Natural Disasters and Economic Growth

Eduardo Cavallo
Inter-American Development Bank
Research Department

Sebastian Galiani
Washington University
in St. Louis

Ilan Noy
University of Hawaii
Department of Economics

Juan Pantano
Washington University
in St. Louis

November 10, 2009

PRELIMINARY

Abstract

We examine the short and long run impact of natural disasters on economic growth by combining information from comparative case studies. We find that large disasters have a negative effect on output both in the short and long run. Using exact inference methods we show that these results are statistically significant.

1 Introduction

Large sudden natural disasters such as earthquakes, tsunamis, hurricanes, and floods generate destruction on impact, both to people – killing, injuring and rendering homeless – and to physical capital – by destroying property and public infrastructure. Recent events such as the Indian Ocean tsunami in 2004, hurricane Katrina in 2005 and the Sichuan earthquake in 2008 have received worldwide media coverage, and there is an increasing sense of awareness among the general public about the destructive nature of disasters. Much research in both the social and natural sciences has been devoted to increasing our ability to predict disasters and prepare for them; though the economic research on natural disasters and their consequences is fairly limited. Here, we are interested in carefully examining the effect of natural disaster occurrence on economic prospects, in particular on gross domestic product.

Traditional neo-classical Solow-Swan growth models with exogenous saving rate and the Ramsey-Cass-Koopman class of growth models with optimizing consumers view technical progress as exogenous. These predict that the destruction of capital (physical or human) will therefore not affect the rate of technological progress and will only enhance short-term growth prospects since it will drive countries away from their balanced-growth steady states. The loss of capital caused by natural disasters will lead to more rapid capital accumulation and thus to a higher temporary growth path until the economy reaches back to its steady state.

On the other hand, endogenous growth frameworks do not suggest such clear-cut predictions with respect to output dynamics. These models predictions depend on the approach used to explain the endogeneity of technological change. For example, models based on Schumpeter's creative destruction process may also ascribe higher growth as a result of negative shocks, as these shocks can be catalysts for re-investment and upgrading of capital goods.[1] These shocks may also be catalysts for adoption of new technologies that may be beneficial in generating (especially long-term) growth. In contrast, the AK-type endogenous growth models in which technology exhibits constant returns to capital predict no change in the growth rate following a negative capital shock; while endogenous growth models that have increasing returns to scale production generally predict that a destruction of part of the physical or human capital stock results in a lower growth path and consequently a permanent deviation from the previous growth trajectory.[2][3]

The theory discussing the short-run effects is equally contradictory. On the one hand, the destruction of capital leads to reduced productive capacity that will lead to lower GDP growth until the reconstruction is complete. On the other hand, the fiscal reconstruction stimulus, and the additional demand for investment to replace destroyed capital leads to a boost in economic activity. Other potential short-run

[1]Schumpeter (1934) and Caballero and Hammour (1994). See Hallegatte and Dumas (2009) for a Schumpeterian model with disasters.

[2]For example, Martin and Rogers (1997) show that if future benefits of learning by doing are not fully internalized by economic agents, then output slumps are periods in which opportunities for acquiring experience are forgone with permanent effects on output dynamics.

[3]For more details and comprehensive discussion, see Barro and Sala-i-Martin (2003), chapter 5

effects can lead to either reduction in growth (e.g., increased perception of future disasters leads to decrease in investment demand) or to a boom (e.g., upgrading of production networks demolishes inefficiencies of the old regime).

The focus of this paper is on assessing the short and long run impacts of large natural disasters on economic growth. Our brief survey of growth theory suggests that whether the initial capital losses incurred following a disaster lead to a full recovery or even a boost to economic activity is ultimately an empirical question; the one we seek to address here. A few papers have already attempted to answer this question, but the evidence they present remains inconclusive, and often contradictory. Furthermore, the bulk of the empirical evidence available focuses on the short-run effects —up to five years after the events—with very few attempts to go beyond that horizon.[4]

Our contribution is to bring a new methodological approach to answer the question of sign and size of the short and long run effects of large natural disasters on growth. In particular, following Abadie et al. (2008), we pursue a comparative event study approach, taking advantage of the fact that the timing of a large sudden natural disasters is an exogenous event. This comparative study approach is more general than the usual panel data models commonly applied in the empirical literature surveyed in the next section. At its core, the idea is to construct an appropriate counterfactual— i.e., what would have happened to the path of GDP of the "treated" country in the absence of natural disasters—and to assess the disaster's impact by comparing the

[4] Cavallo and Noy (2009) present a survey of this literature

counterfactual to the actual path observed. Importantly, the counterfactuals are not constructed by extrapolating pre-event trends from the treated countries but rather, following Abadie and Gardeazabal (2003), by building a synthetic control group—i.e., using as a control group other 'untreated' countries with similar characteristics except for the incidence of the event of interest. The idea behind the synthetic control approach is that a combination of countries often provides a better counterfactual for the country exposed to the event than any single country alone

In the cross-country comparative case studies we describe here, we compare countries affected by natural disasters to a group of unaffected countries. Therefore, the analysis is only feasible when some countries are exposed and others are not. Thus, we focus our analysis only on large events, rather than on recurrent events that are prevalent everywhere. We adapt the synthetic control methods developed by Abadie and Gardeazabal (2003) and Abadie et al. (2008) to combine information from several large disasters.

From the outset, we stress that we are not testing nor distinguishing among theories that predict the same sign for the relationship between natural disasters and economic growth, either in the short- or the long-run. Moreover, we look at the net, overall effect on output growth without trying to untangle the contributing factors or mechanisms that are triggered by the disaster itself.[5]

[5]For example, Nicaragua's devastating earthquake in 1974 had a significant impact on the level of output. More importantly, some argue the earthquake facilitated the Sandinista Revolution a few years later, in part given the growing discontent over the handling of the earthquake's aftermath by

Our results show that only very large disasters –whereby "large" is defined in relation to the world mean of direct damages caused by natural events— have an impact on GDP growth in the affected countries, both in the short- and in the long-run. The effects are both statistically significant and economically meaningful. For example, ten years after the disaster, the GDP per capita of the affected countries is (on average) 10% lower that it was at the time of the disaster whereas it would be about 20% higher in the counterfactual scenario in which the disaster did not occur. Moreover, our results show that by simply extrapolating the pre-disaster trend into post-disaster years to construct the counterfactual, we would be over-estimating the effect of the event. For milder events, we don't find evidence of any significant impact on GDP growth either in the short- or in the long-run.

