11.4% of GDP for the 0.5% largest natural disaster to 2.8% of GDP for the 2.5% largest disasters. A similar pattern is observed for the damages over squared kilometer. The largest 0.5% of natural disaster is equal to 36.2% of GDP, whereas the disaster effect for the 2.5% of largest disaster is equal to 21.4% of GDP. These patterns can also be observed for the median disaster effects, including the deaths over land area.

[Insert Table 19 and Table 20 here]

Second, we divide our sample in quartiles based on the RMSPE. This study constructs a dummy variable which is one if the synthetic case-study belongs to the 25% of case studies with the lowest RMSPEs. We repeat this for a threshold of 50% and 75%. Thus, we only estimate the panel synthetic control using the synthetic case studies which have a good predisaster fit.[33] We consider the economic size of the effect because the statistical significance partly depends on the number of observations. For the standard disaster identification strategy, we find relatively similar results. The findings for the best predisaster fit quartile are somewhat higher for the deadliest disasters compared to the findings for all quartiles, whereas the estimates for the most damaging disasters are somewhat lower in the best predisaster fit group. Although there are minor differences in the economic size of the effect, there is no difference in the postdisaster

[33] The reader should note that the thresholds are selected in an arbitrary fashion, which can influence our results. Furthermore, in contrast to weighting or ranking the RMSPE, this approach excludes disaster countries from the analysis.

pattern. Regarding the land area disaster identification strategy, we find a larger disaster impact for total affected over land area in the best predisaster fit quartile compared to the findings for all quartiles. For the deadliest disaster, we find similar results. In other words, the disasters in the quartile 1 show a higher postdisaster impact. A notable exception is the average disaster impact for the most damaging disaster. Thus, the case-studies with a better predisaster fit show a larger postdisaster impact on government debt. This strengthens our findings because they are not the results of case-studies with a poor predisaster fit.

Third, we test whether the disasters in quick succession influence our outcomes. Large natural disasters in quick succession might have different consequences on the government debt. Therefore, we only investigate the first natural disaster. For the deadliest disasters, we find a substantial larger debt increases after the first disaster compared to our entire sample. Government debt, on average, increases by 12.0% of GDP for the first disaster versus 4.6% of GDP for all disasters. Both estimates are significant at the 1%- level. This finding is also observed for the median disaster effect. For the land area disaster identification strategy, our evidence again reveals a considerable larger increase of debt for the first disaster if we identify disasters using deaths. However, we also observe a lower impact for damages. There is no clear pattern how the government debt is impacted by experiencing multiple disasters.

Fourth, we control for the total societal and interstate major episodes of political violence because the study of Cavallo *et al.* (2013) notes the influence of political revolutions. We account for these revolutions by looking at countries which only experience minor episodes of political violence and conflict. For damages over GDP, we find a large average increase in government debt equaling 13.6% of GDP compared to the synthetic control group. This is considerably larger than if we include all countries. However, we also find a considerable larger debt decline for the disasters which affect most people. The land area disaster identification strategy reveals no substantially altered results.[34]

In summary, this study finds consistent evidence of an increase of government debt compared to the synthetic control group. The increase of government debt is more pronounced for the identification modes deaths and damages than for total affected. Table 21 provides a summary of the government financing needs. The increase of government debt is around 4.6% of GDP, whereas we find a debt increase of 9.8% for damages. These estimates increase substantially if we regard the severity of the disaster impact scaled by country size. In that case, the most damaging disasters lead to a debt increase of 21.4% of GDP compared to the synthetic control group and the deadliest disasters lead to an increase of 6.2% of GDP. For high-income countries, the disaster effect is somewhat more pronounced. Although we

[34] When we identify the disasters using the damage over land area, our findings reveal an average disaster effect ranging between 14.8% and 23.0% of GDP. The median disaster effect shows an increase of government debt between 10.9% and 14.6% of GDP. This study identifies a disaster based on deaths over land area. There is, on average, a government debt increase compared to the synthetic control group. The average disaster effect reveals an increase of government debt between 4.3% and 6.9% of GDP, whereas the median disaster effect equals between 3.8% and 8.9% of GDP.

find a large disaster effect, it is likely that this study underestimates the disaster effect. We do not account for sovereign default in most specifications. Thus, the potential lowering of government debt, because of sovereign default, and the different postdisaster debt trajectory for countries with a default history are not accounted for in most specifications. In addition, our findings do not explicitly control for remittances, private insurance and disaster aid. These inflows can potentially mitigate some of the effects on government finances.

[Insert Table 21 here]

5. **Disaster magnitude and disaster identification**

Natural disasters are often regarded as exogenous events. Although natural disasters are exogenous in their strength, location and occurrence, the impact is not. Several studies indicate possible channels for endogeneity of the impact of natural disaster. The previous disaster identification strategies use the disaster outcomes, for example, the number of deaths to identify the occurrence of a natural disaster. Such an identification strategy has some clear drawbacks. There is consensus in the literature that the outcome of a natural disaster is affected by the level of development (*e.g.* Anbarci *et al*., 2005; Kahn, 2005; Toya and Skidmore 2007; Noy, 2009; Strobl, 2012). Preparedness goes together with economic development. Higher income has a negative effect on the number of deaths and the portion of the population affected due to the better preparedness. However, it has a positive effect on, for example, direct damages. Other effects of economic development can be that people start to live in high risk areas (e.g. coastal areas). Figure 8 uses the logarithm of the GDP per capita as a crude measure of economic development and the readiness index obtained from ND GAIN database as an indication of preparedness for climate change. Figure 8 illustrates the clear relation between economic development and readiness. A higher readiness will reduce the number of fatalities and affected. In other words, the identification of the natural disaster can be endogenous due to the influence of the socio-economic situation in a country. Table 22 shows that there are clear differences in the level of GDP per capita for different disaster identification strategies. There are considerable differences in the level of GDP per capita, especially, between identification by total affected and the other identification strategies. This could also influence our findings.

[Insert Figure 8 and Table 22 here]

We deal with these endogeneity problems in disaster identification by estimating based the disaster magnitude. The reader should note that this approach is only used for the identification of a natural disaster. The natural disaster literature uses the magnitude of a natural disaster to approximate its costs. However, this measure is too crude because it does not take the potential of natural hazard into account. If a large earthquake occurs in a deserted region, it does not qualify as a natural disaster. Therefore, we follow Klomp (2016) by including population density (pop_{it}). The equation takes the following form:

$$dis_{it} = \alpha_i + \beta_1 pop_{it} + \beta_2 mag_{it} + \theta_3 (pop_{it} \times mag_{it}) + \upsilon_{it} \quad (5)$$

The equation gives us a predicted value of the severity of a natural disaster. pop_{it} is the population density of a country[35] and mag_{it} is a vector of the magnitude of a specific disaster category (e.g. the Richter scale). α_i is the country-specific intercept. This variable accounts for climatological and seismological differences at the country-level. The interaction term ($pop_{it} \times mag_{it}$) assures that we do not qualify natural hazards as a natural disaster. Equation (5) allows us to exogenously identify the largest natural disasters. The predicted values of the equation are used for the identification of large natural disaster. These disasters are used in the synthetic control analysis. The magnitude of different disaster categories is not comparable.[36] Therefore, we must make an assumption on the distribution of the types of natural disasters. We keep the composition of natural disasters constant. Thus, this study uses the division as described in Table 2. The reader should note that although the division between disaster types stays constant, the country-year observations identified as natural disasters can change because of our different natural disaster identification strategy.[37]

We obtain these measures of the magnitude of a specific disaster category from Felbermayr and Gröschl (2014). This database provides monthly data on the maximum Richter scale, the maximum Volcanic Explosivity Index (VEI), the maximum wind speed, the difference in monthly mean temperature from long-run monthly mean and difference in monthly rainfall in millimeter from the mean for the period from 1979 to 2010. The droughts are identified using the approach by Felbermayr and Gröschl (2014). We set a dummy equal to one when a drought occurs during a year. To distinguish between the severities of droughts, this study uses how much lower the amount of rainfall is.[38] We construct the measure for

[35] City states are excluded due to their high population density.

[36] Even though, we normalize the disaster severity indicators between zero and one. Zero represents the smallest value and one represents the largest value. However, the reader should note that this does not make the severity indicators compatible with each other.

[37] Of course, there is some overlap between the previous disaster identification strategy and the exogenous disaster identification strategy in terms of observed natural disasters. However, this is not by construction.

[38] Felbermayr and Gröschl (2014) classify a period as a drought when three consecutive months or five months within a year have rainfall below fifty percent of the long-run monthly mean. Because they use a dummy variable approach in which a drought is equal to one, and zero otherwise. We cannot differentiate between the intensity of the droughts. The intensity of the drought is equal to the difference in rainfall during months defined as a drought. These monthly rainfall statistics are average over the drought months to get a yearly drought severity indicator. As a robustness check, we also control for droughts in consecutive years. This does not influence our results.

flooding in a similar way. The only difference is that we use the positive difference in total monthly precipitation.

To assess the robustness of our previous results, we estimate the synthetic control case studies for the exogenous identified natural disaster. This also enables us to assess whether our previous results and the results of previous studies are influenced by the endogenous nature of the disaster identification strategy. We start by estimating the panel synthetic control estimates with no additional controls. When we use the exogenous total affected, our findings reveal mixed evidence for an increase of government debt (see Table 23). The results for damages show an increase of government debt equaling 9.4% of GDP. However, there are a lot of insignificant results for the most damaging disasters. Our findings reveal that the government debt is considerably higher than the synthetic control group for the deadliest disasters. The deadliest disasters show an increase of government debt over 20% of GDP. For all models, we find an increase of government debt of 24.2% of GDP compared to synthetic control group. It is very clear from the median estimations that some government debt increases are even more pronounced. The median disaster effect ranges from 5.3% to 8.9% of GDP.

[Insert Table 23 here]

We deal with domestic and external default to assure that our estimations are not influenced by sovereign defaults in Table 24. For total affected, we find mixed results. When we combine all models, there is a slight increase of government debt. The most damaging disasters show only a very small increase of government debt. The effect is clearly lower than for the previous estimations without additional controls. This indeed means that countries which are severely impacted by a natural disaster do default but they do not seem to be able to lower their debt level by default. This gives some indication that sovereign default is not a viable option in the aftermath of a natural disaster. For the deadliest disaster, we still find a substantial increase of government debt compared to the synthetic control group, although the impact is somewhat lower compared to our previous results. Government debt, on average, increases by 14.8% of GDP compared to the synthetic control group, whereas the median disaster effect equals 7.6% of GDP.

[Insert Table 24 here]

We follow our earlier strategy of weighting the predisaster fit by RMSPE in Table 25. When we consider the evidence for the total affected and most damaging disasters, we find mostly insignificant impacts on government debt. We do find evidence of a positive effect on government debt when we use deaths in our exogenous disaster identification strategy. On average, we find an increase of government equaling between 7.3% and 13.2% of GDP. We check the robustness of our results by ranking the RMSPE in Table 26. When we combine all models, we find a small initial increase of government debt for total affected and the deadliest disaster contrasting the previous results of the weighted RMSPE.

[Insert Table 25 and Table 26 here]

Although the level of development can influence the identification of a disaster, the influence might not be limited to the identification itself. It can still influence the postdisaster trajectory of government debt. For example, the access to financial markets might differ with the level of development (see Melecky and Raddatz, 2015). There is mixed evidence on the sign of the average disaster effect for high income countries (see Table 27). Only the deadliest disasters reveal a clear positive impact on government. All postdisaster estimation show higher government debt compared to the synthetic control groups. Our findings reveal that, on average, the government debt increases between 12.4% and 19.4% of GDP. These findings are all significant at the 1%-level. The median disaster effect tops between two to four years after the occurrence of the natural disaster. The increase of government debt is between 7.9% and 12.2% of GDP higher compared to the synthetic control group.[39]

[Insert Table 27 here]

The findings for low income countries in Table 28 show higher impact on government debt compared to high income countries. For the exogenous total affected, we find some mixed evidence of the impact on government debt. For all models, we find a substantial increase of government debt for the most damaging disaster. Government debt increase by 17.3% of GDP compared to the synthetic control group. The other indicators, damage and deaths, reveal a large impact on government debt. The deadliest disasters reveal an even larger increase of government debt. These result in an increase of government debt equaling 30.4% of GDP. This is an increase of over 50% of the average level of government debt. It should be noted that the median disaster effect only equals 4.0% of GDP. The previous estimates are driven by potential outliers. [40]

[39] As a robustness check, we distinguish between high and low GDP per capita. The results are highly similar for high- and low-income countries. When we use damage for high GDP per capita countries, we find an average disaster effect equalling 8.6% of GDP at a 1%-significance level. For deaths, we, on average, find an impact on government debt of 15.3% of GDP, whereas the median disaster effect equals 11.4% of GDP. Both estimates are significant at the 1%-level.

[40] For the low GDP per capita countries, we reveal a larger increase of government debt for the deadliest disaster than for high GDP per capita countries. The average disaster effect shows an increase of government debt equaling 32.2% of GDP, which is significant at the 1%-level. The reader should not that we find mixed results for total affected over population and damage over GDP.

[Insert Table 28 here]

Table 29 shows an overview of the government financing needs for the exogenous disaster identification strategy. In general, the results for the exogenous identified disasters are relatively similar to the results found by the standard identification strategies. [41] For damages, we sometimes find more mixed evidence compared to our previous results because data availability in the EM-DAT database is the lowest for this outcome indicator. For the exogenous disaster identification, we do not need an estimate of direct damages because we use the disaster magnitude. This resulted in the identification of different natural disaster compared to the ones identified using the standard identification strategy. If we combined all disaster identification strategies, there is an average disaster effect of 11.3% of GDP and a median disaster effect of 6.8% (see Table 30). Thus, there is considerable impact of natural disaster on government debt. This raises concerns regarding debt sustainability in the aftermath of a natural disaster.

[Insert Table 29 and Table 30 here]

6. Policy recommendation

Several scientific sources suggest that anthropogenic climate change increases the frequency of extreme weather events and change the climate in certain regions tremendously (Raschky, 2008). There is no doubt that policymakers must fight climate change. Such action will benefit government finances in the future as the increase of the frequency and the intensity will be less pronounced. However, the solution to climate change is far more complicated than stopping with emitting. Emissions of carbon dioxide and most of the other greenhouse gases remain in the atmosphere for decades if not centuries, and the accumulated stock of such emissions is what leads to environmental problems (Newell *et al.*, 2013). Therefore, natural disasters will occur now and in the future. Furthermore, the frequency is also likely to increase because climate change will not stop at an instant.

Another aspect is the construction of prevention measures. Prevention measures are an important way to limit the potential fiscal impact of a natural disaster. However, there are some limitations in the

[41] The level of government debt depends not only on the debt obligations itself. The denominator is equal to the country-specific GDP. In other words, whether the increase of government debt is driven by counter-cyclical policy remains to be seen. Previous studies have found some mixed results on the development of output after a natural disaster. Albala-Bertrand (1993) and Skidmore and Toya (2002) find a positive effect of natural disaster. In contrast, the majority of the studies find a modest negative effect on output (see Auffret, 2003; Rasmussen, 2004; Heger *et al*. 2008; Noy, 2009; Hochrainer, 2009; Raddatz, 2009; Noy and Nualsri, 2011; Strobl, 2012; Fomby *et al*., 2013; Acevedo, 2014). Thus, part of the increase might be attributed to a decline in output. However, most of these studies find a very modest decline in output, whereas our results show a substantial increase in government debt.

implementation of prevention measures. First, there is a strong relationship between the level of development and the readiness for the occurrence of a natural disaster, as presented by the NG Gain index. Nevertheless, it is important to become more developed which is a long-term effort. It does not alleviate the current fiscal impact of natural disasters. Second, politicians are not judged on the occurrence of the natural disaster but they are judged on their handling of the disaster aftermath. According to the theory of retrospective voting the electorate hold politicians responsible for the humanitarian and economic losses and punish or reward them for their actions in the aftermath of the catastrophe (Klomp, 2016). Healy and Malhorta (2009) also provide empirical evidence that the postdisaster period is crucial for the election results. Thus, there is no predisaster incentive to invest considerable funds in disaster prevention.

Our study reveals that the government must deal with the fiscal impact of a natural disaster which could be substantial. It is important that the relief- and reconstruction efforts are not hampered by financial constraints. Policymakers can deal with the fiscal impact over natural disaster by (mandatory) private insurance, an ex-ante disaster fund and catastrophe bonds (cat bonds). These options can be influenced by the policymakers directly. Another option is the provision of international aid which depends on the willingness of other nations and individuals.

We show that (mandatory) insurance and *ex ante* disaster funds are ill-suited for limiting the fiscal impact of a natural disaster. The private natural disaster insurance market is insufficient or nonexistent in many countries. This is the case because there are demand- and supply side problems with disaster insurance. On the demand side, potential consumers underestimate the risk of low probability high loss events (see Raschky, 2008). Climate change will continue to alter the probability of these high loss events. Furthermore, consumers have bail-out expectations. Consequently, they are not buying insurance because they deem to be covered by the bail-out, so called charity hazard. On the supply side, private insurers must deal with correlated risks (see Borenszstein *et al*., 2009), which limits the diversification option. Actual coverage for some types of natural disasters is limited, even in countries with highly developed insurance markets (Skidmore and Toya, 2002). Thus, disaster insurance has only a limited effect on the adverse fiscal consequences of a natural disaster. The other option, an *ex ante* disaster fund[42], is particularly costly for developing countries. This results from high borrowing costs, unwillingness by politicians to incur upfront costs and misuse of the disaster fund. Another problem is the high likelihood that the disaster fund is insufficient for large natural disasters.