The structure of the paper is as follows. Section 2 starts by reviewing the related literature. Section 3 presents the empirical methodology and Section 4 describes the data. Results are discussed in Section 5. Conclusions follow.

2 Review of Empirical Literature on Disasters and Growth

A spate of papers in the last several years has attempted to understand the determinants of the initial direct costs of disasters –or, more precisely, the underlying

the pre-revolutionary government

vulnerability of countries to natural catastrophes.[6] This literature shows that while the damage caused by disasters is directly related to the physical intensity of the event (i.e., the severity of a storm or earthquake), there are a series of economic, social and political characteristics that also affect vulnerability. But while the initial disaster impact leads to varying degrees of mortality, morbidity, and loss of physical infrastructure in different countries, these observations do not shed any light on how these initial impacts are followed by subsequent impacts on the economy, in particular on the dynamics of domestic production.

The macroeconomic literature generally distinguishes between short-run effects (usually up to five years), and longer-run effects (anything beyond that horizon). The first recent attempt to empirically describe short-run macroeconomic dynamics of natural disasters is Albala-Bertrand (1993). In this seminal monograph, Albala-Bertrand develops an analytical model of disaster occurrence and reaction and collects data on a set of disaster events: 28 disasters in 26 countries during 1960-1979. Based on before and after statistical event-study analysis, he finds that GDP increases after the events.

The more recent literature typically utilizes econometric techniques and finds different results. Raddatz (2007) estimates the effect of external shocks on short-run

[6] Examples of this literature include: Khan (2004) and Kellenberg and Mobarak (2008) study the relationship between economic development and vulnerability to natural disasters. Rasmussen (2004), Heger et al (2008) and Auffret (2003) emphasize the role of country size as a major determinant of vulnerability

output dynamics in developing countries. Using a Panel-VAR framework on a sample of 40 low income countries between 1965 and 1997, he analyses the contribution of various external/exogenous shocks, natural disasters among them, in explaining output fluctuations. He concludes that natural disasters have an adverse short-run impact on output dynamics.[7] Noy (2009) finds a similar negative-impact result using an extended sample of 109 countries for the period 1970-2003, and different panel data techniques.[8] In addition, he describes some of the structural and institutional factors that make the negative effect worse.[9] Subsequently, Raddatz (2009) uses similar methodology to his earlier paper but extends the investigation to study the impact of various types of natural disasters on countries in different income groups. He also extends the sample to 112 countries over the period 1975 – 2006. He concludes that smaller and poorer states are more vulnerable, especially to climatic events, and that most of the output cost occurs during the year of the disaster.[10]

[7] Yet, Raddatz (2007) concludes that only a small fraction of the output volatility in a typical low income country is explained by external adverse shocks; with natural disasters accounting for less than 2% of the output volatility in a typical developing country.

[8] Unlike Raddatz (2007) who focuses on per capita GDP levels and assesses dynamics through impulse response functions, Noy (2009) employs the Hausman-Taylor random effects algorithm to study GDP growth per se.

[9] In particular, Noy (2009) concludes that countries with a higher literacy rate, better institutions, higher per capita income, higher degree of openness to trade, higher levels of government spending, more foreign exchange reserves, and higher levels of domestic credit, but with less-open capital accounts are better able to withstand the initial disaster shock and prevent further spillovers..

[10] He also finds that a country's level of external debt, which is frequently mentioned as a limit

Loayza et al. (2009) extends this analysis applying a dynamic Generalized Method of Moments panel estimator to a panel of 94 countries in the period 1961–2005; and Fomby et. al. (2009) using a similar sample, implements an approach based on a VAR with endogenous variables and exogenous shocks (VARX). A contribution of both of these papers is the disaggregation of the analysis by type of events – distinguishing between droughts, floods, earthquakes, and storms—and their impacts by economic sectors. They conclude that disasters affect economic growth—but not always negatively—, and that the impact is different across disasters and economic sectors.[11]

Finally, Hochrainer (2009) uses autoregressive integrated moving average models (ARIMA) to extrapolate pre-disaster trends in GDP and construct counterfactuals of the medium-term (up to 5 years after the disaster event) evolution of GDP without disasters. By comparing the counterfactuals with observed GDP he finds that natural disasters on average lead to negative consequences, although the effects are significant only in the case of large shocks. Several papers pursue similar investigations but instead of relying on cross country panels they rely on more detailed panels at the county/region/state level.[12]

---

to its fiscal capacity to respond to disasters, has no relation to the output impact of any type of disaster. His evidence also suggests that, historically, aid flows have done little to attenuate the output consequences of climatic disasters.

[11] They find that while small disasters may, on average, have a positive impact (as a result of the reconstruction stimulus), large disasters have severe negative consequences.

[12] See, for example, Strobl (2008), Noy and Vu (2009), and Rodriguez-Oreggia et al. (2009).

In our assessment, a consensus has recently emerged in the literature around the idea that large natural disasters have, on average, a negative impact on short term economic growth.[13] There is more controversy, however, on whether the negative effects are transitory or permanent. Skidmore and Toya (2002), Noy and Nualsri (2008), and Raddatz (2009) examine the long-run impact of natural disasters on growth. The former use the frequency of natural disasters for the 1960-1990 period for each country (normalized by land size) in a cross-sectional dataset of 89 countries, while the rest use panel data based on larger samples.

Interestingly, Skidmore and Toya (2002) and Noy and Nualsri (2008) reach diametrically opposing conclusions with the former identifying expansionary and the latter contractionary effects of natural disasters in the long run. More recently Jaramillo (2009) finds qualified support for the Noy and Nualsri (2008) conclusion. Raddatz (2009), using cumulative impulse response functions of the growth of real GDP per capita to different type of natural disasters finds that in the long run, per capita GDP is lower as a result of climatic events, but instead, that geological disasters do not have a statistically significant output impact either in the short or in the long run.

Instead of using macroeconomic data, Leiter et al. (2009) uses European firm level data to examine the impact of floods on the firms' capital stock, employment, and productivity. They find mixed results on the capital stock (depending on the percent of intangible assets), a positive short term impact on employment and a

[13] Although the effects are not homogenous for all disasters and across economic sectors (see Loayza et al. 2009).

negative impact on productivity; these identified affects therefore cannot determine the impact on the firms' incomes and production.