We recommend the use of cat bonds to deal with the fiscal impact of large natural disasters. The first capital market instrument linked to catastrophe risk was introduced in 1994 as a means for reinsurers

[42] Mexico's FONDEN (Fondo Nacional de Desastres Naturales) is funded upfront to deal with the potential costs of natural disasters.

to transfer some of their own risks to capital markets (Cavallo and Noy, 2010). In 2017, the outstanding value of cat bonds reached almost 30 billion US dollar, whereas already over 10 billion US dollar in cat bonds is issued in this year.[43] It works in the following way: Investors purchase a safe sovereign bond, such as US Treasury bond. This bond is put into a distinct Special Purpose Vehicle (SPV), which has no relation with the investors or a country. Then there are two possible scenarios. 1) When no disaster occurs, the investors receive the interest rate of the government bond. On top of this, they receive an insurance premium from the insured country. Thus, the return for the investors equals the interest payments on the bond plus the insurance premium. 2) When a natural disaster occurs, the first important step is to check whether the factual trigger is reached or surpassed. The factual trigger determines whether there is a pay-out to the insured country. The trigger is an objective measure of disaster severity (such as flood height, wind speed, the Richter scale etc.), which must be reached for pay-out. If this is the case, the safe sovereign bond is sold and the proceeds are transferred from the SPV to the insured country. The investors lose their claim on the government bond and their future returns from the insurance contract (the interest payments from the government bond and the insurance premium).

There are numerous benefits from issuing cat bonds. First, the dependency on foreign emergency and reconstruction aid is less pronounced. Borensztein *et al*. (2009) notes that aid comes with strings attached and it takes a considerable amount of time. Whereas the decision to issue cat bonds is a unilateral decision, it does not depend on the willingness of other countries. Second, the factual trigger assures the immediate pay-out of the proceeds of the government bond to the insured countries. Due to the trigger, there is no necessity to estimate the damages before a pay-out. In this way, funds are quickly attained and received when they are most needed (in the immediate aftermath of the natural disaster). Another aspect of the quick pay-out is that countries that can mobilize resources for disaster reconstruction more quickly generally enjoy less adverse outcomes following disasters (Noy, 2009; Noy and Vu, 2010). Third, the issuing of cat bonds makes the other ‘normal’ government debt more secure. Borensztein *et al*. (2009) find a considerable improvement in debt sustainability for Belize. Furthermore, there are no upfront financing needs as with an ex ante fund. Fourth, it allows countries to transfer their disaster risk to (international) investors. These investors invest in these assets because they do not have a correlation with other investment categories. Therefore, they could improve diversification for investors. In addition, investors are searching for returns due to the low interest rate environment. Cat bonds are an interesting investment option for them. Fifth, the use of cat bonds rewards governments which engage in prevention efforts. Thus, politicians have an incentive to invest in prevention measures during their term.[44] Although

[43] Artemis (2017), Catastrophe bonds & ILS issued and outstanding by year, Retrieved 7 September 2017. http://www.artemis.bm/deal_directory/cat_bonds_ils_issued_outstanding.html

[44] This type of insurance has no moral hazard problems because countries cannot directly influence the occurrence of the natural disaster itself. However, countries can influence the outcome.

there are clear benefits from issuing cat bonds, there are also some potential drawbacks. Cat bonds might be perceived as financial innovation which does not a have a positive reputation after the financial crisis. However, the bond is easy to understand, in contrast to some of the financial instruments which contributed to the financial crisis. Another problem might be the possibility of illiquid markets and high-risk premia. As mentioned earlier, the cat bonds are an interesting investment for international investors. This is also reflected in the growth of the cat bond market which increased almost 40-fold in the past 20-years. Even if the issued cat bonds do not cover the entire fiscal costs of a natural disaster, the government finances are more sustainable than without cat bonds.

Relief and reconstruction aid can also alleviate some of the fiscal strains for the government. Although it can substitute a country's fiscal spending, it also takes a lot of time to receive and negotiate the terms of aid. Empirical evidence also reveals only a modest increase in aid inflows (see Störmberg, 2007 and Becerra, 2012). In a recent study, Klomp (2017) finds no structural differences in the impact of natural disasters between additional aid receiving and nonadditional aid receiving countries. Thus, this also raises the question whether additional aid works. The small effect can be explained by the strings attached to the aid[45], the lengthy disaster aid negotiations and the focus on specific disasters[46]. Policymakers cannot steer the types of aid offered, the amount of aid, the strings attached and the timing of aid, which makes them dependent on the willingness of the international community to provide them with the necessary assistance. Furthermore, the timing of the pay-out differs considerably. Therefore, this study concludes that international aid should be a (small) complement to the issuance of cat bonds.[47]

7. Conclusions

This study investigates the impact of a large natural disaster on the level of government debt. We investigate over 100 natural disasters in the period 1971 to 2014. Our unbalanced sample includes 163 countries. Our study employs a panel synthetic control method to estimate the behavior of the country's government debt, as if the country was not struck by a disaster. To estimate the disaster impact, we take the difference between the disaster country and the synthetic disaster country (which did not experience a natural disaster). This synthetic control disaster country is made up of nondisaster countries which

[45] Donor countries may also provide relief with an eye to their own economic or geostrategic political interest (Strömberg, 2007). Borensztein *et al*. (2009) notes that the funds are often earmarked for specific investments.

[46] Interestingly, Guha-Sapir *et al*. (2004) shows that there is a preference among donors for certain types of disasters over others. Moreover, the interest in a specific disaster is not driven by severity or need. Aid money follows towards the disaster which interest the public and media coverage has played a large part in this shift (the so-called CNN-effect) (Pelling *et al.*, 2002).

[47] United Nations Framework Convention on Climate Report (2015) (the Paris climate agreement), Article 53, gives developing countries an extra mechanism to obtain funds for disaster reconstruction.

approach the disaster country's underlying macroeconomic, institutional, fiscal and geographical characteristics the closest.[48]

This study finds a large positive impact of natural disaster on the level of government debt. The increase of government debt is substantial and will put debt sustainability of the disaster countries under increasing pressure. As we identify a natural disaster using deaths over population, government debt increases, on average, 4.6% of GDP compared to the synthetic control group. For damages, the average positive effect of government debt equals 9.8% of GDP. Our findings reveal no effect when we use total affected over population. To account for the intensity of the natural disaster, we identify by outcomes over land area. The disaster effect for damages over land area is even more pronounced with an average increase of 21.4% of GDP, and an average disaster effect for the deadliest disaster equal to 6.2% of GDP. Various robustness checks show relatively similar results when we control for the possibility of domestic and external sovereign default, conflicts and the predisaster fit of the control group. This study also identifies disaster based on the disaster magnitude. For this strategy, we find an average disaster impact for the most damaging disaster using this strategy of 9.4% of GDP. For the deadliest disasters, we even find a debt increase of 24.2% of GDP compared to the synthetic control group. Our findings reveal substantial increase of government debt after a natural disaster. This enables us to give a possible explanation why previous studies find only a modest negative impact on output for a large natural disaster (Auffret, 2003; Rasmussen, 2004; Heger *et al*., 2008; Noy, 2009; Hochrainer, 2009; Raddatz, 2009; Noy and Nualsri, 2011; Strobl, 2012; Fomby *et al*., 2013; Acevedo, 2014). The adverse effect on output is partly mitigated by government intervention, and therefore, the government debt increases substantially after a large natural disaster.

This study employs multiple disaster identification modes (*e.g.* total affected, damage or deaths) and strategies (*e.g.* measuring the impact over population or country size) to prevent that the selection of these strategies and modes influences our results. In general, we find considerably larger impacts when we use deaths and damages as modes of disaster identification. This proves that the selection of multiple disaster identification modes is a necessity. We employ multiple disaster identification strategies because it is impossible to determine *a priori* which strategy best captures the impact occurrence of a disaster. This study also deals with the possible endogeneity of disaster identification strategies using disaster outcomes. The outcomes of natural disasters are affected by the level of development (*e.g.* Anbarci et al., 2005; Kahn, 2005; Toya and Skidmore 2007; Noy, 2009; Strobl, 2012). There is some evidence that the indicators using damage are influenced by the level of development.

[48] This is a mix of different nondisaster countries which also receive a weight. A higher weight indicates a better resemblance of the underlying characteristics.

We find evidence that larger disaster result in a substantially larger increase of government debt. This study divides the natural disaster severity in the 0.5%, 1%, 1.5%, 2% and 2.5% largest natural disasters. In general, the 0.5% largest natural disasters give the largest median effect on government debt. Especially, the land area disaster identification strategy shows a very large median impact for largest disasters. There is no clear relation between the level of development and the disaster impact on government debt. When we account for country size, we find evidence that high income countries increase government debt considerably more compared to the synthetic control group than low income countries. However, for the exogenous disaster identification strategy, we find the opposite result. Overall, we find no clear postdisaster pattern regarding government debt for developing and developed countries. This contrasts with the findings on output where generally developed countries suffer less from a disaster impact (see, amongst others, Anbarci et al., 2005; Kahn, 2005; Toya and Skidmore, 2007; Noy, 2009; Strobl, 2012).[49]

Our study clearly shows that natural disaster will have an adverse effect on the government's fiscal position. Disaster relief and reconstruction are essential tasks of a government, and the electorate expects governments to intervene in the postdisaster phase. Policymakers must deal with the aftermath of the disaster but its costs put pressure on the government's fiscal position. A policy recommendation of this study is to prepare the government budget ex ante to deal with these disaster costs. Policymakers can issue cat bonds. These bonds transfer some of the disaster risks towards the international investors and it limits the natural disaster costs for the disaster country. Cat bonds assure the financing for relief and reconstruction is available when these funds are needed most. The cat bonds are paid-out to the disaster country when a factual trigger coupled to disaster severity is reached. Anthropogenic climate change will increase the frequency and intensity of natural disaster, this will increase the necessity of issuing of cat bonds. The cat bonds immediately alleviate some of the constraints on public financing, whereas, in the long-term, development aid can supplement domestic fiscal spending.

Our study suffers from several limitations. This study does not distinguish between the types of natural disasters. There are potentially heterogeneous impacts of different types of natural disasters. We leave this for further research. Another issue is data availability. This is particularly an issue for the earlier part of our sample and for some developing countries. A limitation of our study is that it does not determine the underlying reasons for the debt increase. An increase of government debt can be the result of an increase of spending or a decline in revenue. It can also result from a decline in output. Output and output growth can be reduced due to the natural disaster (Auffret, 2003; Rasmussen, 2004; Heger et al., 2008; Noy, 2009; Hochrainer, 2009; Raddatz, 2009; Noy and Nualsri, 2011; Strobl, 2012; Fomby et al.,

[49] The reader should note that we deem the ability to engage in counter-cyclical fiscal policies as very important. Thus, a higher level of government debt is not negative in itself but it does put increasing pressure on debt sustainability.

2013; Acevedo, 2014). It is beyond the scope of this study to identify the various effects and their contribution to the increase of government debt. Another issue is that we arbitrary select the postdisaster trajectory to end after 10-years. The effect on government debt might not be limited to our postdisaster trajectory, especially for the estimates which show a continuing increase over the postdisaster period. Even though, this might be the case, the underlying structure of the economy might also change. As a consequence, a long postdisaster period limits the validity of our synthetic control group, which is determined based on the predisaster period. Our study does not consider the frequency of occurrence of a natural disaster. Estimates of the impact on debt sustainability cannot only be determined by the size of the effect, it also depends on the frequency of the occurrence of a natural disaster. Nevertheless, it is clear that natural disaster can considerably hamper debt sustainability if a natural disaster occurs.

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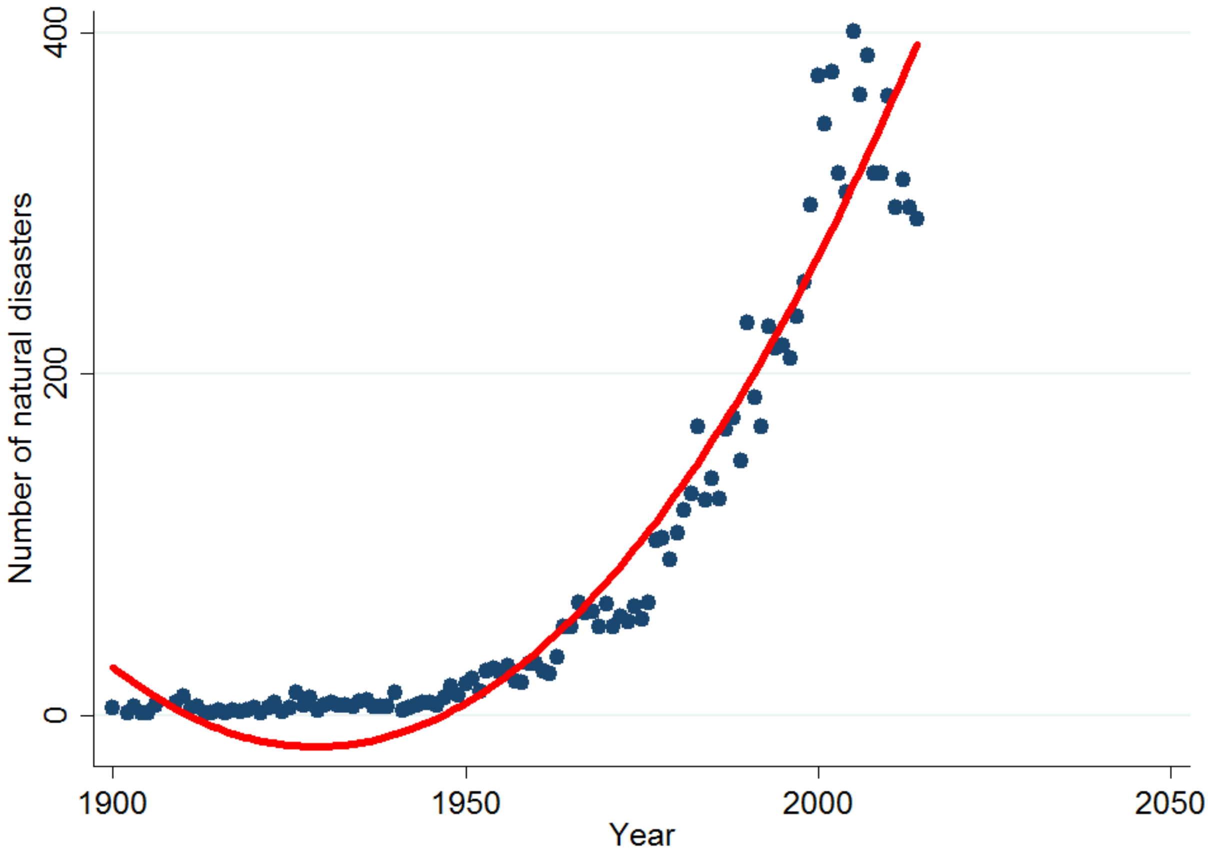
9. Appendix

Figure 1. The development of the number of natural disaster over 115 years.



Source: Koetsier (2017).

Figure 2. Countries included in this study.

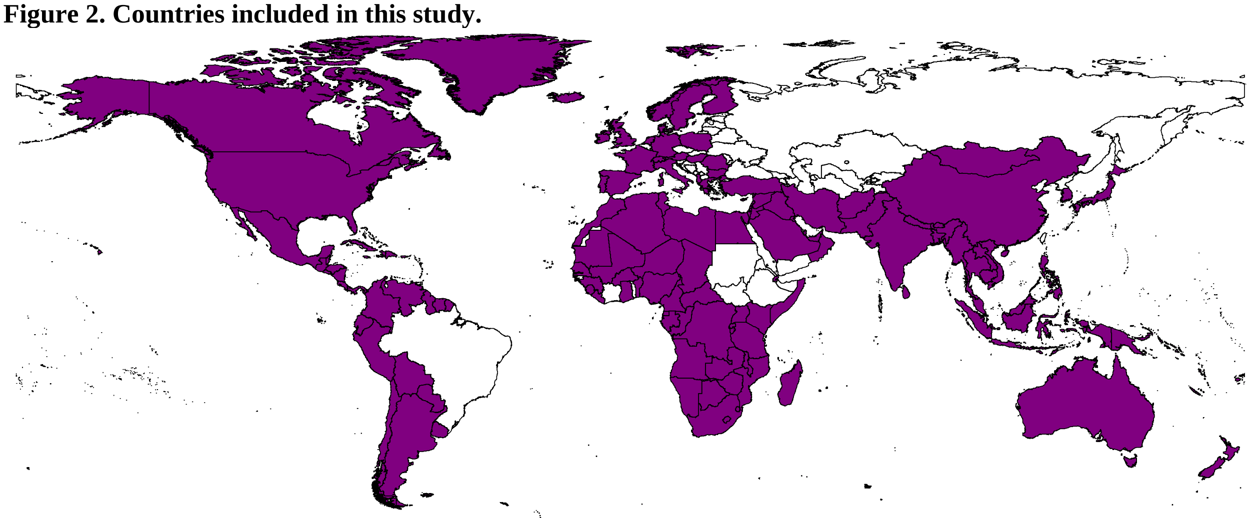


Table 1. The list of countries included in this study.

Afghanistan	Denmark	Laos	Rwanda
Albania	Djibouti	Lebanon	Saint Kitts and Nevis
Algeria	Dominica	Lesotho	Saint Lucia
Andorra	Dominican Republic	Liberia	Saint Vincent and the Grenadines
Angola	Ecuador	Libya	Samoa
Antigua and Barbuda	Egypt	Liechtenstein	San Marino
Argentina	El Salvador	Madagascar	Sao Tome and Principe
Aruba	Equatorial Guinea	Malawi	Saudi Arabia
Australia	Fiji	Malaysia	Senegal
Austria	Finland	Maldives	Seychelles
Bahamas	France	Mali	Sierra Leone
Bahrain	French Polynesia	Malta	Singapore
Bangladesh	Gabon	Mauritania	Solomon Islands
Barbados	Gambia	Mauritius	Somalia
Belize	Germany	Mexico	South Africa
Benin	Ghana	Mongolia	South Korea
Bermuda	Greece	Morocco	Spain
Bhutan	Greenland	Mozambique	Sri Lanka
Bolivia	Grenada	Myanmar	Suriname
Botswana	Guatemala	Namibia	Swaziland
Brunei	Guinea	Nepal	Sweden
Bulgaria	Guinea-Bissau	Netherlands	Switzerland
Burkina Faso	Guyana	New Caledonia	Syria
Burundi	Haiti	New Zealand	Tanzania
Cambodia	Honduras	Nicaragua	Thailand
Cameroon	Hong Kong	Niger	Tonga
Canada	Hungary	Nigeria	Tunisia
Cape Verde	Iceland	Norway	Turkey
Cayman Islands	India	Oman	Turks and Caicos Islands
Central African Republic	Indonesia	Pakistan	Tuvalu
Chad	Iran	Palestine	Uganda
Chile	Iraq	Panama	United Arab Emirates
China	Ireland	Papua New Guinea	United Kingdom
Colombia	Israel	Paraguay	United States
Comoros	Italy	Peru	Uruguay
Congo	Jamaica	Philippines	Vanuatu
Costa Rica	Japan	Poland	Venezuela
Cote d'Ivoire	Jordan	Portugal	Vietnam
Cuba	Kenya	Puerto Rico	Zambia
Cyprus	Kiribati	Qatar	Zimbabwe
Democratic Republic of the Congo	Kuwait	Romania	

Table 2. The types of natural disaster by disaster identification strategy.

Deaths over population

Disaster severity	Extreme temperatures	Storms	Wildfires	Droughts	Mass movements	Volcanic activity	Earthquakes	Landslides	Floods	Total
0.5%	1	10	0	5	0	1	15	1	2	35
1%	6	21	0	5	0	2	27	2	8	71
1.5%	8	36	0	6	0	2	36	2	17	107
2%	12	48	0	6	0	2	41	7	27	143
2.5%	14	64	0	7	0	2	48	10	34	179

Affected population over population

Disaster severity	Extreme temperatures	Storms	Wildfires	Droughts	Mass movements	Volcanic activity	Earthquakes	Landslides	Floods	Total
0.5%	0	13	0	20	0	0	1	0	1	35
1%	1	19	0	41	0	1	3	0	6	71
1.5%	2	28	0	57	0	1	4	0	15	107
2%	2	38	0	77	0	2	4	0	20	143
2.5%	3	43	0	92	0	2	5	0	34	179

Damage (% of GDP)

Disaster severity	Extreme temperatures	Storms	Wildfires	Droughts	Mass movements	Volcanic activity	Earthquakes	Landslides	Floods	Total
0.5%	0	24	2	1	0	0	6	0	2	35
1%	1	44	2	2	0	0	12	1	9	71
1.5%	2	65	3	2	0	0	18	2	15	107
2%	2	82	3	5	0	0	26	2	23	143
2.5%	2	98	4	8	0	0	29	3	35	179

Table 3. Summary statistics of identified natural disasters.

Deaths over population

disaster severity	Observations	Mean	Std. Dev.	Min	Max
0.5%	35	0.2040	0.3884	0.0355	2.2265
1%	71	0.1109	0.2861	0.0110	2.2265
1.5%	107	0.0764	0.2375	0.0064	2.2265
2%	143	0.0585	0.2076	0.0045	2.2265
2.5%	179	0.0475	0.1867	0.0034	2.2265
Disasters	179	0.0475	0.1867	0.0034	2.2265
Nonclassified	179	0.0020	0.0006	0.0013	0.0034
Nondisasters	6814	0.0001	0.0002	0.0000	0.0013

Total affected over population

disaster severity	Observations	Mean	Std. Dev.	Min	Max
0.5%	35	80.20	21.41	51.57	111.77
1%	71	59.27	25.91	32.28	111.77
1.5%	107	48.58	25.93	23.68	111.77
2%	143	41.61	25.46	18.32	111.77
2.5%	179	36.59	24.85	14.72	111.77
Disasters	179	36.59	24.85	14.72	111.77
Nonclassified	179	9.65	2.48	6.09	14.58
Nondisasters	6814	0.24	0.80	0.00	6.08

Damage (% of GDP)

disaster severity	Observations	Mean	Std. Dev.	Min	Max
0.5%	35	72.94	61.41	23.30	265.39
1%	71	42.79	52.30	9.11	265.39
1.5%	107	30.81	45.75	5.50	265.39
2%	143	24.17	41.16	3.60	265.39
2.5%	179	19.93	37.73	2.74	265.39
Disasters	179	19.93	37.73	2.74	265.39
Nonclassified	179	1.42	0.52	0.81	2.73
Nondisasters	6814	0.03	0.10	0.00	0.81

Table 4. The summary statistics of identified natural disasters using land area (sq. km).

Deaths over land area

disaster intensity	Observations	Mean	Std. Dev.	Min	Max
0.5%	35	0.3762	1.3539	0.0340	8.0784
1%	71	0.1978	0.9601	0.0159	8.0784
1.5%	107	0.1348	0.7852	0.0080	8.0784
2%	143	0.1025	0.6807	0.0052	8.0784
2.5%	179	0.0828	0.6093	0.0041	8.0784
Disasters	179	0.0828	0.6093	0.0041	8.0784
Nonclassified	179	0.0022	0.0008	0.0012	0.0041
Nondisasters	6814	0.0001	0.0002	0.0000	0.0012

Total affected over land area

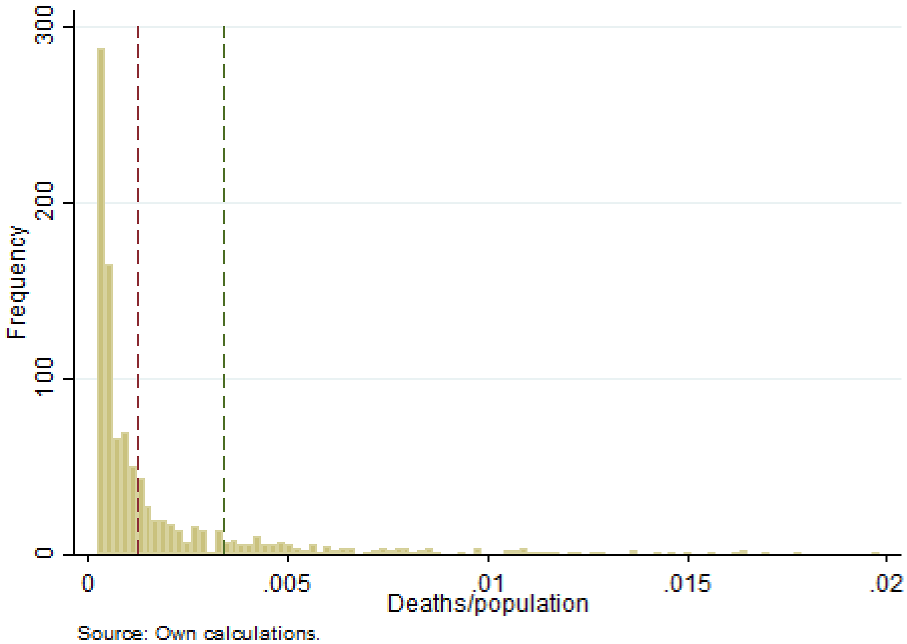
disaster intensity	Observations	Mean	Std. Dev.	Min	Max
0.5%	35	157.43	91.02	74.25	426.94
1%	71	102.05	84.19	36.77	426.94
1.5%	107	77.71	76.59	23.39	426.94
2%	143	63.24	70.76	16.47	426.94
2.5%	179	53.58	66.08	14.12	426.94
Disasters	179	53.58	66.08	14.12	426.94
Nonclassified	179	8.85	2.64	5.18	14.00
Nondisasters	6814	0.19	0.66	0.00	5.14

Damage over land area

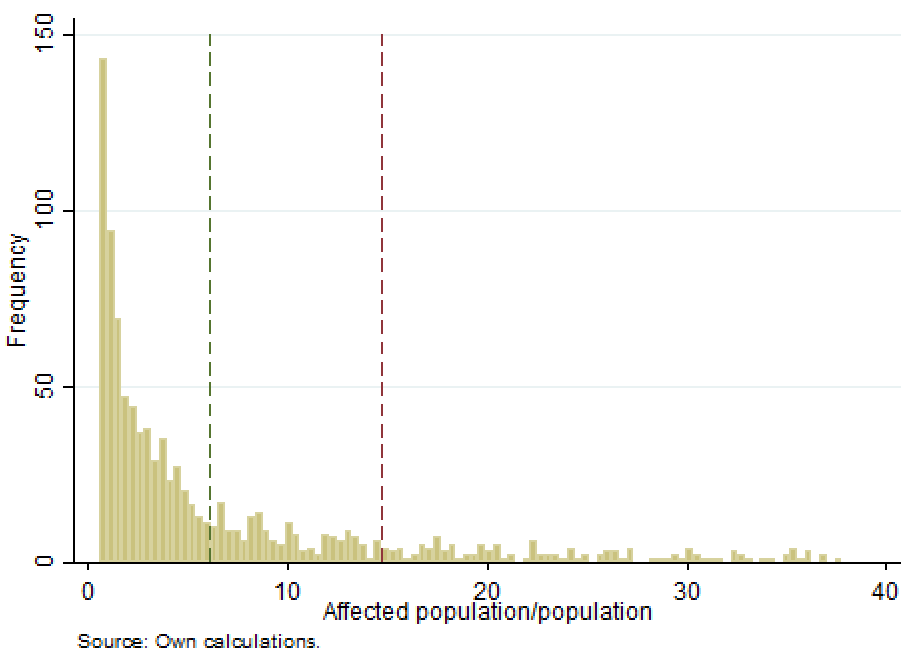
disaster intensity	Observations	Mean	Std. Dev.	Min	Max
0.5%	35	1014172	2560291	82641	14312833
1%	71	527244	1848723	37374	14312833
1.5%	107	359202	1520935	20440	14312833
2%	143	272906	1322528	13194	14312833
2.5%	179	220227	1185925	9010	14312833
Disasters	179	220227	1185925	9010	14312833
Nonclassified	179	4631	1791	2448	8958
Nondisasters	6814	70	281	0	2435

Figure 3. Frequency distribution of identified natural disasters.
These figures represent the thresholds for disaster, nonclassified and nondisaster country-year observations. The country-year observations are ranked based on disaster severity (from 1 to 7,172). One is the largest natural disaster. In some country-years, there are no natural disasters. These are also classified but receive the highest rankings. In these figures, the disasters ranked between 50 and 1,000 are presented. As a consequence, the largest natural disasters, the smallest disasters and nondisasters are not shown. Left of the dashed line (left dashed line) are the nondisaster country-year observations. In between the dashed lines, there are the nonclassified country-year observations. Right of the dashed line (right dashed line) are the disaster country-year observations.

Disaster identification of deaths over population



Disaster identification of affected population over population



Disaster identification of damage (% of GDP)

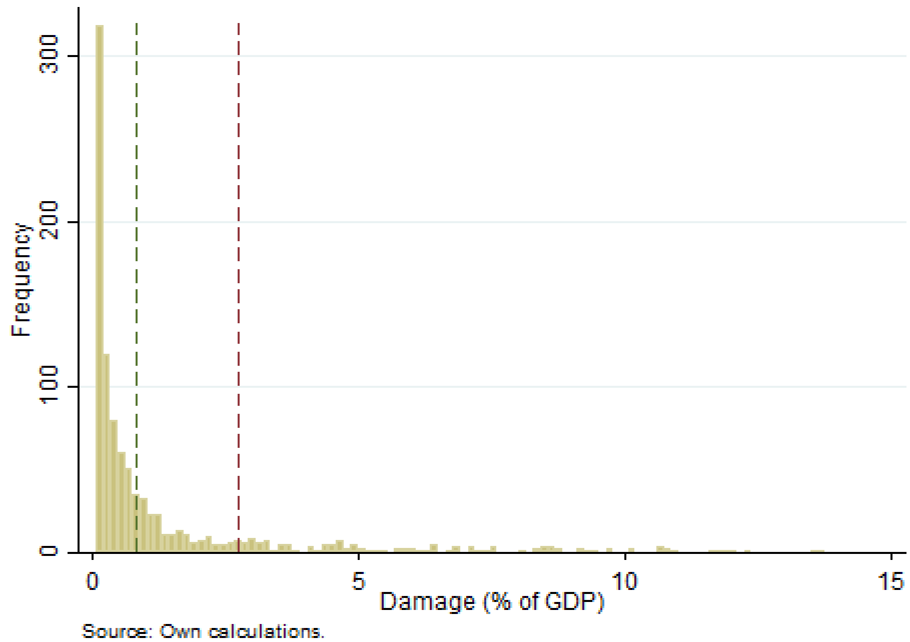
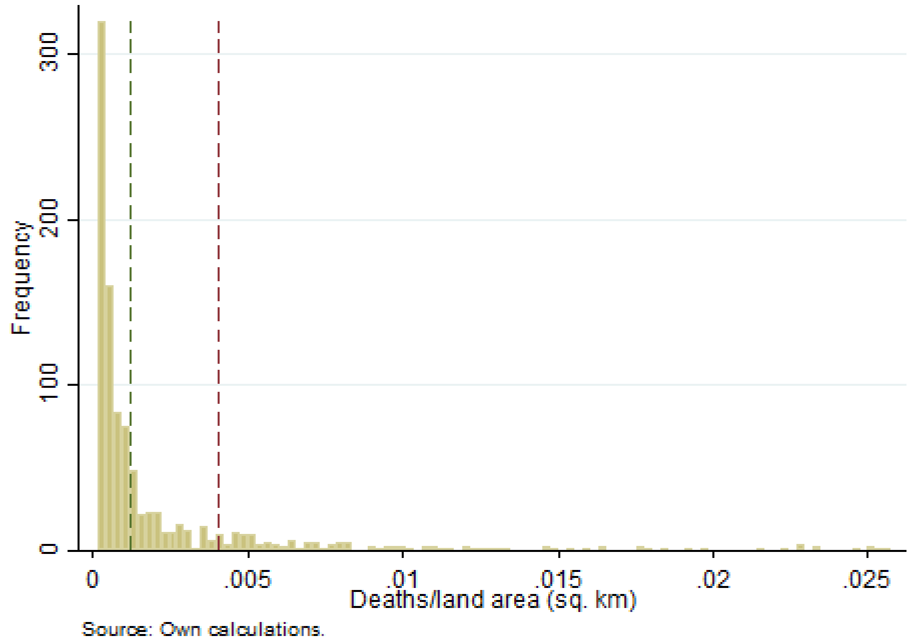
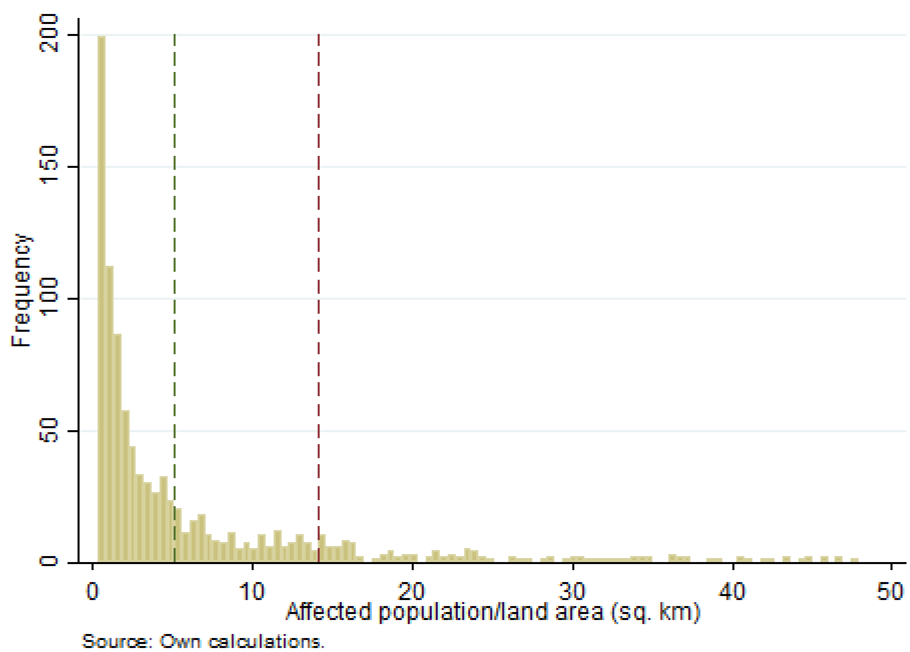


Figure 4. Frequency distribution of identified natural disasters over land area (sq. km).
These figures represent the thresholds for disaster, nonclassified and nondisaster country-year observations. The country-year observations are ranked based on disaster severity (from 1 to 7,172). One is the largest natural disaster. In some country-years, there are no natural disasters. These are also classified but receive the highest rankings. In these figures, the disasters ranked between 50 and 1,000 are presented. As a consequence, the largest natural disasters, the smallest disasters and nondisasters are not shown. Left of the dashed line (left dashed line) are the nondisaster country-year observations. In between the dashed lines, there are the nonclassified country-year observations. Right of the dashed line (right dashed line) are the disaster country-year observations.

Disaster identification of deaths over land area (sq. km).



Disaster identification of affected population over land area (sq. km).



Disaster identification of damage over land area (sq. km).

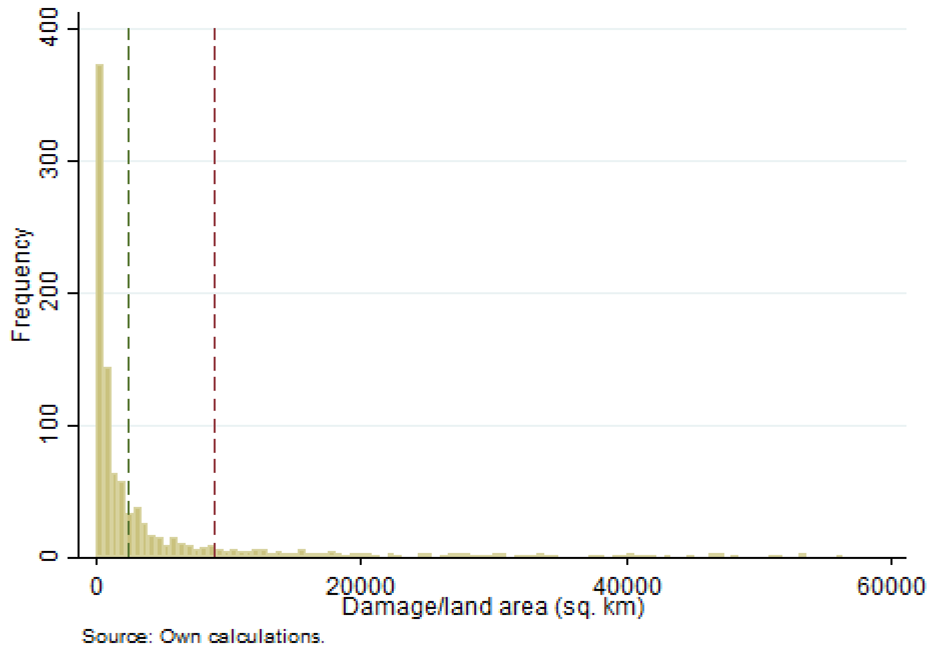


Figure 5. An example of the synthetic control method.
This figure represents the synthetic control method for Belize in 2000. The vertical dashed line represents the disaster-year. The red line is the actual development of Belize's government debt and the dashed line represents the synthetic Belize without a natural disaster.