Skidmore and Toya (2002) explain their finding about the positive correlation between disaster incidence and GDP growth by suggesting that disasters may be speeding up the Schumpeterian "creative destruction" process that is at the heart of the development of market-economies. Cuaresma et al. (2008) attempts to investigate this hypothesis empirically by examining the evolution of R&D from foreign origin and how it is affected by catastrophic risk. The idea is that if natural disasters foster technological upgrades in laggard countries through the importation of technologies from advanced economies, the frequency of events should be positively correlated to the rate of technological transfer between developing and developed countries. They, however, conclude that the creative destruction dynamic most likely only occurs in countries with high income per capita. For developing countries, disaster occurrence is associated with less knowledge spillovers and reduction in the amount of new technology being introduced.

In short, the literature on the long-run effects of natural disasters is less voluminous and the results remain inconclusive, even more so than in the case of the papers focusing on the short run growth effects. In the next section we explain the methodology we employ to seek to provide new evidence on this topic.

3 Empirical Methodology

We contribute to the literature on natural disasters and growth by adopting a novel methodological approach: comparative case studies. This approach is more general than the usual difference-in-differences (fixed-effects) model commonly applied in the empirical literature. The difference-in-differences model allows for the presence of unobserved confounders but restricts the effect of those confounders to be constant in time. Our approach allows the effects of confounding unobserved characteristics to vary with time. Below we describe this approach in detail.

Identification of the causal effect of natural disasters on economic growth is difficult. Exploiting the cross-sectional variability across countries, and assuming that natural disasters indeed affect negatively the level, and perhaps also, the rate of growth of GDP, estimates of the effect of natural disasters on GDP (growth) are likely to be severely biased upward (in absolute value) due to the fact that, ceteris paribus, the magnitude of natural disasters is endogenously larger among poor countries. This implies that measured natural disasters are more likely to occur in poor countries, which in turn have displayed lower growth rates even in the absence of natural shocks. Though stratifying the analysis by income level might help to reduce this omitted variable problem, it can hardly be argued that will solve the problem.

Therefore, a natural solution is to rely on longitudinal data to control for time-invariant unobservable variables. Nevertheless, as it is always the case, moving from exploiting the between country variability to the within country variation is not free of problems. Exploiting the within country variability requires that the group of countries that are not shocked by natural disasters (i.e., the control group) allow us to estimate what would have been the growth rates of the affected countries (i.e., the treatment group) in the absence of the shocks. Unfortunately, this assumption is difficult to be satisfied in general. If the countries in the control group, on average, were going to growth at a faster rate even in the absence of any shock to the group affected by natural disasters in the sample, panel data estimates will also tend to be biased upward (in absolute value).

Being aware of this problem, some authors attempt to control the differential trends across countries by controlling by country specific rates in the econometric model. This entails to extrapolate to the post-shock period the pre-shock trends, which is certainly a strong assumption, especially over long-periods of time.

Essentially, to overcome the problems of identification outlined above, we need to find a group of countries that a) have had the same secular trends in the dependent variable analyzed (i.e., GDP or GDP growth rates) and b) likely would have had the same secular behavior in the absence of the shocks studied. Then, we can use this group to estimate the counterfactual and conduct a causal analysis.

3.1 Estimating the Impact of Large Disasters with Comparative Case Studies

Case studies focus on particular occurrences of the events or interventions of interest. Often, the motivation behind case studies is to detect the effects of an event or policy intervention on some outcome of interest. In a cross-country comparative case study, we compare countries affected by the event or intervention of interest to a group of unaffected countries. Therefore, comparative case studies are only feasible when some countries are exposed and others are not. To simplify, let's assume that only one country is subject to the intervention of interest: a large natural disaster. We will later aggregate the country specific effects into an average effect.

Suppose that we observe $J+1$ countries. Without loss of generality, suppose also that only the first country is exposed to a large natural disaster, so that we have J remaining countries that serve as potential controls or "donors". In a comparative case study it is generally assumed that the treated unit is uninterruptedly exposed to the intervention of interest after some initial intervention period. In our case however, we consider the occurrence of the catastrophic event as the initiation of the intervention period (which includes the disaster's aftermath).

Let Y_{it}^{N} it be the GDP per capita that would be observed for country i at time t in the absence of the disaster, for countries $i = 1, ..., J+1$, and time periods $t = 1, ..., T$. Let T_0 be the number of periods before the disaster, with $1 \leq \; T_0 < T$. Let Y_{it}^{I} be the outcome that would be observed for country i at time t if country i is exposed to the disaster and its aftermath from period T_0+1 to T. Of course, to the extent that the occurrence of a large disaster is unpredictable, it has no effect on the outcome before the intervention, so for $t \in \{1, ..., T_0\}$ and all $i \in \{1, ..., N\}$, we have that $Y_{it}^I = Y_{it}^N$.

Let $\alpha_{it} = Y_{it}^I - Y_{it}^N$ be the effect of the disaster for country i at time t, if country i is exposed to the intervention in periods $T_0+1, T_0+2, ..., T$ (where $1 \leq T_0 < T$). Note that we allow this effect to potentially vary over time, Again, the intervention, in our context, is the disaster *and* its aftermath. Therefore:

$$Y_{it}^I = Y_{it}^N + \alpha_{it}$$

Let D_{it} be an indicator that takes value one if country i is exposed to the intervention at time t, and value zero otherwise. The observed output percapita for country i at time t is

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it}$$

Because only the first country (country "one") is exposed to the intervention and only after period T_0 (with $1 \leq T_0 < T$), we have that:

$$D_{it} = \begin{cases} 1 & \text{if } i = 1 \text{ and } t > T_0 \\ 0 & \text{otherwise} \end{cases}$$

We aim to estimate $(\alpha_{1,T_0+1}, ..., \alpha_{1,T})$. For $t > T_0$,

$$\alpha_{1t} = Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N$$

Because Y_{1t}^I is observed, to estimate α_{1t} we just need to estimate Y_{1t}^N .

Suppose that Y_{it}^N is given by a factor model:

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it} \tag{1}$$

where δ_t is an unknown common factor with constant factor loadings across countries, Z_i is a $(r \times 1)$ vector of observed predictors for GDP percapita (not affected by the natural disaster), θ_t is a $(1 \times r)$ vector of unknown parameters, λ_t is a $(1\times\ F)$ vector of unobserved common factors, μ_i is an $(F \times 1)$ vector of unknown factor loadings, and the error terms ε_{it} are unobserved transitory shocks at the country level with zero mean for all i. It is important to notice that this model does not rule out the existence of time-varying measured determinants of Y_{it}^N. The vector Z_i may contain pre- and post-disaster values of time-varying variables, as long as they are not affected by the disaster. Moreover, the generality of the model can be appreciated by noting that the traditional difference-in-differences (fixed-effects) model can be obtained if we impose that λ_t in Equation 1 is constant for all t.