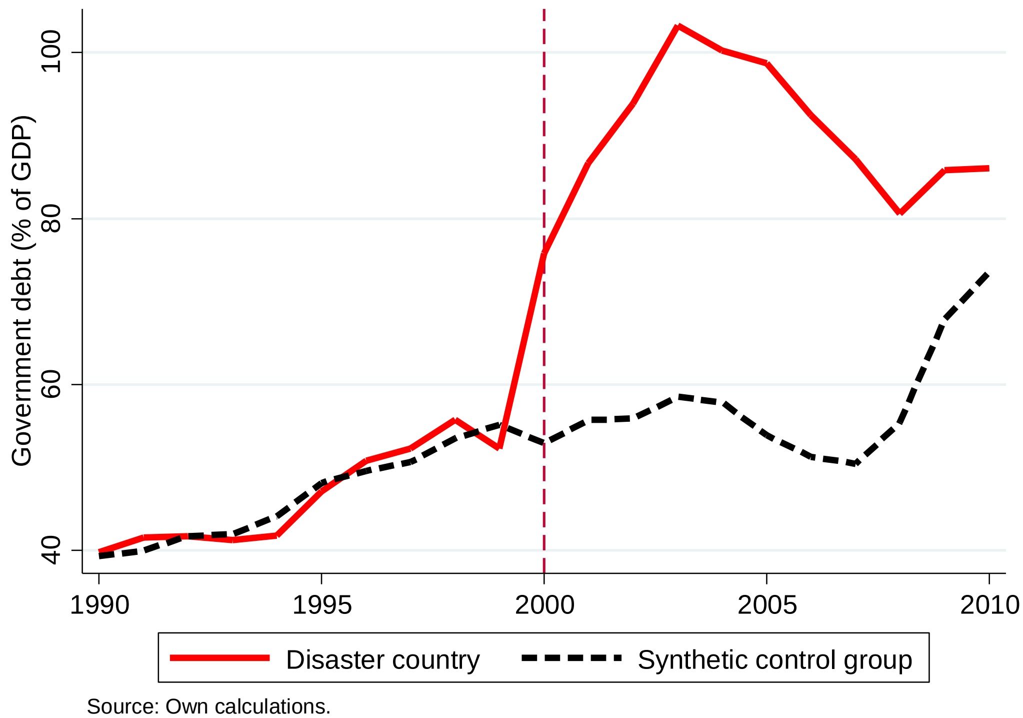


Table 5. Summary statistics and model specifications

The summary statistics of the variables used in the synthetic control estimations

	Observations	Mean	Std. Dev.	Min*	Max*
Government debt (% of GDP)	5432	61.58	64.44	0.00	2092.92
GDP growth	7172	3.83	6.74	-66.12	124.71
Current account (% of GDP)	7172	-5.88	21.40	-186.95	84.84
Openness (% of GDP)	7172	78.31	58.50	1.23	593.49
Population density	7172	193.10	630.08	0.14	7788.66
Population growth	7172	1.93	1.67	-18.05	19.27
GDP per capita	7172	10077.44	15602.74	56.14	137395.71
GDP share of agriculture, hunting and minerals	7172	0.15	0.18	0.00	0.79
General government consumption (% of GDP)	7172	17.35	9.45	1.11	201.02
Gross capital formation (% of GDP)	7172	24.14	10.03	-13.41	113.31
Average latitude	7172	15.34	23.40	-41.00	72.00
Years of schooling	6405	6.03	3.10	0.00	14.20
Total societal and interstate major episodes of political violence	5396	0.85	1.94	0.00	14.00

*The country and year for the minimum and maximum observations are shown in Table 32.

Variables included in the different models

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	XXX	XXX		XXX	
	XXX	XXX		XXX	
	XXX	XXX		XXX	
	XXX	XXX		XXX	
	XXX	XXX	XXX	XXX	XXX
GDP growth		XXX	XXX	XXX	XXX
Current account (% of GDP)		XXX	XXX	XXX	XXX
Openness (% of GDP)		XXX	XXX	XXX	XXX
Population density		XXX	XXX	XXX	XXX
Population growth		XXX	XXX	XXX	XXX
GDP per capita		XXX	XXX	XXX	XXX
GDP share of agriculture, hunting and minerals		XXX	XXX	XXX	XXX
General government consumption (% of GDP)		XXX	XXX	XXX	XXX
Gross capital formation (% of GDP)		XXX	XXX	XXX	XXX
Average latitude				XXX	XXX
Years of schooling				XXX	XXX
Total societal and interstate major episodes of political violence				XXX	XXX

Table 6. Correlation coefficients of the variables used in the synthetic control estimations.

	Government debt (% of GDP)	GDP growth	Current account (% of GDP)	Openness (% of GDP)	Population density	Population growth	GDP per capita at constant 2005 prices in US Dollars	GDP share of agriculture, hunting and minerals	General government consumption (% of GDP)	Gross capital formation (% of GDP)	Average latitude	Year of schooling	Total societal and interstate major episodes of political violence
Government debt (% of GDP)	1												
GDP growth	-0.09***	1											
Current account (% of GDP)	-0.07***	0.01	1										
Openness (% of GDP)	-0.01	0.11***	0.00	1									
Population density	0.01	0.05***	0.08***	0.48***	1								
Population growth	-0.05**	0.13***	0.07***	0.10***	0.00	1							
GDP per capita at constant 2005 prices in US Dollars	-0.11***	-0.05**	0.34***	0.09***	0.11***	-0.10***	1						
GDP share of agriculture, hunting and minerals	0.14***	0.03*	-0.29***	-0.14***	-0.07***	0.14***	-0.43***	1					
General government consumption (% of GDP)	0.03*	-0.11***	-0.19***	0.11***	-0.10***	-0.08***	0.19***	-0.16***	1				
Gross capital formation (% of GDP)	-0.16***	0.25***	-0.08***	0.25***	0.09***	-0.03*	0.08***	-0.21***	0.07***	1			
Average latitude	-0.02	-0.04*	0.13***	-0.04**	0.01	-0.25***	0.50***	-0.19***	0.07***	0.09***	1		
Year of schooling	-0.03*	-0.05***	0.25***	0.13***	0.09***	-0.44***	0.62***	-0.45***	0.10***	0.15***	0.27***	1	
Total societal and interstate major episodes of political violence	0.03*	-0.05***	-0.06***	-0.17***	-0.01	0.02	-0.18***	0.18***	-0.06***	-0.09***	0.00	-0.14***	1

Table 7. The panel synthetic control estimates with no additional controls.

The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disasters are identified using the standard disaster identification strategy. The numbers are expressed as a percentage of GDP.

Total affected over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-2.2	-2.0	-2.6*	-3.9***	-5.0***	-3.1***	0.2	-0.5	-0.3	-0.9**	-2.1**	-0.6***
(T_0 + 2) - (T_0 + 4)	-0.6	-1.3	-3.0	-6.4***	-9.0***	-3.8***	1.0	-0.4	-1.6	-3.4**	-5.2***	-1.9**
(T_0 + 4) - (T_0 + 6)	-3.3	-5.4**	-6.1*	-11.3***	-16.1***	-8.1***	-0.9	-3.3	-5.5	-5.9**	-11.4***	-4.8***
(T_0 + 6) - (T_0 + 8)	-4.0	-7.0**	-7.4	-12.0***	-18.9***	-9.5***	-3.0**	-7.2***	-7.4***	-10.0***	-12.3***	-8.1***
(T_0 + 8) - (T_0 + 10)	-2.3	-6.0**	-8.9**	-11.5***	-19.3***	-9.3***	-3.2	-5.9**	-12.1**	-7.1**	-14.7***	-7.9***
No. of natural disasters	94	94	98	79	82	447	94	94	98	79	82	447

Damage (% of GDP)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	4.4***	3.1***	5.6**	2.7*	5.3*	4.3***	2.5***	1.2	1.2	0.4	0.2	1.2***
(T_0 + 2) - (T_0 + 4)	7.2***	5.4***	14.8	5.1**	16.2	9.8***	5.6***	3.7**	4.4***	3.7**	3.1	4.1***
(T_0 + 4) - (T_0 + 6)	7.3***	4.9**	5.9**	2.7	5.4	5.4***	5.5	3.4	2.5	0.2	1.0	2.5**
(T_0 + 6) - (T_0 + 8)	4.9	5.2	4.3	3.5	4.1	4.5**	1.5	0.2	-0.7	-1.2	-3.1	-0.4
(T_0 + 8) - (T_0 + 10)	1.8	9.8	4.2	9.2	6.2	6.1	0.0	-2.2	-8.2	-1.1	-6.3**	-4.1***
No. of natural disasters	95	100	106	72	76	449	95	100	106	72	76	449

Deaths over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.8**	1.9	2.2	0.3	-0.7	1.4**	3.0***	1.3**	1.9***	0.5	0.6	1.5***
(T_0 + 2) - (T_0 + 4)	6.6***	4.8***	5.1***	3.8**	2.2	4.6***	8.7***	4.3***	5.4***	4.3***	4.3**	5.2***
(T_0 + 4) - (T_0 + 6)	3.8*	1.1	3.0	0.5	-2.0	1.5	3.7	2.3	5.3**	2.4	1.0	3.1***
(T_0 + 6) - (T_0 + 8)	3.2	0.9	0.6	1.0	-4.4	0.4	1.8	0.9	2.9	4.4	0.2	1.8*
(T_0 + 8) - (T_0 + 10)	2.8	-0.3	-5.3	-1.3	-9.3**	-2.5	3.4	-0.4	-0.9	-0.2	-4.0**	-0.7
No. of natural disasters	95	97	100	74	78	444	95	97	100	74	78	444

***p<0.01, **p<0.05, *p<0.1

Table 8. The panel synthetic control estimates using land area with no additional controls.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disasters are identified using the land area in squared kilometers. The numbers are expressed as a percentage of GDP.

Total affected over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-0.4	-0.5	0.1	-1.0	-1.2	-0.6	0.7**	0.8	0.2	0.8	-0.1	0.6**
(T_0 + 2) - (T_0 + 4)	-2.2	0.7	-0.3	-2.1	-2.7	-1.3	1.5	2.2*	1.2	2.6	0.7	1.9**
(T_0 + 4) - (T_0 + 6)	-2.7	2.6	2.2	-0.6	0.6	0.5	-1.0	3.9	2.4	1.1	2.8	1.6**
(T_0 + 6) - (T_0 + 8)	-2.4	3.3	5.1**	-0.3	4.1	1.9*	1.4	4.8**	5.2***	2.5	9.8***	4.7***
(T_0 + 8) - (T_0 + 10)	-1.7	2.2	5.1**	0.9	7.9***	2.8**	2.1	2.2	5.1**	2.5	13.8***	4.6***
No. of natural disasters	113	113	113	104	103	546	113	113	113	104	103	546

Damage over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.6***	2.7***	2.3***	3.5***	2.7***	2.7***	2.3***	2.1***	1.7***	2.2***	1.7***	2.1***
(T_0 + 2) - (T_0 + 4)	8.2***	8.9***	6.7***	8.9***	7.9***	8.1***	6.4***	6.7***	4.9***	6.4***	6.8***	6.1***
(T_0 + 4) - (T_0 + 6)	13.3***	14.0***	11.9***	15.6***	12.9***	13.5***	8.6***	11.4***	8.7***	11.3***	14.0***	10.4***
(T_0 + 6) - (T_0 + 8)	18.4***	18.1***	15.7***	20.3***	17.0***	17.8***	11.5***	12.4***	10.5***	10.7***	12.2***	11.6***
(T_0 + 8) - (T_0 + 10)	23.6***	21.4***	17.6***	24.9***	20.3***	21.4***	16.0***	12.9***	12.3***	14.2***	12.8***	13.3***
No. of natural disasters	124	124	124	91	90	553	124	124	124	91	90	553

Deaths over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-0.5	0.5	-0.3	-0.2	-1.8	-0.4	0.9***	1.5***	0.9**	1.4**	0.2	1.1***
(T_0 + 2) - (T_0 + 4)	4.6***	7.0***	5.1***	5.0**	4.5**	5.3***	5.3***	7.3***	5.5***	5.6***	4.8***	5.6***
(T_0 + 4) - (T_0 + 6)	2.0	4.9**	5.0**	3.3	4.0*	3.8***	4.9***	6.2***	5.1***	5.2**	5.1***	5.4***
(T_0 + 6) - (T_0 + 8)	4.2	6.3***	7.5***	5.3**	7.6***	6.2***	4.5**	6.2***	7.4***	7.4**	7.7***	6.5***
(T_0 + 8) - (T_0 + 10)	3.4	4.5*	5.7**	2.6	6.7**	4.6***	4.5**	4.7	7.4***	2.5	9.9***	6.6***
No. of natural disasters	106	106	105	92	93	502	106	106	105	92	93	502

***p<0.01, **p<0.05, *p<0.1

Table 9. The panel synthetic control estimates controlling for sovereign default.

The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disaster is identified using the standard disaster identification strategy. A country is qualified as in default if it is either in domestic or external default in our sample period ($T_0 - 10 \dots . T_0 + 10$). The numbers are expressed as a percentage of GDP.

Total affected over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-0.9	0.0	-2.1	-1.0	-2.2	-1.2	0.0	-0.6	-0.3	-0.2	-0.5	-0.3**
(T_0 + 2) - (T_0 + 4)	-2.8	-1.5	-3.5	-1.9	-4.6	-2.9**	-2.7	-2.6	-1.6	-1.1	0.3	-1.4
(T_0 + 4) - (T_0 + 6)	-8.4**	-6.4*	-7.1*	-6.4*	-9.8**	-7.6***	-8.1**	-5.1**	-8.6	-4.8	-7.4*	-6.7***
(T_0 + 6) - (T_0 + 8)	-5.2	-4.2	-5.9	-3.5	-9.2**	-5.7***	-7.9**	-7.1**	-9.6	-8.5	-10.9	-8.5***
(T_0 + 8) - (T_0 + 10)	-5.3	-8.0***	-7.3*	-6.7*	-12.0**	-7.9***	-6.2*	-10.1**	-13.3	-10.2*	-13.4*	-11.0***
No. of natural disasters	28	28	30	28	30	144	28	28	30	28	30	144

Damage (% of GDP)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.7***	3.7***	2.3*	1.7*	2.7**	2.8***	2.8**	2.3*	1.3	2.1*	1.4	2.1***
(T_0 + 2) - (T_0 + 4)	4.2*	4.4**	1.9	1.8	3.2*	3.1***	5.7*	1.7	4.1	2.3	3.2*	3.0**
(T_0 + 4) - (T_0 + 6)	0.8	-1.7	-1.6	-2.6	1.2	-0.8	0.1	-3.6	-4.5	-5.0	0.7	-2.2
(T_0 + 6) - (T_0 + 8)	1.8	-2.9	-4.7	-3.0	0.7	-1.6	-1.5	-4.4	-6.8	-2.4	0.4	-1.7
(T_0 + 8) - (T_0 + 10)	5.3	-0.5	-6.3	0.4	1.8	0.0	7.5	0.4	-7.7	0.8	0.8	-0.1
No. of natural disasters	26	27	28	25	27	133	26	27	28	25	27	133

Deaths over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.7**	3.3***	3.2***	2.8***	3.5***	3.1***	3.1***	2.1*	3.9***	1.5***	1.7*	2.6***
(T_0 + 2) - (T_0 + 4)	5.4**	6.6***	7.0***	7.9***	7.7***	6.9***	6.3**	5.5**	6.6***	7.9***	6.4***	6.3***
(T_0 + 4) - (T_0 + 6)	1.2	3.1	5.9	5.1	4.5	4.0**	2.1	3.4*	7.9***	10.2***	5.9**	6.1***
(T_0 + 6) - (T_0 + 8)	3.1	6.4	8.5	8.9	7.5	6.9***	-2.5	2.0	6.8*	5.4	2.6*	2.6**
(T_0 + 8) - (T_0 + 10)	6.1	12.2*	9.3	15.7**	10.1	10.7***	3.2	4.2	2.1	4.4	0.2	4.1
No. of natural disasters	23	25	26	24	25	123	23	25	26	24	25	123

***p<0.01, **p<0.05, *p<0.1

Table 10. The panel synthetic control estimates using land area controlling for sovereign default.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disasters are identified using the land area in squared kilometers. A country is qualified as in default if it is either in domestic or external default in our sample period ($T_0 - 10 \ldots . T_0 + 10$). The numbers are expressed as a percentage of GDP.