Consider a $(J \times 1)$ vector of weights $W = (w_2, ..., w_{J+1})'$ such that $w_j \geq 0$ for $j = 2, ..., J+1$ and $w_2 + w_3 + ... + w_{J+1} = 1$. Each particular value of the vector W represents a potential synthetic control, that is, a particular weighted average of control countries.

The real GDP percapita for each synthetic control indexed by W is:

$$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_j + \sum_{j=2}^{J+1} w_j \varepsilon_{jt}$$

Suppose that there are $(w_2^*, ..., w_{J+1}^*)$ such that:

$$\begin{aligned}
\sum_{j=2}^{J+1} w_j^* Y_{j1} &= Y_{1,1} \qquad (2)\\
&\vdots \\
\sum_{j=2}^{J+1} w_j^* Y_{j,T0} &= Y_{1,T0} \qquad (3)\\
\sum_{j=2}^{J+1} w_j^* Z_j &= Z_1 \qquad (4)\\
\sum_{j=2}^{J+1} w_j^* &= 1
\end{aligned}$$

Then, it can be shown that if $\sum_{t=1}^{T0} \lambda_t' \lambda_t$ is non-singular, then,

$$Y_{1t}^N - \sum_{j=2}^{J+1} w_j^* Y_{jt} = \sum_{j=2}^{J+1} w_j \sum_{s=1}^{T_0} \lambda_t \left(\sum_{n=1}^{T0} \lambda_n' \lambda_n \right)^{-1} \lambda_s' \left(\varepsilon_{js} - \varepsilon_{1s}\right) - \sum_{j=2}^{J+1} w_j^* \left(\varepsilon_{js} - \varepsilon_{1s}\right) \quad (5)$$

Abadie, Diamond and Hainmueller (2008) show that, under standard conditions, the average of the right hand side of this equation will be close to zero if the number of pre-disaster periods is large relative to the scale of the transitory shocks. This suggests using

$$\widehat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

for $t \in \{T_0 + 1, ..., T\}$ as an estimator of α_{1t}.

The system of equations in (2), (3) and (4) can hold exactly only if $(Y_{1,1}, ..., Y_{1,T0}; Z_1')$ belongs to the convex hull of

$$\left\{ \left(Y_{2,1}, ..., Y_{2,T0}; Z_2'\right), ..., \left(Y_{J+1,1}, ..., Y_{J+1,T0}; Z_{J+1}'\right) \right\}$$

In practice, it is often the case that no set of weights exists such that these equations hold exactly in the data. Then, the synthetic control country is selected so that they hold approximately.

3.2 Computational Issues

Let W be a $(J \times 1)$ vector of positive weights that sum to one. Each value of W represents a weighted average of the available control countries and, therefore, a synthetic control. The outcome variable of interest, say GDP per capita, is observed for T periods for the country affected by the natural disaster $Y_{1t}, (t = 1, ..., T)$ and the unaffected countries $Y_{jt}, (j = 2, ..., J+1; t = 1, ..., T)$. Let $T_1 = T - T_0$ be the number of available post-disaster periods. Let Y_1 be the $(T_1 \times 1)$ vector of post-disaster outcomes for the exposed country, and Y_0 be the $(T_1 \times J)$ matrix of post-disaster outcomes for the potential control countries. Let the $(T_0 \times 1)$ vector $K = (k_1, ..., k_{T_0})$ define a linear combination of pre-disaster outcomes: $\overline{Y}_i^K = \sum_{s=1}^{T_0} k_s Y_{is}$. Consider M of such linear combinations defined by the vectors $K_1, ..., K_M$. Let $X_1 = (Z_1'; \overline{Y}_1^{K_1}, ..., \overline{Y}_1^{K_M})'$ be a $(k \times 1)$ vector of pre-disaster output linear combinations and output predictors not affected by the disaster for the exposed country, with $k = r + M$. Similarly, let X_0 be a $(k \times J)$ matrix that contains the same variables for the unaffected countries. That is, the j^{th} column of X_0 is $(Z_j'; \overline{Y}_j^{K_1}, ..., \overline{Y}_j^{K_M})'$.

The vector W^* is chosen to minimize some distance, $\|X_1 - X_0 W\|$, between X_1 and $X_0 W$, subject to $w_2 \geq 0, ..., w_{J+1} \geq 0$ and $\sum_{j=2}^{J+1} w_j^* = 1$. In particular, we will consider

$$\|X_1 - X_0 W\|_V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$$

where V is some $(k \times k)$ symmetric and positive semidefinite matrix.

Although the inferential procedures we use are valid for any choice of V, the choice of V influences the mean square error of the estimator (that is, the expectation of $(Y_1 - Y_0 W^*)'(Y_1 - Y_0 W^*)$). The optimal choice of V assigns weights to a linear combination of the variables in X_0 and X_1 to minimize the mean square error of the synthetic control estimator. The choice of V can also be data-driven. One possibility is to choose V such that the resulting synthetic control country approximates the trajectory of the outcome variable of the affected country as well as outcome predictors in the pre-disaster periods. Indeed we will choose V such that the mean squared prediction error of the outcome variable is minimized for the pre-intervention periods. One obvious choice for the set of linear combinations of pre-disaster outcomes $\left(\overline{Y}_{i1}^{K_1}, \ldots.., \overline{Y}_{i1}^{K_M}\right)$ would be

$$\begin{aligned} \overline{Y}_{i1}^{K_1} &= Y_{i1} \\ &\vdots \\ \overline{Y}_{1}^{K_{T_0}} &= Y_{iT_0} \end{aligned}$$

This would in essence include the entire pre-disaster output trend as input to build the synthetic control. Alternatively, we can use the first half of the pre-disaster trend outcomes to match the affected country with the donors.[14] That is $\left(\overline{Y}_{i1}^{K_1}, \ldots.., \overline{Y}_{i1}^{K_M}\right)$

[14] This period varies across countries, depending on when the disaster occurs relative to the start

would be

$$\overline{Y}_{i1}^{K_1} = \overline{Y}_{i1}^{K_1} = Y_{i,1}$$

$$\vdots$$

$$\overline{Y}_{i1}^{K_M} = \overline{Y}_{1}^{K_{\frac{T_0-1}{2}}} = Y_{i,\frac{T_0-1}{2}}$$

By only exploiting the first half of the pre-disaster trend to form the synthetic match, we are more confident in its ability to replicate the counterfactual trajectory.

3.3 Statistical Significance of Estimated Effects

The standard errors commonly reported in regression-based comparative case studies measure uncertainty about aggregate data. This mode of inference would logically produce zero standard errors if aggregate data were used for estimation. However, perfect knowledge of the value of aggregate data does not reduce to zero our uncertainty about the parameter of interest: the effect of a large disaster on output percapita. Not all uncertainty about the value of the estimated parameters come from lack of knowledge of aggregate data. In comparative case studies such as ours, an additional source of uncertainty derives from our ignorance about the ability of the control group to reproduce the counterfactual. There is some uncertainty about how the affected country would have evolved in the absence of the disaster. Large sample inferential techniques are not well-suited to comparative case studies when the number of units in the comparison group and the number of periods in the sample are

of our sample.

relatively small. Following Abadie and Gardeazabal (2003) and Abadie et al. (2008), we use exact inferential techniques, similar to permutation tests, to conduct inference in comparative case studies. These methods allow for valid inference regardless of the number of available donor countries and the number of available pre-disaster periods. However, as shown by Abadie et al. (2008), the quality of inference increases with the number of donor countries or the number of available time periods. As in classical permutation tests, we apply the synthetic control method to every potential control in our sample. This allows us to assess whether the effect estimated by the synthetic control for the country affected by the disaster is large relative to the effect estimated for a country chosen at random (which was not exposed to a large disaster). This inferential exercise is exact in the sense that, regardless of the number of available comparison countries, time periods, it is always possible to calculate the exact distribution of the estimated effect of the placebo disasters. More generally, this inferential exercise examines whether or not the estimated effect of an actual natural disaster is large relative to the distribution of the effects estimated for the countries not exposed to such disasters. More formally, let's assume that we are doing inference about negative point estimates at every lead (every year in the disaster's aftermath). We can then compute a lead specific significance level (p-value) for the estimated disaster impact as

$$p - value_l = \Pr\left(\widehat{\alpha}_{1,l}^{PL} < \widehat{\alpha}_{1,l}\right) = \frac{\sum_{j=2}^{J+1} I\left(\widehat{\alpha}_{1,l}^{PL} < \widehat{\alpha}_{1,l}\right)}{\#\text{ of donors}} = \frac{\sum_{j=2}^{J+1} I\left(\widehat{\alpha}_{1,l}^{PL(j)} < \widehat{\alpha}_{1,l}\right)}{J}$$

where $\widehat{\alpha}_{1,l}^{PL(j)}$ is the lead l -specific effect of a disaster when donor country j is assigned a placebo-disaster at the same time as country 1. $\widehat{\alpha}_{1,l}^{PL(j)}$ is computed following the same procedure outlined above for $\widehat{\alpha}_{1,l}$. By computing $\widehat{\alpha}_{1,l}^{PL(j)}$ for every country j in the donor pool for country 1, we can characterize the distribution of placebo effects and assess how the estimate $\widehat{\alpha}_{1,l}$ ranks in that distribution.

In this paper, we extend the idea in Abadie et al. (2008) generalizing the placebo approach to produce quantitative inference in comparative case studies. Before describing the data we discuss how to combine the placebo effects to account for the fact that we will be interested in doing inference about the average (normalized) effect found across the country specific comparative case studies of each disaster.

Recall our lead specific estimates of the disaster on the country of interest (say, country 1) are denoted by $(\widehat{\alpha}_{1,T_0+1}, ..., \widehat{\alpha}_{1,T})$ for leads $1, 2, ..., T-T_0$, Now consider taking the average disaster effect across G disasters of interest, say, the G largest disasters. Assume for simplicity that for all these G disasters we are able to compute the $T - T_0$ lead specific estimates of disaster impact. Then the estimated average effect for the G largest disasters is given by

$$\overline{\alpha} = (\overline{\alpha}_{T_0+1}, ..., \overline{\alpha}_T) = \frac{1}{G}\sum_{g=1}^{5}(\widehat{\alpha}_{g,T_0+1}, ..., \widehat{\alpha}_{g,T})$$

To conduct valid inference we need to account for the fact that the average smooths out some noise. We then construct a distribution of average placebo effects according to the following steps:

1. For each disaster g of interest we compute all the placebo effects using the

available donors $j_g = 2, ..., J_g + 1$ corresponding to disaster g

2. At each lead, we compute every possible placebo average effect by picking a single placebo estimate corresponding to each disaster g, and then taking the average across the G placebos. There are many possible placebo averages:

$$N_{\overline{PL}} = \text{Number of possible placebo averages} = \prod_{g=1}^{G} J_g$$

Let's index all these possible placebo averages by $np = 1, ..., N_{\overline{PL}}$ This number grows very quickly in G and the typical J_g. For example if $J_g = J = 50 \;\; \forall g$ and $G = 10$ we have $N_{\overline{PL}} = 97,660,000,000,000,000$ (that is about 98 thousand trillions) possible placebo averages.

3. We rank the actual lead specific average disaster effect $\overline{\alpha}_l$ in the distribution of $N_{\overline{PL}}$ average placebo effects (This involves $N_{\overline{PL}}$ comparisons)

4. We compute the lead l specific p-value for the average as

$$\begin{aligned}
\text{p-value}_l &= \Pr\left(\frac{1}{K}\sum_{k=1}^{5}\widehat{\alpha}_{k,l}^{PL} < \overline{\alpha}_l\right) \\
&= \Pr\left(\overline{\alpha}_l^{PL} < \overline{\alpha}_l\right) \\
&= \frac{\sum_{np=1}^{N_{\overline{PL}}} I\left(\overline{\alpha}_l^{PL(np)} < \overline{\alpha}_l\right)}{\#\text{ of possible placebo averages}} \\
&= \frac{\sum_{j=2}^{J+1} I\left(\overline{\alpha}_l^{PL(np)} < \overline{\alpha}_l\right)}{N_{\overline{PL}}}
\end{aligned}$$

4 The Data

4.1 Data Sources

We use a comprehensive dataset of 202 countries covering the period 1968-2008. Our data on GDP comes from the World Bank's World Development Indicators. Our GDP predictors include Trade Openness from WDI, Capital Stock[15], Land Area, Population, Education, Latitud (in absolute value) and Polity 2 which is a Polity Combined 20-pt score with mean subs for special polity conditions

The data on natural disasters and their human impact are documented in the EM-DAT database collected by the Centre for Research on the Epidemiology of Disasters (CRED). The EM-DAT database has worldwide coverage, and contains data on the occurrence and effects of natural disasters from 1900 to the present. The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutions and press agencies. The data is publicly available on CRED's web site at: www.cred.be. CRED defines a disaster as a natural situation or event which overwhelms local capacity, necessitating a request for external assistance. For a disaster to be entered into the EM-DAT database at least one of the following criteria must be fulfilled: (1) 10 or more people reported killed;

[15] We construct series for capital stock using data from the PWT. Total investment in PPP terms is obtained by multiplying the PPP adjusted investment ratios to GDP (ki) by real GDP per capita (rgdpl) and the population (pop). Then, following the methodology presented in Easterly and Levine (2001), the perpetual inventory method is used to construct the capital stock.