Total affected over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.3*	2.1**	1.3	1.2	0.8	1.5***	0.7**	1.7**	0.6	1.0*	0.7	0.9***
(T_0 + 2) - (T_0 + 4)	2.2	3.6***	2.5	1.8	2.0	2.4***	3.1*	2.5***	2.2**	3.6*	3.7**	3.0***
(T_0 + 4) - (T_0 + 6)	0.1	2.8	4.0	0.9	7.4**	3.1**	1.9	3.5	2.4	2.8	12.3***	4.8***
(T_0 + 6) - (T_0 + 8)	3.3	4.9*	9.9***	2.6	15.3***	7.3***	2.7	3.2*	10.5***	5.5	22.0***	8.9***
(T_0 + 8) - (T_0 + 10)	5.3	4.4	12.1***	4.0	20.4***	9.3***	5.2***	2.1	17.1***	4.8	21.6***	9.9***
No. of natural disasters	51	51	53	54	53	262	51	51	53	54	53	262

Damage over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.2***	4.0***	3.3***	4.9***	4.2***	3.9***	3.0***	3.1***	2.2***	2.4***	3.0***	2.8***
(T_0 + 2) - (T_0 + 4)	8.9***	9.0***	7.7***	11.1***	9.9***	9.3***	7.3***	6.3***	5.1***	7.7***	8.1***	7.0***
(T_0 + 4) - (T_0 + 6)	13.6***	12.7***	12.4***	16.8***	15.3***	14.2***	7.5***	9.9***	9.7***	11.3***	14.5***	11.0***
(T_0 + 6) - (T_0 + 8)	21.9***	19.6***	17.9***	23.4***	22.0***	20.9***	11.1***	11.9***	10.1***	12.2***	16.1***	12.0***
(T_0 + 8) - (T_0 + 10)	30.5***	24.7***	20.8***	29.0***	26.0***	26.2***	16.1***	9.5***	11.0***	14.5***	15.9***	13.7***
No. of natural disasters	69	69	69	68	67	342	69	69	69	68	67	342

Deaths over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.5	2.0**	2.2**	1.6*	2.1**	1.9***	0.6**	2.3***	0.9*	1.4**	1.4	1.4***
(T_0 + 2) - (T_0 + 4)	5.8***	5.1***	6.0***	6.3***	7.6***	6.1***	5.2***	5.3***	5.2***	5.6***	5.2***	5.3***
(T_0 + 4) - (T_0 + 6)	5.5**	5.1**	8.0***	7.6***	10.9***	7.4***	6.9***	6.2**	7.6***	7.7**	11.0***	8.1***
(T_0 + 6) - (T_0 + 8)	8.2**	5.1	11.6***	8.9***	16.4***	10.1***	6.2***	9.0**	10.4***	8.7*	17.2***	9.5***
(T_0 + 8) - (T_0 + 10)	14.0***	6.7	14.3***	11.5***	20.8***	13.5***	8.5***	10.7	10.3***	12.8*	19.2***	13.1***
No. of natural disasters	44	44	44	44	44	220	44	44	44	44	44	220

***p<0.01, **p<0.05, *p<0.1

Table 11. The panel synthetic control estimates weighted by the RMSPE.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disaster is identified using the standard disaster identification strategy. The numbers are expressed as a percentage of GDP. The highest weights are given to the case studies with the lowest RMSPE which represent the best matches in the predisaster period.

Total affected over population

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-2.1*	-1.2	-2.6***	-3.1***	-3.1***	-2.4***
(T_0 + 2) - (T_0 + 4)	-0.7	-0.3	-3.5**	-4.4***	-4.7***	-2.7***
(T_0 + 4) - (T_0 + 6)	-1.1	-1.2	-7.3***	-6.7***	-9.2***	-5.1***
(T_0 + 6) - (T_0 + 8)	-2.5	-2.5	-7.8***	-8.1***	-9.9***	-6.2***
(T_0 + 8) - (T_0 + 10)	-4.9*	-6.4**	-11.2***	-12.4***	-13.1***	-9.7***
No. of natural disasters	94	94	98	79	82	447

Damage (% of GDP)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.7***	3.2***	3.0***	2.4**	3.1**	2.9***
(T_0 + 2) - (T_0 + 4)	3.9***	5.9***	7.4**	4.0**	5.9*	5.5***
(T_0 + 4) - (T_0 + 6)	1.6	3.5**	4.1*	1.2	3.1	2.7***
(T_0 + 6) - (T_0 + 8)	1.4	2.3	1.7	-1.3	0.2	0.9
(T_0 + 8) - (T_0 + 10)	-0.7	-2.4	-4.5	-6.3	-6.6	-4.1*
No. of natural disasters	95	100	106	72	76	449

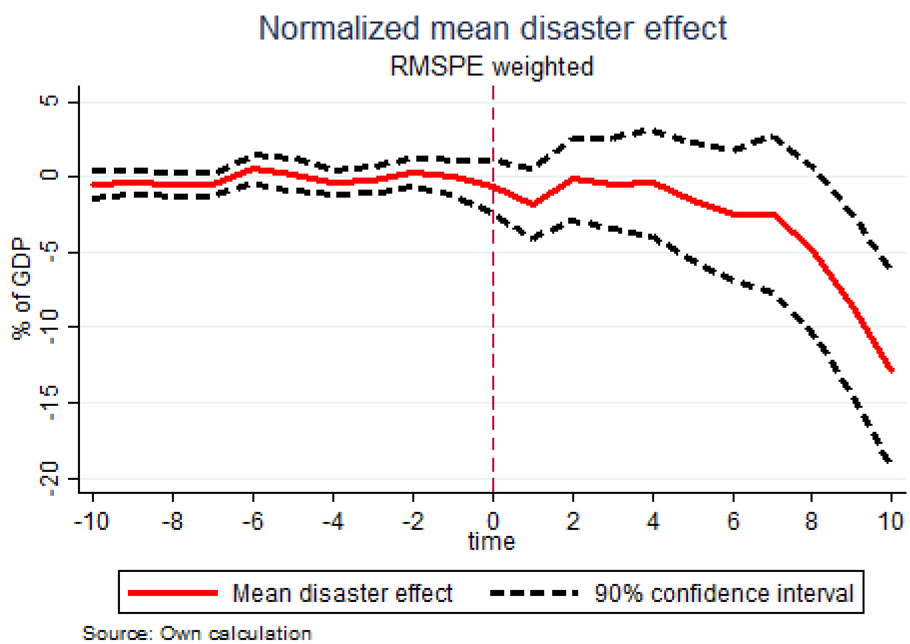
Deaths over population

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.4***	2.2***	2.8***	1.2	0.7	1.9***
(T_0 + 2) - (T_0 + 4)	5.3***	6.8***	7.7***	5.6***	5.2***	6.1***
(T_0 + 4) - (T_0 + 6)	4.4**	6.2***	7.6***	4.7**	2.9	5.2***
(T_0 + 6) - (T_0 + 8)	3.2	6.0***	7.0***	4.5*	0.9	4.3***
(T_0 + 8) - (T_0 + 10)	1.6	3.5	3.6	2.6	-1.8	1.9
No. of natural disasters	95	97	100	74	78	444

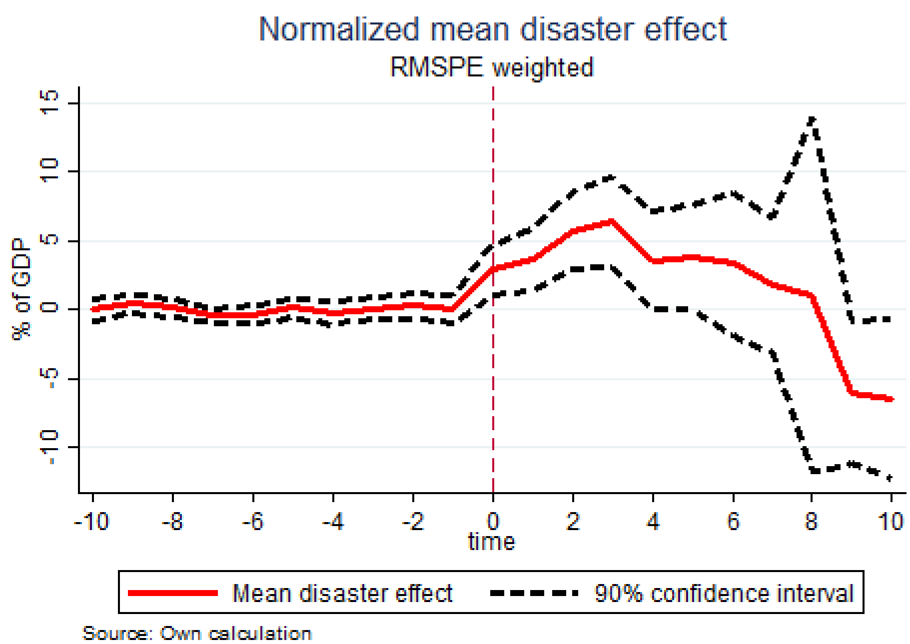
***p<0.01, **p<0.05, *p<0.1

Figure 6. The panel synthetic control estimates weighted by the RMSPE.
This figure represents mean disaster effect with a 90% confidence interval. These figures present model (2). The mean disaster effect is normalized at $T_0 - 1$, which is set equal to zero. The disasters are identified using the standard identification strategy. The numbers are expressed as a percentage of GDP. The highest weights are given to the case studies with the lowest RMSPE which represent the best matches in the predisaster period.

Total affected over population



Damage (% of GDP)



Deaths over population

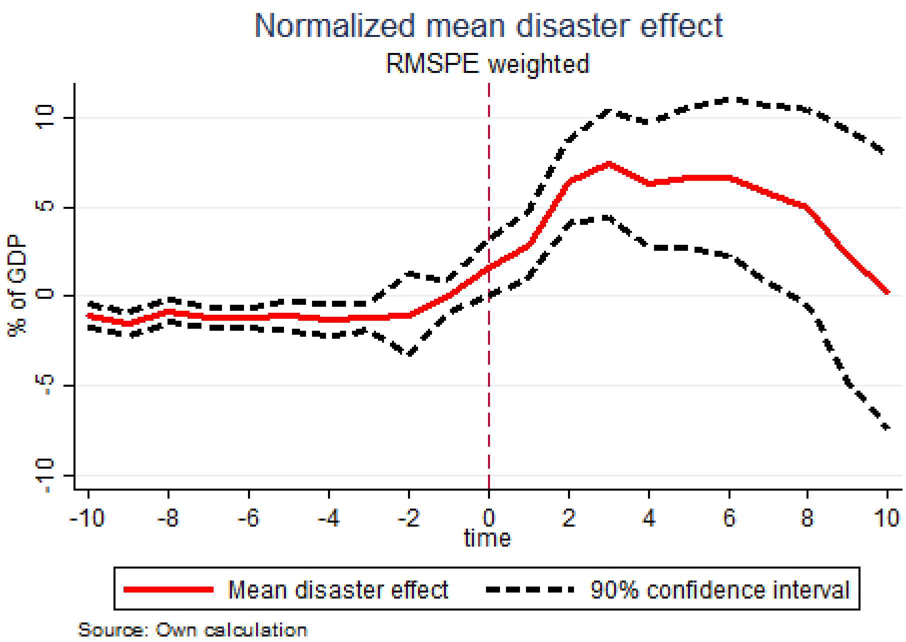


Table 12. The panel synthetic control estimates using land area weighted by the RMSPE.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disasters are identified using the land area in squared kilometers. The numbers are expressed as a percentage of GDP. The highest weights are given to the case studies with the lowest RMSPE which represent the best matches in the predisaster period.

Total affected over land area (sq. km)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	0.2	-0.1	-0.6	0.3	-0.9	-0.2
(T_0 + 2) - (T_0 + 4)	1.2	1.5	-0.5	1.1	-1.7	0.3
(T_0 + 4) - (T_0 + 6)	3.1*	3.8**	1.9	2.9*	1.6	2.6***
(T_0 + 6) - (T_0 + 8)	2.9	6.3***	6.6***	5.1***	5.5**	5.3***
(T_0 + 8) - (T_0 + 10)	5.5**	4.8**	7.7***	4.9**	7.5***	6.1***
No. of natural disasters	113	113	113	104	103	546

Damage over land area (sq. km)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.3**	0.3	1.3*	1.7***	1.8***	1.3***
(T_0 + 2) - (T_0 + 4)	5.5***	4.9***	4.6***	6.1***	6.9***	5.6***
(T_0 + 4) - (T_0 + 6)	8.9***	8.3***	7.9***	11.1***	12.2***	9.6***
(T_0 + 6) - (T_0 + 8)	16.2***	14.0***	12.4***	15.8***	18.9***	15.4***
(T_0 + 8) - (T_0 + 10)	24.0***	17.3***	14.6***	19.5***	20.8***	19.2***
No. of natural disasters	124	124	124	91	90	553

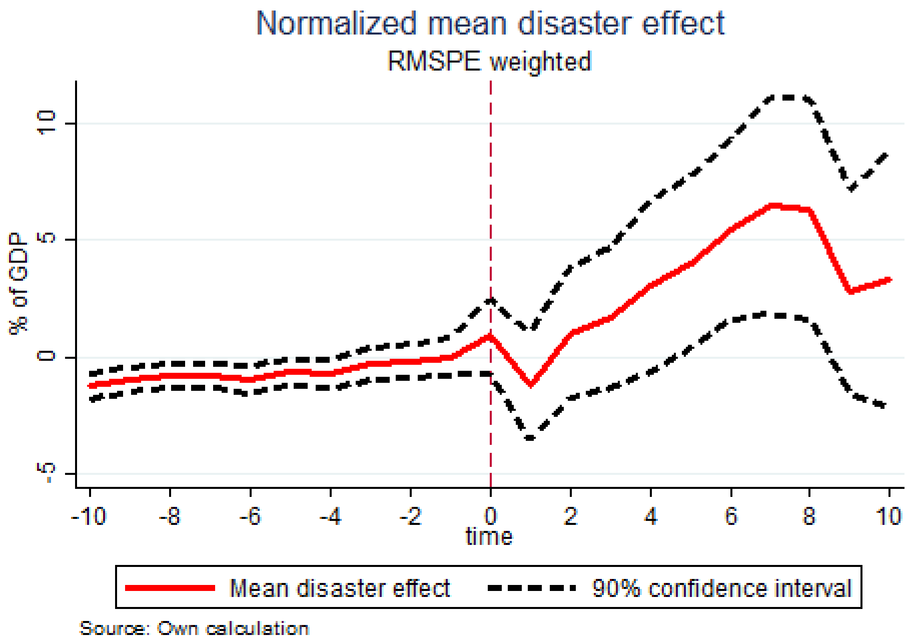
Deaths over land area (sq. km)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.2*	1.8***	0.4	1.8***	0.7	1.2***
(T_0 + 2) - (T_0 + 4)	5.8***	9.9***	7.1***	9.5***	8.7***	8.2***
(T_0 + 4) - (T_0 + 6)	7.3***	10.1***	7.8***	10.9***	9.9***	9.2***
(T_0 + 6) - (T_0 + 8)	8.5***	10.7***	13.2***	12.5***	13.8***	11.7***
(T_0 + 8) - (T_0 + 10)	9.1***	8.4***	12.3***	8.3***	9.6***	9.5***
No. of natural disasters	106	106	106	92	93	503

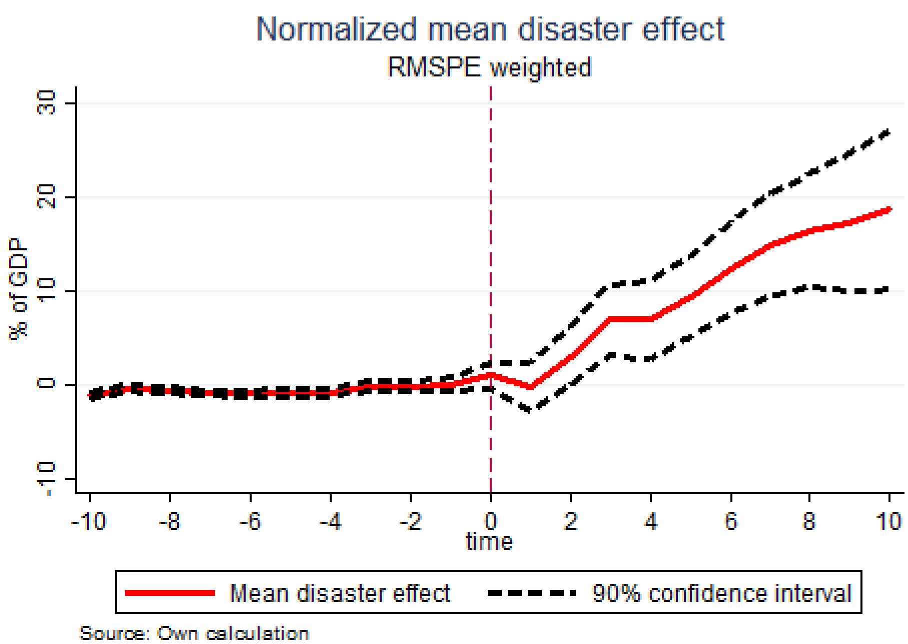
***p<0.01, **p<0.05, *p<0.1

Figure 7. The panel synthetic control estimates using land area weighted by the RMSPE.
This figure represents mean disaster effect with a 90% confidence interval. These figures present model (2). The mean disaster effect is normalized at $T_0 - 1$, which is set equal to zero. The disasters are identified using the land area in squared kilometers. The numbers are expressed as a percentage of GDP. The highest weights are given to the case studies with the lowest RMSPE which represent the best matches in the predisaster period.

Total affected over land area (sq. km)



Damage over land area (sq. km)



Deaths over land area (sq. km)

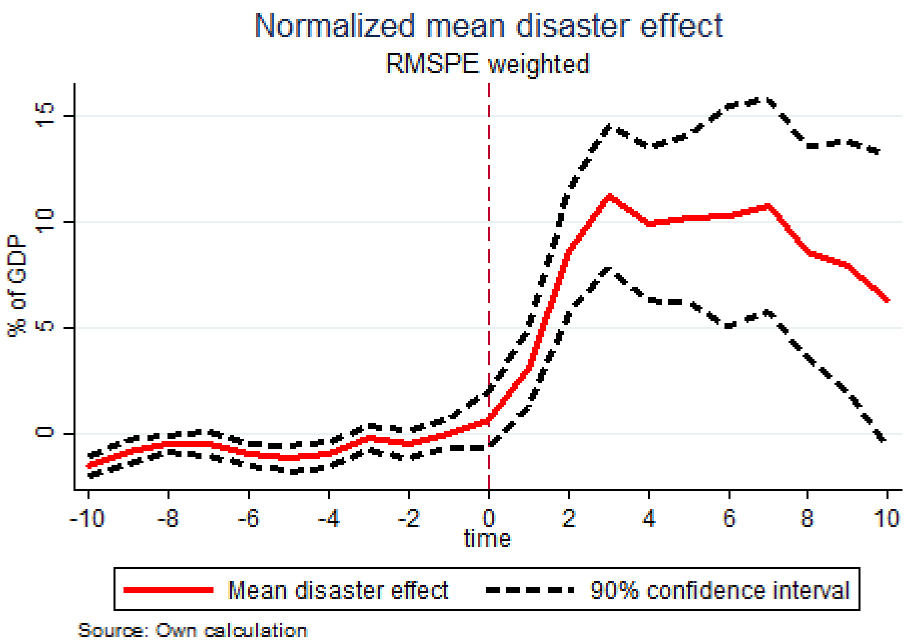


Table 13. The panel synthetic control estimates ranked by the RMSPE.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disaster is identified using the standard disaster identification strategy. The numbers are expressed as a percentage of GDP. The ranks are based on the RMSPE. The highest rank is given to the case study with the lowest RMSPE and the lowest rank is given to the case study with the highest RMSPE.

Total affected over population

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-2.4**	-1.3	-2.8***	-3.4***	-3.4***	-2.7***
(T_0 + 2) - (T_0 + 4)	-0.4	-0.2	-3.0*	-4.9***	-5.7***	-2.8***
(T_0 + 4) - (T_0 + 6)	-0.6	-1.4	-6.2***	-7.7***	-11.4***	-5.5***
(T_0 + 6) - (T_0 + 8)	-1.0	-1.7	-5.9**	-7.6***	-11.6***	-5.6***
(T_0 + 8) - (T_0 + 10)	-2.8	-4.1	-7.8**	-9.8***	-12.7***	-7.5***
No. of natural disasters	94	94	98	79	82	447

Damage (% of GDP)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.2***	3.5***	3.1***	2.0*	3.0**	3.0***
(T_0 + 2) - (T_0 + 4)	5.1***	7.0***	7.6**	4.6**	6.7	6.2***
(T_0 + 4) - (T_0 + 6)	2.9	5.0***	5.1**	2.5	4.5*	4.0***
(T_0 + 6) - (T_0 + 8)	3.4	3.0	3.0	0.5	2.2	2.4*
(T_0 + 8) - (T_0 + 10)	0.4	-1.2	-3.0	-4.3	-3.2	-2.3
No. of natural disasters	95	100	106	72	76	449

Deaths over population

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.3***	2.2***	2.2***	0.6	0.3	1.5***
(T_0 + 2) - (T_0 + 4)	5.6***	6.5***	6.4***	4.9***	4.6***	5.6***
(T_0 + 4) - (T_0 + 6)	4.6**	5.6***	6.4***	4.0*	2.1	4.5***
(T_0 + 6) - (T_0 + 8)	3.9*	5.3**	5.8**	4.3	0.4	3.9***
(T_0 + 8) - (T_0 + 10)	2.6	3.3	1.9	2.6	-2.4	1.6
No. of natural disasters	95	97	100	74	78	444

***p<0.01, **p<0.05, *p<0.1

Table 14. The panel synthetic control estimates using land area ranked by the RMSPE.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disasters are identified using the land area in squared kilometers. The numbers are expressed as a percentage of GDP. The ranks are based on the RMSPE. The highest rank is given to the case study with the lowest RMSPE and the lowest rank is given to the case study with the highest RMSPE.

Total affected over land area (sq. km)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	0.2	-0.2	0.1	-0.1	-0.4	-0.1
(T_0 + 2) - (T_0 + 4)	1.0	2.1	1.7	1.1	-0.4	1.1
(T_0 + 4) - (T_0 + 6)	2.7	4.5***	4.9**	3.1*	3.5	3.7***
(T_0 + 6) - (T_0 + 8)	3.1	6.4***	8.7***	4.8**	6.7***	6.0***
(T_0 + 8) - (T_0 + 10)	4.8*	5.0**	9.4***	4.7**	9.0***	6.6***
No. of natural disasters	113	113	113	104	103	546

Damage over land area (sq. km)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.6***	1.4*	1.3*	2.1***	1.6**	1.6***
(T_0 + 2) - (T_0 + 4)	7.0***	6.6***	4.8***	7.0***	6.2***	6.3***
(T_0 + 4) - (T_0 + 6)	10.5***	9.4***	8.3***	11.3***	10.5***	10.0***
(T_0 + 6) - (T_0 + 8)	15.9***	15.2***	13.6***	16.9***	16.1***	15.5***
(T_0 + 8) - (T_0 + 10)	21.7***	19.1***	15.2***	21.6***	19.9***	19.5***
No. of natural disasters	124	124	124	91	90	553

Deaths over land area (sq. km)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	0.9	1.5**	0.7	1.3*	0.6	1.0***
(T_0 + 2) - (T_0 + 4)	6.4***	9.3***	7.1***	8.6***	7.8***	7.8***
(T_0 + 4) - (T_0 + 6)	7.3***	9.7***	7.4***	9.6***	8.4***	8.5***
(T_0 + 6) - (T_0 + 8)	10.0***	11.0***	12.5***	11.7***	12.2***	11.5***
(T_0 + 8) - (T_0 + 10)	9.5***	8.3***	10.4***	7.4***	8.5***	8.8***
No. of natural disasters	106	106	105	92	93	502

Table 15. The panel synthetic control estimates for high income countries.

The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The definitions are taken from the United Nations 2017 World Economic Situation and Prospects. This study defines high income countries as high- and higher-middle income countries. The numbers are expressed as a percentage of GDP.

Total affected over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-0.7	0.0	0.1	-3.1*	-3.3**	-1.3	-0.7	-0.6	-0.3	-1.8***	-2.4*	-0.9***
(T_0 + 2) - (T_0 + 4)	-0.4	-1.1	-1.4	-6.9***	-8.3***	-3.5***	0.4	-1.7	-0.1	-2.7*	-4.1**	-2.3**
(T_0 + 4) - (T_0 + 6)	-3.4	-5.1	-7.3	-11.6***	-14.9***	-8.4***	-1.7*	-3.6***	-6.0	-9.0**	-13.0***	-6.0***
(T_0 + 6) - (T_0 + 8)	-9.6*	-12.1**	-12.1	-18.5***	-20.9***	-14.5***	-10.8**	-8.5***	-9.8**	-11.7***	-15.1***	-10.9***
(T_0 + 8) - (T_0 + 10)	-13.1**	-17.1***	-19.4***	-22.8***	-25.3***	-19.5***	-7.8*	-14.1***	-13.8***	-11.5***	-15.2***	-13.2***
No. of natural disasters	29	29	32	25	29	144	29	29	32	25	29	144

Damage (% of GDP)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.3	1.3	2.0	1.1	0.3	1.5*	1.4	1.2	1.4	1.7	0.5	1.2**
(T_0 + 2) - (T_0 + 4)	1.0	-0.9	0.6	-1.7	-2.3	-0.5	1.6	-0.6	0.7	0.8	-2.1	0.3
(T_0 + 4) - (T_0 + 6)	-1.8	-4.2	-2.8	-4.3	-2.4	-3.0*	-1.9	-3.3*	-3.2	-4.2	-2.7*	-3.2***
(T_0 + 6) - (T_0 + 8)	-3.3	-5.7	-3.8	-6.2	-4.4	-4.6**	7.0	-2.4	-1.0	-3.1	-4.2	-1.2
(T_0 + 8) - (T_0 + 10)	-8.9*	-12.2**	-14.5***	-14.9**	-12.0*	-12.4***	-3.7	-4.4	-7.5	-5.1	-7.5**	-5.2***
No. of natural disasters	37	38	41	28	31	175	37	38	41	28	31	175

Deaths over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.5***	1.2	3.8**	0.8	1.6	2.3***	3.4***	1.3	3.2***	0.7	0.7	1.6***
(T_0 + 2) - (T_0 + 4)	8.7***	4.2**	7.7***	4.8**	3.9	5.9***	6.8***	4.1**	6.7***	5.2***	5.7**	5.9***
(T_0 + 4) - (T_0 + 6)	8.7***	2.9	8.1***	3.6	3.7	5.5***	4.1	3.4	5.5**	8.2	4.1	4.1***
(T_0 + 6) - (T_0 + 8)	9.5**	3.5	9.6**	4.6	4.4	6.4***	10.0	1.2	6.3*	1.8	1.9	2.3**
(T_0 + 8) - (T_0 + 10)	5.3	0.5	2.9	0.9	2.0	2.4	6.1	0.3	2.8	1.6	-1.0	1.7
No. of natural disasters	38	40	41	34	35	188	38	40	41	34	35	188

***p<0.01, **p<0.05, *p<0.1

Table 16. The panel synthetic control estimates using land area for high income countries.

The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disasters are identified using the land area in squared kilometers. The definitions are taken from the United Nations 2017 World Economic Situation and Prospects. This study defines high income countries as high- and higher-middle income countries. The numbers are expressed as a percentage of GDP.

Total affected over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-1.5	-0.8	-0.1	-0.1	0.7	-0.3	-0.6	-0.6	0.0	0.6	1.4	-0.1
(T_0 + 2) - (T_0 + 4)	-7.4**	0.8	-0.8	-1.8	0.2	-1.7	-4.1	2.3	2.0	2.8	2.8	2.0
(T_0 + 4) - (T_0 + 6)	-9.2**	2.7	-1.2	-0.8	1.9	-1.2	-8.3*	0.9	-3.0	0.6	2.4	-1.2
(T_0 + 6) - (T_0 + 8)	-14.1**	0.1	-1.4	-4.1	-1.6	-4.0	-14.8**	0.3	0.8	1.2	1.0	-0.2
(T_0 + 8) - (T_0 + 10)	-12.0*	-0.3	1.5	-2.4	2.5	-1.9	-6.9	0.2	-1.3	1.1	0.3	-0.3
No. of natural disasters	22	23	25	23	23	116	22	23	25	23	23	116

Damage over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.6***	3.6***	3.6***	4.9***	3.7***	3.9***	2.3***	2.5***	2.3***	2.4***	1.7***	2.3***
(T_0 + 2) - (T_0 + 4)	9.5***	8.8***	8.2***	10.9***	9.0***	9.2***	5.8***	5.7***	5.0***	6.9***	8.0***	6.1***
(T_0 + 4) - (T_0 + 6)	17.2***	15.5***	14.0***	19.9***	15.0***	16.3***	9.3***	11.1***	10.0***	15.5***	14.1***	11.5***
(T_0 + 6) - (T_0 + 8)	23.7***	21.3***	18.4***	26.3***	19.7***	21.8***	16.5***	13.8***	13.4***	14.5***	12.2***	13.9***
(T_0 + 8) - (T_0 + 10)	31.2***	26.3***	21.6***	32.8***	24.4***	27.2***	19.4***	14.9***	13.1***	18.7***	12.5***	14.8***
No. of natural disasters	82	82	82	71	70	387	82	82	82	71	70	387

Deaths over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.2	3.4**	2.0	2.6*	2.5	2.5***	1.0	2.3**	0.3	0.8	2.1*	1.1***
(T_0 + 2) - (T_0 + 4)	4.9*	7.2***	5.1**	5.9**	6.8**	6.0***	5.3***	9.9***	5.9***	8.1***	8.1***	7.2***
(T_0 + 4) - (T_0 + 6)	3.4	5.9*	3.3	6.5*	6.3*	5.1***	6.9*	6.1	5.1*	6.7**	4.6	5.8***
(T_0 + 6) - (T_0 + 8)	4.3	5.1	5.4	7.4	8.4*	6.1***	8.3*	9.4	9.4**	11.5	7.7**	9.4***
(T_0 + 8) - (T_0 + 10)	7.3	6.1	7.1	9.0	9.9*	7.9***	8.4	4.7	8.9*	11.6	8.2**	8.9***
No. of natural disasters	30	30	30	29	29	148	30	30	30	29	29	148

***p<0.01, **p<0.05, *p<0.1

Table 17. The panel synthetic control estimates for low income countries.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The definitions are taken from the United Nations 2017 World Economic Situation and Prospects. This study defines low- income countries as low and lower-middle income countries. The numbers are expressed as a percentage of GDP.

Total affected over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-4.4**	-4.3**	-4.9***	-4.3**	-6.0***	-4.8***	0.2	-0.9	-0.9	-0.5	-0.9	-0.6**
(T_0 + 2) - (T_0 + 4)	-3.2	-3.8	-5.3**	-6.2**	-9.4***	-5.5***	0.9	-2.7	-4.9**	-6.0*	-6.3*	-2.8***
(T_0 + 4) - (T_0 + 6)	-5.8*	-8.0**	-7.4**	-11.1***	-16.9***	-9.6***	0.5	-3.4	-5.6	-5.1	-7.7***	-4.9***
(T_0 + 6) - (T_0 + 8)	-3.8	-7.1*	-7.7*	-8.5**	-17.6***	-8.7***	-2.9	-7.3**	-7.1**	-2.5	-11.4***	-7.2***
(T_0 + 8) - (T_0 + 10)	1.9	-1.2	-4.7	-5.1	-15.2***	-4.6**	6.0	-3.2	-10.6	-5.2	-11.1***	-5.2**
No. of natural disasters	60	60	61	54	53	288	60	60	61	54	53	288

Damage (% of GDP)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	5.4***	4.3**	8.8*	3.7*	8.8*	6.3***	2.4**	-0.5	-0.6	0.1	0.0	0.2
(T_0 + 2) - (T_0 + 4)	10.8***	8.8***	27.2	9.2***	28.6	17.2***	8.8***	4.4	6.9**	7.1**	5.9**	6.6***
(T_0 + 4) - (T_0 + 6)	11.7***	8.4**	9.9**	7.2	10.8*	9.6***	12.8**	4.9*	7.3	6.6	5.7**	6.2***
(T_0 + 6) - (T_0 + 8)	5.5	10.0	7.0	10.3	10.4	8.6**	-0.6	0.7	-2.8	1.8	-0.2	-0.2
(T_0 + 8) - (T_0 + 10)	3.6	26.9	16.3	27.7	20.2	18.9	2.0	-2.8	-13.5**	1.1	-5.4	-4.1
No. of natural disasters	45	49	52	44	45	235	45	49	52	44	45	235

Deaths over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	0.7	1.6	0.3	-0.1	-2.6	0.0	1.3	0.9	0.6	0.2	0.6	0.7
(T_0 + 2) - (T_0 + 4)	2.6	3.5*	1.9	3.0	0.9	2.4**	6.0**	3.1	2.2	3.8	3.1	3.2***
(T_0 + 4) - (T_0 + 6)	-3.6	-3.7	-3.6	-1.9	-6.4*	-3.8**	-2.3	-2.3	0.7	0.2	-0.5	-0.8
(T_0 + 6) - (T_0 + 8)	-5.8*	-5.6	-10.5**	-1.9	-11.3**	-7.1***	-4.0	-2.6	-5.6	4.6	-3.1	-1.4
(T_0 + 8) - (T_0 + 10)	-3.3	-5.5	-17.0***	-3.2	-18.3***	-9.5***	-2.7	-4.1	-16.7**	-0.4	-11.1**	-5.3***
No. of natural disasters	49	49	51	40	43	232	49	49	51	40	43	232

***p<0.01, **p<0.05, *p<0.1

Table 18. The panel synthetic control estimates using land area for low income countries.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disasters are identified using the land area in squared kilometers. The definitions are taken from the United Nations 2017 World Economic Situation and Prospects. This study defines low income countries as low- and lower-middle income countries. The numbers are expressed as a percentage of GDP.

Total affected over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-1.1	-1.1	-0.7	-1.2	-1.8	-1.2	0.8**	0.8	-0.2	0.9	-0.3	0.6
(T_0 + 2) - (T_0 + 4)	-2.7	-0.7	-1.1	-2.2	-3.5	-2.1*	1.4	1.8	-0.2	0.9	0.0	0.9
(T_0 + 4) - (T_0 + 6)	-2.7	1.0	2.6	-0.6	0.2	0.1	1.0	5.2	2.4*	1.5	2.8	2.3**
(T_0 + 6) - (T_0 + 8)	-1.7	1.7	5.8**	0.8	5.7*	2.4*	2.9*	5.4**	6.4***	6.9	10.8***	6.7***
(T_0 + 8) - (T_0 + 10)	-0.6	1.4	6.1**	1.9	9.5***	3.6**	4.6**	6.5	6.9***	3.4	14.2***	6.9***
No. of natural disasters	84	83	81	81	80	409	84	83	81	81	80	409

Damage over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-1.0	-1.2	-2.0	-1.7	-0.9	-1.3*	0.8	1.3	-1.0	0.9	0.7	0.6
(T_0 + 2) - (T_0 + 4)	0.8	4.6	1.0	1.6	4.1	2.4*	6.0	3.9*	1.4	4.4	4.8*	4.6***
(T_0 + 4) - (T_0 + 6)	-7.4	1.1	1.4	-1.6	4.6	-0.5	4.2	6.1*	2.7	2.2	9.8	4.2***
(T_0 + 6) - (T_0 + 8)	-8.5	-1.2	2.3	-2.3	6.7	-0.8	-3.4	1.5	3.1	2.5	14.3*	3.1*
(T_0 + 8) - (T_0 + 10)	-15.8	-5.7	-2.0	-9.9	2.7	-6.4**	0.7	-10.7	0.2	-9.3*	15.3	-3.8
No. of natural disasters	25	25	25	20	20	115	25	25	25	20	20	115

Deaths over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	-2.4	-1.0	-1.7	-1.5	-3.8	-2.1	0.8*	1.4***	1.0**	1.6**	-0.2	1.0***
(T_0 + 2) - (T_0 + 4)	3.5	5.4**	4.7**	4.5*	3.5	4.3***	4.7**	3.9***	5.4***	4.4**	3.7*	4.6***
(T_0 + 4) - (T_0 + 6)	-0.1	1.8	5.0*	1.7	3.0	2.3*	4.4**	5.9**	5.1***	4.2	5.1**	4.6***
(T_0 + 6) - (T_0 + 8)	2.5	4.1	7.9***	4.3	7.1**	5.2***	1.7	5.3***	6.3***	5.0*	7.1***	5.1***
(T_0 + 8) - (T_0 + 10)	-1.5	-0.4	3.4	-0.9	5.0	1.1	1.4	0.5	4.8	-0.9	12.0***	3.7**
No. of natural disasters	67	67	66	63	64	327	67	67	66	63	64	327

***p<0.01, **p<0.05, *p<0.1

Table 19. The panel synthetic control estimates and disaster severity

The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. This table shows the maximum postdisaster effect for the different disaster severities. We classify the largest 0.5%, 1%, 1.5%, 2% and 2.5% of natural disasters in our sample. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The numbers are expressed as a percentage of GDP.