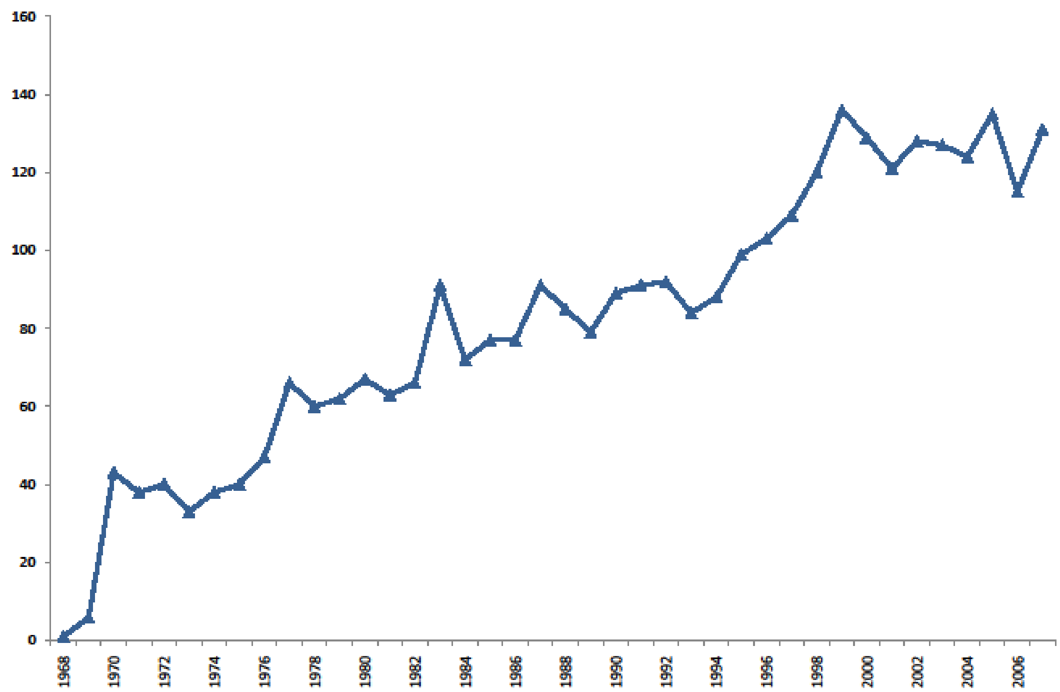
(2) 100 people reported affected; (3) declaration of a state of emergency; or (4) call for international assistance. These disasters can be hydro-meteorological disasters including floods, wave surges, storms, droughts, landslides and avalanches; geophysical disasters - earthquakes, tsunamis and volcanic eruptions; and biological disasters covering epidemics and insect infestations (these are much less frequent).

The amount of damage reported in the database consists only of direct damages (e.g. damage to infrastructure, crops, housing) and does not include the indirect or secondary damages. The EM-DAT database includes three measures of the magnitude of the disaster: (1) The number of people killed; (2) the number of people affected; and (3) the amount of direct damage. We will be focusing most of our analysis on the variable "number of people killed" to define disaster magnitude.

Since we presume that the impact of a specific natural disaster on the economy depends on the magnitude of the disaster relative to the size of the economy, we standardize our disaster measures. We divide the measures for the number of people killed or affected by the population size in the year prior to the disaster year; and divide the direct cost measure of the disaster by the last year's GDP (since the current year's population and GDP have been affected by the disaster itself).

From the total of (41 x 202 =) 8,282 year-country observations, 7,669 have information on whether a disaster occurred. From a first look at the data, disasters are fairly common. 43% of the country-years (that is, 3,323 observations) have an event that meets the requirements to be designated as a natural disaster. Moreover, every country has a disaster of some magnitude over the period (See Table 1 in Appendix) and as can be seen in Figure 1 there is a clear positive trend in prevalence of disasters over the period (See also Table 2 in Appendix).

Figure 1: Increasing Prevalence of Disasters (1968-2008)



Several countries suffer more than one disaster in a given year. In those cases we add up the corresponding disaster magnitudes and define a "combined" disaster for that country-year. These "combined" disasters are indeed the most prevalent in the data. (See Table 3)

Of course many of these events do not correspond to the catastrophic notion of natural disaster that one has in mind when thinking about effects on output. Therefore we will be focusing on disasters whose magnitude are particularly large.

Table 3: Distribution of Disaster Type

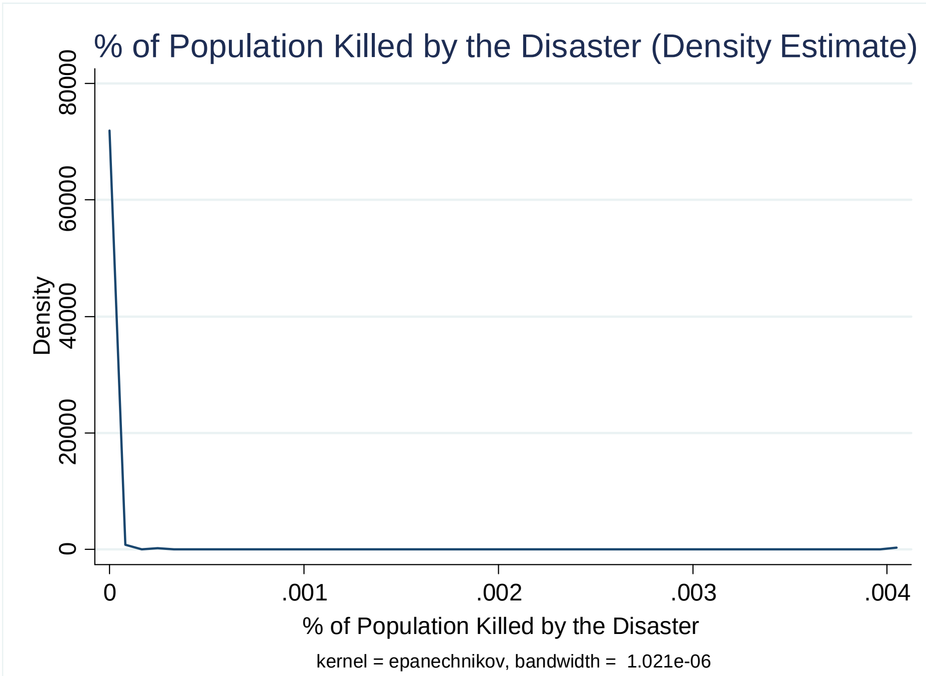
	N	%
Earthquake	100	3.01
Storm	394	11.86
Flood	477	14.35
Else	576	17.33
Combined	1,776	53.45
Total	3,323	100