Total affected over population

	Normalized average disaster effect						Normalized median disaster effect					
Disaster severity	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
0.5%	14.0**	8.0	2.6	-0.3	-3.9	4.4	15.4*	7.3	4.2	0.0	-3.2	4.2
1.0%	-2.3	-2.3	-5.2*	-6.7*	-9.4**	-5.5***	5.2	0.0	-1.6	6.7	-4.4***	-2.3**
1.5%	-0.3	-1.2	-4.3**	-5.4***	-7.2***	-4.4***	4.8	-0.3	-1.6*	-1.5	-3.0**	-1.4***
2.0%	-1.6	-2.2	-3.8**	-5.1***	-6.2***	-4.2***	0.1	-0.8	-1.2*	-1.3**	-2.9***	-0.9***
2.5%	-0.6	-1.3	-2.6*	-3.9***	-5.0***	-3.1***	1.0	-0.4	-0.3	-0.9**	-2.1**	-0.6***

Damage (% of GDP)

	Normalized average disaster effect						Normalized median disaster effect					
Disaster severity	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
0.5%	12.3**	4.9	7.7*	-14.7***	-14.2***	2.9	16.9***	9.1	17.6	-16.3**	-15.7***	7.7**
1.0%	9.7*	32.5	32.3	44.3	47.5	24.5	12.4***	6.2	7.7**	7.9	-0.9	6.7***
1.5%	5.2**	14.0	19.7	14.6	25.5	10.8*	4.7***	2.7	2.6	3.7	-1.2	3.2**
2.0%	5.2**	12.8	16.9	11.3	19.2	9.7**	4.2***	3.1	4.3**	3.1	0.6	3.4***
2.5%	7.3***	9.8	14.8	9.2	16.2	9.8***	5.6***	3.7**	4.4***	3.7**	3.1	4.1***

Deaths over population

	Normalized average disaster effect						Normalized median disaster effect					
Disaster severity	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
0.5%	1.2	2.3	-0.8	0.1	1.3	-0.1	8.7	4.0	2.7	4.4	-0.9	3.6
1.0%	7.0***	5.6***	5.0**	4.3	2.6	5.0***	10.4***	7.8	7.8**	9.8	6.4**	6.9***
1.5%	5.2***	4.6***	3.7**	2.4	0.8	3.5***	9.1***	5.0***	5.4***	4.6***	4.9**	5.6***
2.0%	4.6**	5.3***	4.6**	2.8	1.7	3.9***	7.7***	5.0***	6.7**	6.6	5.0***	5.6***
2.5%	6.6***	4.8***	5.1***	3.8**	2.2	4.6***	8.7***	4.3***	5.4***	4.4	4.3**	5.2***

***p<0.01, **p<0.05, *p<0.1

Table 20. The panel synthetic control estimates using land area and disaster severity

The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. This table shows the maximum postdisaster effect for the different disaster severities. We classify the largest 0.5%, 1%, 1.5%, 2% and 2.5% of natural disasters in our sample. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The disasters are identified using the land area in squared kilometers. The numbers are expressed as a percentage of GDP.

Total affected over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
Disaster severity	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
0.5%	10.1*	7.3*	17.6***	4.4	21.9***	11.4***	8.9**	8.2	20.7***	2.5	21.5***	12.1***
1.0%	0.4	0.8	7.2	-4.7	7.9	1.9	7.2	5.7	8.6**	-0.8	16.4**	5.6**
1.5%	0.9	3.9	4.6	0.8	9.2**	2.7	3.4	6.0**	5.4**	2.8	17.0***	5.2***
2.0%	0.0	2.2	3.7	-0.3	6.9**	1.7	2.5	5.4*	5.0	2.4	11.1***	4.2***
2.5%	-0.4	3.3	5.1**	0.9	7.9***	2.8**	2.1	4.8**	5.2***	2.6	13.8***	4.7***

Damage over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
Disaster severity	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
0.5%	44.0***	37.3***	30.4***	37.1*	33.4	36.2***	33.0***	31.2***	35.4***	38.7	28.8	30.4***
1.0%	20.6***	17.9***	12.3**	14.5**	10.5*	14.9***	14.2***	12.2***	12.7*	12.3*	13.0	11.4***
1.5%	19.5***	17.1***	11.2***	18.3***	12.7***	15.8***	12.9***	11.0***	8.8***	11.4***	11.5*	10.3***
2.0%	20.9***	19.7***	15.0***	22.6***	17.9***	19.1***	13.6***	11.4***	9.7***	12.1***	14.1***	12.0***
2.5%	23.6***	21.4***	17.6***	24.9***	20.3***	21.4***	16.0***	12.9***	12.3***	14.2***	14.0***	13.3***

Deaths over land area (sq. km)

	Normalized average disaster effect						Normalized median disaster effect					
Disaster severity	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
0.5%	-1.3	8.2	9.8*	0.8	4.3	3.8	9.2*	14.4**	14.6*	10.7	16.4	11.8**
1.0%	2.0	5.9**	7.1**	1.1	3.2	3.6**	7.4***	8.7***	11.1***	7.9*	7.7**	7.9***
1.5%	6.2*	9.2***	10.9***	5.7	11.9***	8.7***	7.2**	10.2***	14.6***	7.4*	16.4***	10.5***
2.0%	6.0**	8.2***	9.2***	8.0***	10.0***	8.3***	6.2***	8.1***	9.3***	8.2***	12.0***	7.7***
2.5%	4.6***	7.0***	7.5***	5.3**	7.6***	6.2***	5.3***	7.3***	7.4***	7.4**	9.9***	6.6***

****p*<0.01, ***p*<0.05, **p*<0.1

Table 21. Additional government financing needs (% of GDP) for the standard and land area identification strategy.

This table presents the maximal additional financing needs compared to the synthetic control group. Our definition of a debt decline is that there is a negative sign, either statistically significant or insignificant, for the first four years $(T_0, \dots, T_0 + 4)$; or when eight out of ten years have a negative sign which is either significant or insignificant. Our definition of a debt increase is that there is a positive sign, either statistically significant or insignificant, for the first four years $(T_0, \dots, T_0 + 4)$; or when eight out of ten years have a negative sign which is either significant or insignificant. We define a disaster impact as mixed for the other estimations.

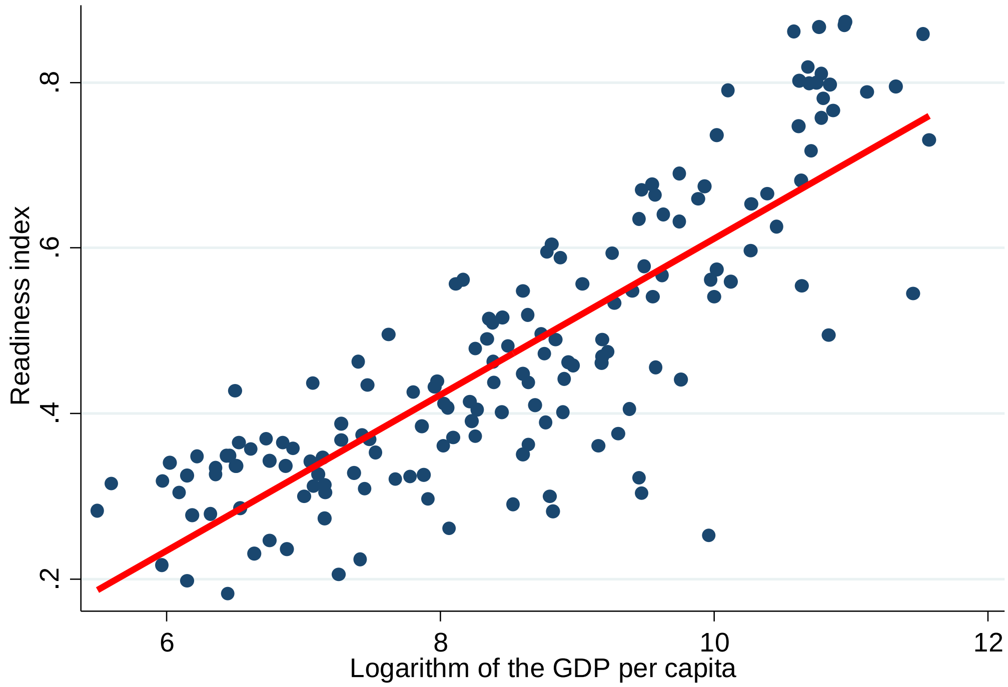
Standard disaster identification strategy

	Average disaster effect			Median disaster effect		
	Total affected over population	Damage (% of GDP)	Deaths over population	Total affected over population	Damage (% of GDP)	Deaths over population
No additional controls	decline	9.8%	4.6%	decline	4.1%	5.2%
No sovereign defaults	decline	3.1%	10.7%	decline	3.0%	6.3%
RMSPE weighted	decline	5.5%	6.1%	n/a	n/a	n/a
RMSPE ranked	decline	6.2%	5.6%	n/a	n/a	n/a
High income countries	decline	decline	6.4%	decline	1.2%	5.9%
Low income countries	decline	17.2%	2.4%	decline	6.6%	3.2%
High GDP per capita	decline	4.2%	10.3%	0.4%	3.2%	8.2%
Low GDP per capita	decline	14.9%	decline	decline	mixed	2.8%
Low agricultural dependency	decline	6.5%	8.8%	decline	4.3%	7.1%
High agricultural dependency	decline	15.6%	1.7%	decline	mixed	3.0%
SIDS	decline	9.4%	8.6%	decline	5.7%	9.5%
RMSPE quartile 1	decline	6.6%	8.0%	decline	3.5%	7.5%
RMSPE quartile 1-2	decline	5.9%	6.5%	decline	3.9%	6.6%
RMSPE quartile 1-3	decline	6.3%	4.9%	decline	4.3%	5.3%
RMSPE quartile 1-4	decline	9.8%	4.6%	decline	4.1%	5.2%
No multiple disasters	decline	9.6%	12.0%	decline	6.8%	13.1%
No conflicts	decline	13.6%	5.0%	decline	4.4%	5.2%

Land area disaster identification strategy

	Average disaster effect			Median disaster effect		
	Total affected over land area	Damage over land area	Deaths over land area	Total affected over land area	Damage over land area	Deaths over land area
No additional controls	decline	21.4%	6.2%	4.7%	13.3%	6.6%
No sovereign defaults	9.3%	26.2%	13.5%	9.9%	13.7%	13.1%
RMSPE weighted	6.1%	19.2%	11.7%	n/a	n/a	n/a
RMSPE ranked	6.6%	19.5%	11.5%	n/a	n/a	n/a
High income countries	decline	27.2%	7.9%	decline	14.8%	9.4%
Low income countries	decline	decline	5.2%	6.9%	4.6%	5.1%
High GDP per capita	1.8%	32.1%	6.4%	2.9%	19.7%	8.5%
Low GDP per capita	mixed	10.3%	7.4%	6.4%	8.6%	5.5%
Low agricultural dependency	decline	37.3%	8.7%	mixed	23.3%	9.0%
High agricultural dependency	6.1%	6.6%	7.9%	8.9%	7.1%	6.1%
SIDS	decline	13.6%	mixed	decline	12.1%	4.5%
RMSPE quartile 1	5.5%	20.0%	11.7%	5.5%	14.9%	8.8%
RMSPE quartile 1-2	7.6%	19.7%	14.0%	6.6%	14.2%	9.5%
RMSPE quartile 1-3	7.5%	18.5%	11.0%	6.9%	13.1%	8.4%
RMSPE quartile 1-4	decline	21.4%	6.2%	4.7%	13.3%	6.6%
No multiple disasters	decline	13.0%	20.4%	decline	7.9%	17.2%
No conflicts	decline	23.2%	5.8%	mixed	13.2%	7.1%

Figure 8. The relationship between GDP per capita and the ND GAIN readiness index in 2012.



Source: Own calculations based on ND GAIN (2015) and UNSTAT (2015).

Table 22. Disaster identification strategies and GDP per capita.
This table presents the mean and median GDP per capita for the year preceding the natural disaster. The standard measures include total affected over population, damage as percent of GDP and deaths over population. The land area measures include total affected over land area, damage over land area and deaths over land area. The exogenous measures use the exogenous disaster identification strategy using total affected over population, damages as percent of GDP and deaths over population.

Average GDP per capita

Disaster identification measure	Total affected	Damage	Deaths
Standard measures	2711	4513	6756
Land area measures	1616	17397	5830
Exogenous measures	4391	5662	6992

Median GDP per capita

Disaster identification measure	Total affected	Damage	Deaths
Standard measures	902	2496	2439
Land area measures	877	12469	1377
Exogenous measures	1064	2551	2425

Table 23. The panel synthetic control estimates using an exogenous disaster identification strategy with no additional controls.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The natural disasters are exogenously determined by equation (4). The numbers are expressed as a percentage of GDP.

Exogenous disaster identification for total affected over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.2***	2.1**	-1.1	1.1	-2.1	0.6	2.0***	1.3***	-0.5	0.4	-0.1	0.7***
(T_0 + 2) - (T_0 + 4)	3.6**	1.9	-4.4*	1.9	-4.5	-0.4	3.5***	2.2**	-1.7	1.7	0.1	1.5**
(T_0 + 4) - (T_0 + 6)	2.7	1.5	-7.3*	1.7	-6.2	-1.7	1.7	0.9	-3.1	1.5	0.6	0.7
(T_0 + 6) - (T_0 + 8)	0.7	-0.4	-10.8**	0.4	-11.5**	-4.6**	-0.4	-3.2	-6.8**	-1.8	-8.6*	-3.2***
(T_0 + 8) - (T_0 + 10)	-1.8	-2.1	-14.0**	-0.5	-16.2**	-7.3**	-1.9	-7.3**	-6.6**	-3.0	-7.3***	-5.9***
No. of natural disasters	105	107	118	89	99	518	105	107	118	89	99	518

Exogenous disaster identification for damage (% of GDP)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.0**	3.6*	0.7	0.6	0.0	1.5*	0.7	0.4	0.6	0.1	-0.9	0.3
(T_0 + 2) - (T_0 + 4)	6.4***	13.7	7.5	4.5	5.3	7.8**	3.0**	2.4**	0.6	0.8	-3.0**	1.2*
(T_0 + 4) - (T_0 + 6)	15.0	15.7	7.0	14.1	-6.7	9.4**	0.6	2.2	-1.1	-2.4	-4.5**	-0.3
(T_0 + 6) - (T_0 + 8)	2.0	1.8	-5.9	-4.5	-14.9***	-3.9**	-1.3	-1.7	-3.1	-4.0	-7.0***	-3.1***
(T_0 + 8) - (T_0 + 10)	1.5	-1.0	-8.4	-3.4	-19.2***	-5.7**	0.8	-3.8	-3.9*	-7.6**	-10.0***	-5.8***
No. of natural disasters	115	120	126	86	91	538	115	120	126	86	91	538

Exogenous disaster identification for deaths over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	4.4***	7.1***	6.2***	4.5***	7.6**	6.0***	3.1***	2.3***	2.9***	2.0***	2.6**	2.7***
(T_0 + 2) - (T_0 + 4)	9.4***	19.6**	16.9*	11.0***	18.8	15.2***	6.6***	7.2***	7.0***	6.3***	5.3**	6.8***
(T_0 + 4) - (T_0 + 6)	22.7*	27.0**	22.4**	30.0*	13.6***	23.2***	7.1***	6.6***	3.8**	6.8***	3.4**	5.9***
(T_0 + 6) - (T_0 + 8)	22.8*	26.0**	21.3*	28.4*	23.3	24.2***	8.9**	5.4***	2.6	4.5**	2.0	5.0***
(T_0 + 8) - (T_0 + 10)	10.4**	11.3***	11.2***	14.6***	6.9*	10.9***	6.2	4.2	2.9	3.3	-1.0	3.2**
No. of natural disasters	100	102	107	75	76	460	100	102	107	75	76	460

***p<0.01, **p<0.05, *p<0.1

Table 24. The panel synthetic control estimates using an exogenous disaster identification strategy controlling for sovereign default.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The natural disasters are exogenously determined by equation (4). A country is qualified as in default if it is either in domestic or external default in our sample period ($T_0 - 10 \dots . T_0 + 10$). The numbers are expressed as a percentage of GDP.

Exogenous disaster identification for total affected over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.9**	2.6*	0.1	1.2	-0.9	1.1	0.7	1.0	-1.3	0.6	-0.7	0.2
(T_0 + 2) - (T_0 + 4)	5.6**	5.0**	-0.4	3.0	-0.5	2.4**	3.5**	1.9	-2.0	1.9	0.8	1.3*
(T_0 + 4) - (T_0 + 6)	1.7	2.2	-3.1	1.0	-0.7	0.1	4.4	1.2	-4.7**	-0.6	0.9	0.0
(T_0 + 6) - (T_0 + 8)	-2.5	-1.6	-5.1**	2.4	-3.0	-2.1	-1.4	0.2	-4.6**	6.8	-0.9	-1.4
(T_0 + 8) - (T_0 + 10)	-2.0	-3.4	-2.6	4.6	1.1	-0.5	1.9	-1.4	-2.0	9.8	4.6	1.9
No. of natural disasters	25	26	29	25	28	133	25	26	29	25	28	133

Exogenous disaster identification for damage (% of GDP)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	0.6	0.6	0.6	0.4	-0.8	0.3	0.2	0.7	1.3	0.9	-0.8	0.5
(T_0 + 2) - (T_0 + 4)	4.3	3.2	1.7	3.8	-0.5	2.5**	-0.6	-0.1	-0.6	0.7	-2.4	-0.5
(T_0 + 4) - (T_0 + 6)	5.0	4.4	1.5	4.8	-0.4	3.1*	-1.1	0.7	-3.3	-2.5	-1.8	-0.9
(T_0 + 6) - (T_0 + 8)	3.2	-0.6	-0.4	2.4	-1.4	0.6	-2.6*	-1.6	-3.5*	2.8	-2.5	-1.7*
(T_0 + 8) - (T_0 + 10)	5.6	1.4	1.1	6.2	2.2	3.3	1.5	1.8	0.3	5.1	-0.5	1.0
No. of natural disasters	33	34	34	31	31	163	33	34	34	31	31	163

Exogenous disaster identification for deaths over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.8**	3.3**	5.6***	3.2**	4.1**	4.0***	3.1***	3.0***	5.2***	2.5***	2.8**	3.0***
(T_0 + 2) - (T_0 + 4)	8.1***	5.7***	8.2***	7.7***	6.4***	7.2***	7.4***	7.9***	7.9***	7.7***	3.3	7.6***
(T_0 + 4) - (T_0 + 6)	7.1*	5.3	6.2*	7.5*	4.9	6.2***	7.9**	5.2***	6.9*	6.3*	3.7	5.6***
(T_0 + 6) - (T_0 + 8)	13.5**	9.8*	9.9**	13.8**	8.4*	11.1***	10.0	4.8	7.7	5.0**	3.7	6.0***
(T_0 + 8) - (T_0 + 10)	15.6**	13.0*	13.7**	18.1**	13.7**	14.8***	5.4	7.5	5.4***	7.8	5.2	6.2***
No. of natural disasters	26	26	26	24	23	125	26	26	26	24	23	125

***p<0.01, **p<0.05, *p<0.1

Table 25. The panel synthetic control estimates using an exogenous disaster identification strategy weighted by the RMSPE.