4.2 Defining Large Disasters

As detailed below, our treatment effects methodology requires us to have a binary treatment indicator for the occurrence of a disaster. The question is then how to define a binary treatment measure of disaster. For example, we could define a large disaster as one in which the magnitude is more than 2 standard deviations above the country-specific mean. Note, however, that we are interested in large disasters where "large" is defined from a world wide perspective. While a given disaster might be large relative to the history of disasters within the country, it may be small in a more global context. Then, we can define a large disaster using the pooled world-wide mean. In this case, a disaster is large when its magnitude exceeds 2 standard deviations above the world mean. We find that there are only 35 (GDP-based), 55 (# Killed-based) and 108 (# Affected) "world-wide large disasters" out of 8,282 possible country-year observations. The following Figure 2 presents the distribution of disaster magnitudes.

Since the distribution is so skewed, the mean is a poor indicator of location, so we

Figure 2: Distribution of Disaster Magnitudes



prefer to work with percentile-based definitions for "large disaster". We will consider the 99th, 90th and 75th percentiles of the world distribution as cutoff values that define a large disaster

Finally, note that for some countries we have several "large disasters" over the sample period. In those cases we only use data before and after the first large disaster observed during the sample period

Exogenous Disaster Magnitude Measures. The three measures of disaster magnitude considered so far can be biased for the following reason. Places prone to disasters are less likely to expose wealth or lives. Indeed, places with recurrent natural disasters are likely to be less developed and barely inhabited. While it is not possible to completely overcome this problem we can examine which of the magnitude variables correlates more with truly exogenous measures of disaster intensity such as Richter scale for earthquakes and wind speed for storms. The following table shows the correlations between these exogenous measures and our damage measures for disaster magnitude.

Exogeneity of Disaster Magnitude Variables

	GDP damage		# Killed		# Affected	
richter_max	0.0012221		0.0000502**		0.0047957	
	[0.0047202]		[0.0000222]		[0.0038262]	
windspeed_max		0.0002357		0.0000002*		0.0002723***
		[0.0001906]		[0.0000001]		[0.0000839]
Constant	0.0092656	0.0126021	-0.0002603*	-0.0000168	-0.0081895	0.0021655
	[0.0308494]	[0.0381285]	[0.0001429]	[0.0000241]	[0.0245195]	[0.0163026]
Observations	279	231	384	275	404	288
R-squared	0.00	0.01	0.01	0.01	0.00	0.04

*** p<0.01, ** p<0.05, * p<0.1, Standard errors in brackets

Population killed by the disaster correlates better with these exogenous measures. We will then use it as our disaster magnitude variable when selecting a pool of large disasters.

5 Results

Below we can see the average causal impact of large disasters on real GDP per capita for countries with population exceeding 1 million that experienced such large disasters between 1968 and 2000 and that have the available data required for a comparative case study. For those countries that experienced several large disasters only the first is used, and their post disaster data is only used up to the year preceding the 2nd large disaster.

Figures 3, 4 and 5 show the average causal impact of a large disaster on real GDP per-capita for three different definitions of "large disaster" : P99, P90 and P75. P"X" for $X = 75, 90$, and 99 denotes the group of countries exposed to disasters in which the magnitude is above the X^{th} percentile in the (normalized) world distribution of disaster damages.