The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The natural disasters are exogenously determined by equation (4). The numbers are expressed as a percentage of GDP. The highest weights are given to the case studies with the lowest RMSPE which represent the best matches in the predisaster period.

Exogenous disaster identification for total affected over population

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.0	-0.5	0.2	0.6	0.7	0.4
(T_0 + 2) - (T_0 + 4)	1.5	-1.8	-1.7	0.5	-0.1	-0.3
(T_0 + 4) - (T_0 + 6)	1.1	-2.8	-2.4	-0.4	-0.4	-1.0
(T_0 + 6) - (T_0 + 8)	-2.4	-5.9***	-3.1	-3.2	-4.2*	-3.8***
(T_0 + 8) - (T_0 + 10)	-5.1**	-9.8***	-2.9	-5.8**	-4.1	-5.7***
No. of natural disasters	105	107	118	89	99	518

Exogenous disaster identification for damage (% of GDP)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.2*	1.1	0.6	-0.1	-0.2	0.5
(T_0 + 2) - (T_0 + 4)	2.6**	2.8	1.3	0.6	0.1	1.4
(T_0 + 4) - (T_0 + 6)	1.9	2.3	1.9	0.4	-1.9	0.9
(T_0 + 6) - (T_0 + 8)	-1.7	0.4	1.2	-1.4	-5.1**	-1.3
(T_0 + 8) - (T_0 + 10)	-4.1*	0.2	2.0	-0.9	-4.1	-1.3
No. of natural disasters	115	120	126	86	91	538

Exogenous disaster identification for deaths over population

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.3***	3.6***	3.6***	2.9***	3.1***	3.3***
(T_0 + 2) - (T_0 + 4)	7.7***	8.9***	7.3***	6.9***	8.1**	7.8***
(T_0 + 4) - (T_0 + 6)	10.9***	9.3***	6.9*	8.2**	6.2**	8.3***
(T_0 + 6) - (T_0 + 8)	13.2***	8.5**	6.8	7.4	3.5	7.9***
(T_0 + 8) - (T_0 + 10)	11.1***	4.2*	4.9**	3.9	2.3	5.3***
No. of natural disasters	100	102	107	75	76	460

***p<0.01, **p<0.05, *p<0.1

Table 26. The panel synthetic control estimates using an exogenous disaster identification strategy ranked by the RMSPE.

The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The natural disasters are exogenously determined by equation (4). The numbers are expressed as a percentage of GDP. The ranks are based on the RMSPE. The highest rank is given to the case study with the lowest RMSPE and the lowest rank is given to the case study with the highest RMSPE.

Exogenous disaster identification for total affected over population

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.3	0.8	0.1	0.8	0.3	0.7*
(T_0 + 2) - (T_0 + 4)	2.3*	0.7	-2.2	1.3	-0.6	0.3
(T_0 + 4) - (T_0 + 6)	2.1	0.3	-2.4	0.8	-0.1	0.1
(T_0 + 6) - (T_0 + 8)	-1.0	-2.8	-3.2	-2.4	-4.5*	-2.8**
(T_0 + 8) - (T_0 + 10)	-1.7	-3.8	-1.8	-2.9	-3.6	-2.8**
No. of natural disasters	105	107	118	89	99	518

Exogenous disaster identification for damage (% of GDP)

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.6**	1.5**	0.7	-0.1	-0.2	0.7*
(T_0 + 2) - (T_0 + 4)	3.4***	3.6*	1.7	1.3	0.9	2.2**
(T_0 + 4) - (T_0 + 6)	2.3	3.1	2.4	0.8	-1.2	1.5
(T_0 + 6) - (T_0 + 8)	0.3	1.7	1.2	-1.2	-5.0*	-0.6
(T_0 + 8) - (T_0 + 10)	-1.3	1.2	2.2	-0.4	-4.1	-0.5
No. of natural disasters	115	120	126	86	91	538

Exogenous disaster identification for deaths over population

	Normalized average disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.1***	3.1***	3.5***	2.8***	2.8**	3.1***
(T_0 + 2) - (T_0 + 4)	7.1***	7.3***	6.6***	6.9***	7.3**	7.0***
(T_0 + 4) - (T_0 + 6)	7.9***	7.9***	6.8*	7.6**	6.2**	7.3***
(T_0 + 6) - (T_0 + 8)	7.5**	7.6**	6.6	6.7	3.7	6.4***
(T_0 + 8) - (T_0 + 10)	4.0	3.6	5.4**	3.4	2.4	3.8***
No. of natural disasters	100	102	107	75	76	460

***p<0.01, **p<0.05, *p<0.1

Table 27. The panel synthetic control estimates using an exogenous disaster identification strategy for high income countries.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The natural disasters are exogenously determined by equation (4). The definitions are taken from the United Nations 2017 World Economic Situation and Prospects. This study defines high income countries as high- and higher-middle income countries. The numbers are expressed as a percentage of GDP.

Exogenous disaster identification for total affected over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.6**	2.1	-4.7	1.5	-7.5*	-1.3	1.8*	0.6	-1.4*	0.0	-2.8*	-0.1
(T_0 + 2) - (T_0 + 4)	3.8	2.6	-11.1	3.4	-11.4	-3.2	5.8**	2.0	-4.2	2.0*	-1.5	1.2*
(T_0 + 4) - (T_0 + 6)	1.1	1.9	-20.4*	3.3	-18.0	-7.8*	2.0	0.7	-10.4**	2.4	-2.3	-1.5
(T_0 + 6) - (T_0 + 8)	-0.7	0.0	-27.8*	0.6	-26.4*	-12.9**	-1.1	-5.9	-10.9***	5.6	-9.4*	-6.1***
(T_0 + 8) - (T_0 + 10)	-2.6	-3.0	-31.8*	-1.3	-31.1*	-16.0**	-1.6	-3.1	-7.4*	-2.3	-1.8	-3.1**
No. of natural disasters	31	33	40	29	35	168	31	33	40	29	35	168

Exogenous disaster identification for damage (% of GDP)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.5	0.3	-3.9	0.8	-6.8*	-1.6	0.4	0.2	0.2	0.0	-3.6*	-0.5
(T_0 + 2) - (T_0 + 4)	2.8	3.6	-7.1	4.3	-10.4	-1.5	0.3	0.8	-0.1	1.0	-8.5	-0.2
(T_0 + 4) - (T_0 + 6)	3.6	6.6*	-9.2	6.5	-12.5	-1.2	-2.1	0.4	-2.6	0.3	-3.7	-2.0
(T_0 + 6) - (T_0 + 8)	-1.2	1.5	-14.6	-0.9	-22.0**	-7.4**	-3.0*	-2.8	-1.6	-2.1	-4.9**	-3.0***
(T_0 + 8) - (T_0 + 10)	-4.0	-1.8	-20.4	-4.2	-28.0**	-11.6***	-1.8	-4.6	-3.9	-7.7	-6.5***	-4.9***
No. of natural disasters	43	45	48	34	37	207	43	45	48	34	37	207

Exogenous disaster identification for deaths over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	5.3***	4.3***	5.6***	4.8***	4.0***	4.9***	5.3***	3.3***	5.4***	3.4***	3.7**	3.8***
(T_0 + 2) - (T_0 + 4)	9.4***	9.3***	9.6***	12.3***	10.8***	10.2***	7.9***	9.6***	8.7***	12.2***	10.6***	10.0***
(T_0 + 4) - (T_0 + 6)	9.5***	11.8***	11.9***	15.9***	12.1**	12.1***	1.8	4.8	7.8**	9.7**	9.2	7.8***
(T_0 + 6) - (T_0 + 8)	14.0***	15.7***	15.8***	19.4***	12.4**	15.5***	4.7	6.8	9.5**	8.1**	8.3	8.3***
(T_0 + 8) - (T_0 + 10)	7.9	11.0*	14.0***	15.8**	11.8*	12.0***	-0.9	3.1	5.8**	8.2	1.6	3.4**
No. of natural disasters	38	39	39	31	29	176	38	39	39	31	29	176

****p*<0.01, ***p*<0.05, **p*<0.1

Table 28. The panel synthetic control estimates using an exogenous disaster identification strategy for low income countries.
The synthetic control panel is normalized at $T_0 - 1$, which is set equal to zero. Periods are averaged due to space considerations. These tables present the median and mean disaster effects for an unbalanced panel of synthetic control case studies. The natural disasters are exogenously determined by equation (4). The definitions are taken from the United Nations 2017 World Economic Situation and Prospects. This study defines low income countries as low- and lower-middle income countries. The numbers are expressed as a percentage of GDP.

Exogenous disaster identification for total affected over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	2.3**	1.1	0.4	1.2	1.1	1.2**	1.9*	1.4**	0.0	1.2*	1.2	1.1***
(T_0 + 2) - (T_0 + 4)	2.6	0.1	-1.8	1.6	-0.7	0.3	2.9	1.3	-1.7	1.1	2.5	1.3
(T_0 + 4) - (T_0 + 6)	2.4	-0.1	-1.8	1.2	-0.7	0.1	1.2	0.8	-1.4	1.7	1.7	0.9
(T_0 + 6) - (T_0 + 8)	-0.3	-2.8	-4.3	0.6	-4.4	-2.3	-0.8	-3.8	-3.0	-2.9	-8.0	-3.5**
(T_0 + 8) - (T_0 + 10)	-2.5	-2.5	-5.5*	-0.1	-7.0*	-3.6**	-5.6	-8.9*	-6.6*	-3.8	-7.1***	-7.7***
No. of natural disasters	67	67	71	59	63	327	67	67	71	59	63	327

Exogenous disaster identification for damage (% of GDP)

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	1.7	5.7	3.5	0.4	4.7	3.2**	0.5	-0.2	0.0	0.5	0.1	0.1
(T_0 + 2) - (T_0 + 4)	8.3*	22.2	18.4	4.7	16.3	14.3**	3.1*	1.2	-0.5	0.8	-1.4	0.6
(T_0 + 4) - (T_0 + 6)	26.0	23.5	18.9	19.7	-2.2	17.3**	2.8	0.6	-5.7*	-4.9	-5.9*	-1.1
(T_0 + 6) - (T_0 + 8)	2.0	-1.0	-2.8	-7.1	-9.5**	-3.5	-2.5	-4.2	-5.8**	-10.5*	-12.2***	-6.2***
(T_0 + 8) - (T_0 + 10)	2.6	-4.1	-2.1	-2.7	-11.8***	-3.5	-0.9	-6.7	-6.7*	-7.5*	-17.6***	-7.2***
No. of natural disasters	55	58	61	52	54	280	55	58	61	52	54	280

Exogenous disaster identification for deaths over population

	Normalized average disaster effect						Normalized median disaster effect					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	All models (1)-(5)
T_0 - (T_0 + 2)	3.8**	9.6**	7.0*	4.4**	9.8**	6.9***	2.4**	1.3*	1.6	1.7*	1.5	1.7***
(T_0 + 2) - (T_0 + 4)	9.9**	28.1	22.4	10.2**	23.5	19.1***	4.9***	5.1***	1.8	4.1**	1.3	4.0***
(T_0 + 4) - (T_0 + 6)	33.3*	37.6*	28.8	37.7	14.3**	30.4***	8.0***	5.1***	0.3	4.7**	2.3**	3.6***
(T_0 + 6) - (T_0 + 8)	29.8	33.1	24.7	33.1	28.3	29.6***	9.6*	4.8**	-3.5	2.8	1.3	2.7
(T_0 + 8) - (T_0 + 10)	12.1*	11.4*	9.4*	14.0*	4.7	10.3***	6.9*	4.3	-4.5	-0.4	-3.9	0.8
No. of natural disasters	52	53	58	44	47	254	52	53	58	44	47	254

***p<0.01, **p<0.05, *p<0.1

Table 29. Additional government financing needs (% of GDP) for the exogenous disaster identification strategy.

This table presents the maximal additional financing needs compared to the synthetic control group. Our definition of a debt decline is that there is a negative sign, either statistically significant or insignificant, for the first four years $(T_0, \ldots, T_0 + 4)$; or when eight out of ten years have a negative sign which is either significant or insignificant. Our definition of a debt increase is that there is a positive sign, either statistically significant or insignificant, for the first four years $(T_0, \ldots, T_0 + 4)$; or when eight out of ten years have a negative sign which is either significant or insignificant. We define a disaster impact as mixed for the other estimations.

Exogenous disaster identification strategy

	Average disaster effect			Median disaster effect		
	Total affected over population	Damage (% of GDP)	Deaths over population	Total affected over population	Damage (% of GDP)	Deaths over population
No additional controls	decline	9.4%	24.2%	1.5%	1.2%	6.8%
No sovereign defaults	2.4%	3.1%	14.8%	1.3%	mixed	7.6%
RMSPE weighted	decline	1.4%	8.3%	n/a	n/a	n/a
RMSPE ranked	0.7%	2.2%	7.3%	n/a	n/a	n/a
High income countries	decline	decline	15.5%	decline	decline	10.0%
Low income countries	1.2%	17.3%	30.4%	1.3%	0.6%	4.0%
High GDP per capita	decline	8.6%	15.3%	2.1%	7.1%	11.4%
Low GDP per capita	decline	10.3%	32.2%	1.0%	decline	3.4%
Low agricultural dependency	4.9%	5.2%	23.6%	5.1%	4.8%	12.8%
High agricultural dependency	decline	13.7%	29.0%	decline	decline	2.9%
SIDS	decline	2.8%	13.4%	mixed	4.1%	6.3%
RMSPE quartile 1	decline	decline	8.0%	0.8%	decline	7.8%
RMSPE quartile 1-2	0.8%	0.9%	5.9%	0.7%	decline	6.3%
RMSPE quartile 1-3	1.2%	3.3%	6.9%	0.8%	0.8%	5.8%
RMSPE quartile 1-4	decline	9.4%	24.2%	1.5%	1.2%	6.8%
No multiple disasters	decline	mixed	9.1%	decline	decline	7.4%
No conflicts	decline	11.8%	30.1%	1.8%	decline	8.0%

Table 30. The average government debt impact per disaster type.
This table presents the average impact of the different disaster types. This study takes the averages for the average and median disaster effect. The results are the simple averages of all disaster identification strategies, which treats these strategies as equally valuable. To prevent overestimation of the government debt impact, this study assumes that no additional borrowing is necessary for estimates where there is a decline of government debt. These set equal to zero. The mixed results are treated in a similar way.

	Average positive government financing needs		All disaster identification modes and strategies	
Controls	Average disaster effect	Median disaster effect	Average disaster effect	Median disaster effect
No additional controls	12.6%	5.4%	8.4%	4.8%
No sovereign defaults	10.4%	7.8%	9.2%	6.1%
RMSPE weighted	8.3%	n/a	6.5%	n/a
RMSPE ranked	7.5%	n/a	6.6%	n/a
High income countries	14.3%	8.3%	6.3%	4.6%
Low income countries	12.3%	4.0%	8.2%	3.6%
High GDP per capita	11.2%	7.1%	8.7%	7.1%
Low GDP per capita	15.0%	4.6%	8.3%	3.1%
Low agricultural dependency	13.6%	9.5%	10.6%	7.4%
High agricultural dependency	11.5%	5.6%	9.0%	3.1%
SIDS	9.6%	7.0%	5.3%	4.7%
RMSPE quartile 1	10.0%	7.0%	6.6%	5.4%
RMSPE quartile 1-2	7.7%	6.8%	6.8%	5.3%
RMSPE quartile 1-3	7.5%	5.7%	6.6%	5.0%
RMSPE quartile 1-4	12.6%	5.4%	8.4%	4.8%
No multiple disasters	12.8%	10.5%	7.1%	5.8%
No conflicts	14.9%	6.6%	9.9%	4.4%
Average impact	**11.3%**	**6.8%**	**7.8%**	**5.0%**

Table 31. Overview of the sources per indicator.

Indicators	Sources
Government debt (% of GDP)	IMF, World Bank, clio infra
GDP growth	UNSD
Current account (% of GDP)	UNSD
Openness (% of GDP)	UNSD
Population density	UNSD
Population growth	UNSD
GDP per capita	UNSD
GDP share of agriculture, hunting and minerals	UNSD
General government consumption (% of GDP)	UNSD
Gross capital formation (% of GDP)	UNSD
Average latitude	World Bank
Year of schooling	Barro and Lee (2013) and Lutz et al. (2014)
Total societal and interstate major episodes of political violence	Center for Systemic Peace

Table 32. Minimum and maximum country-year observations.

	Minimum	Maximum
Variable name	Country-year observations	Country-year observations
General government debt (% of GDP)	2007-2012 Libya	1990 Nicaragua
GDP growth	1991 Iraq	2012 Libya
Current account (% of GDP)	1991 Kuwait	2000 Equatorial Guinea
Openness (% of GDP)	1991 Somalia	1992 San Marino
Population density	1997 Greenland	2014 Singapore
Population growth	1974 Cyprus	2007 Qatar
GDP per capita	1995 Liberia	2007 Liechtenstein
GDP share of agriculture, hunting and minerals	2014 Hong Kong	1973 Afghanistan
General government consumption (% of GDP)	1973 Bangladesh	1991 Kuwait
Gross capital formation (% of GDP)	1973 Saudi Arabia	1996 Equatorial Guinea
Average latitude	New Zealand	Greenland
Years of schooling	61 country-year observations	2011-2014 Finland
Total societal and interstate major episodes of political violence	4178 country-year observations	1980-1988 Iraq