Figure 3: Large Disasters = above 99 Percentile

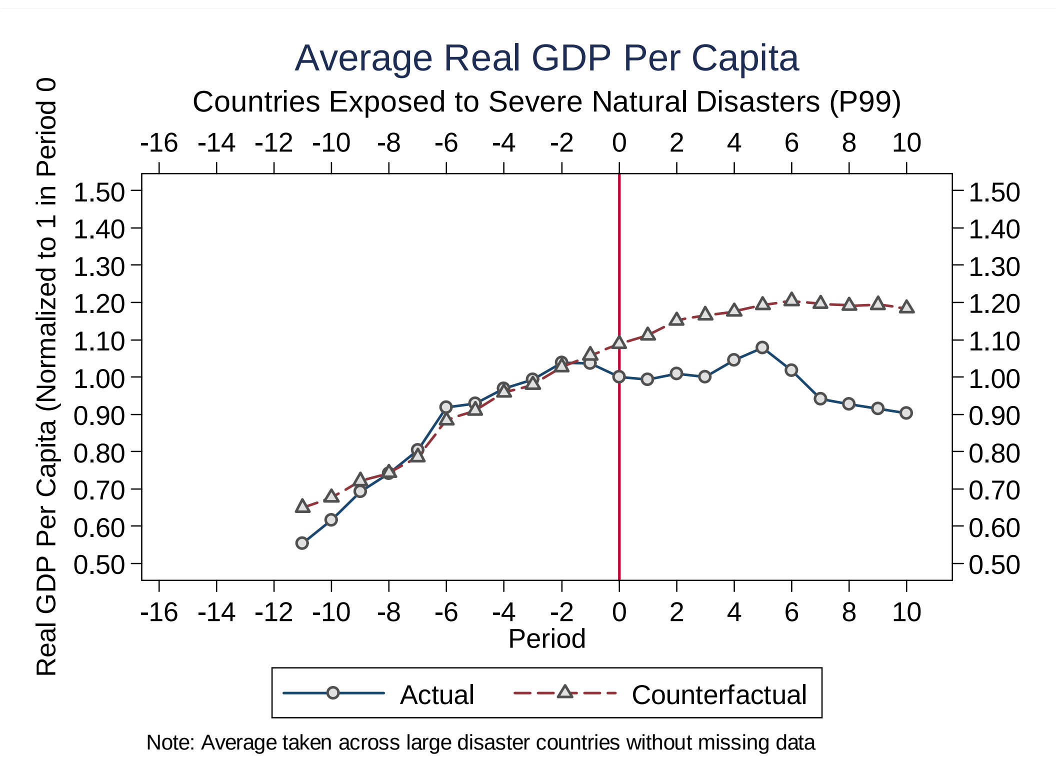
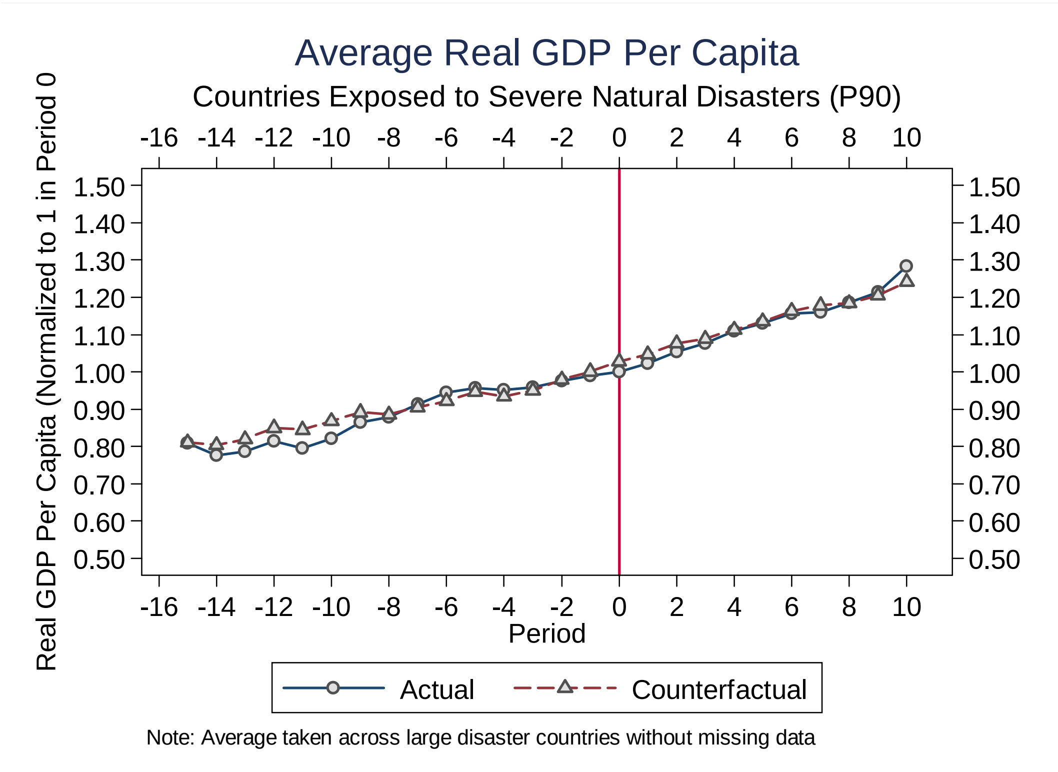
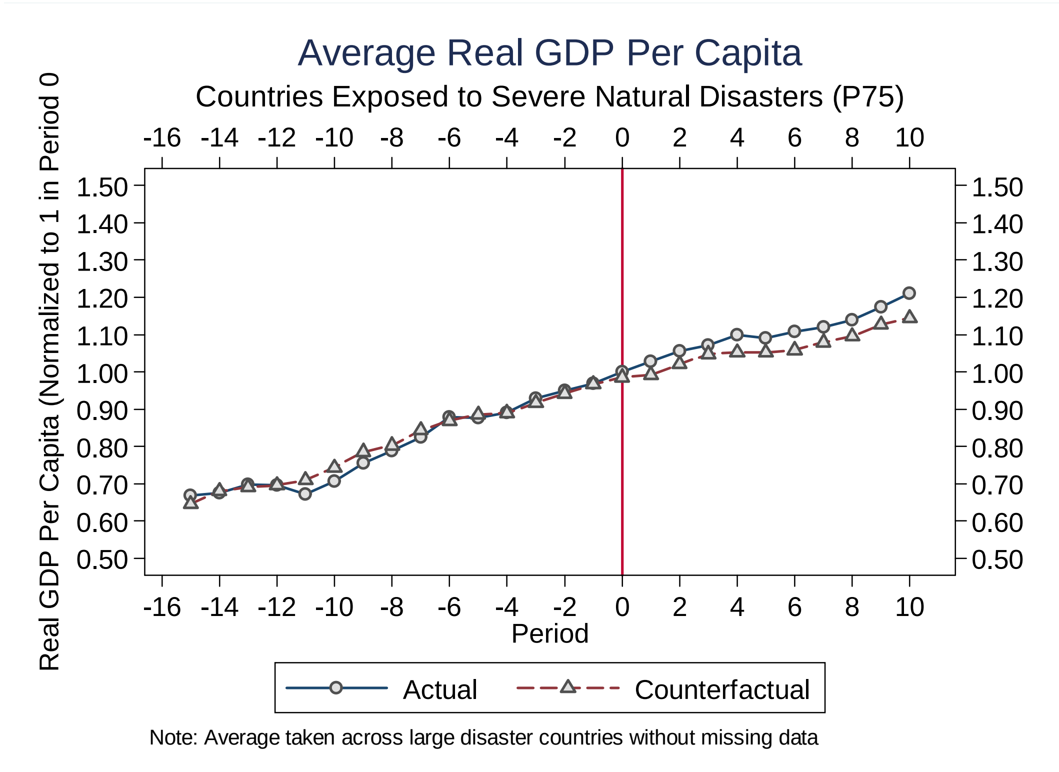


Figure 4: Large Disasters = above 90th Percentile



As can be seen, large disasters have a lasting impact on GDP percapita when we define a large disaster to be one in the 99th percentile of the magnitude distribution. The effects are sizable. For example, ten years after the disaster, the GDP per capita of the affected countries is (on average) 10 % lower that it was at the time of the disaster whereas it would be about 20% higher in the counterfactual scenario in which the disaster did not occur. Moreover, note that by extrapolating the pre-disaster trend into post-disaster years to construct the counterfactual, we would be over-estimating the effect of the disaster. When we define a large disaster using the 90th percentile, there is no effect of disasters on output actual and counterfactual GDP percapita

Figure 5: Large Disasters = above 75 Percentile

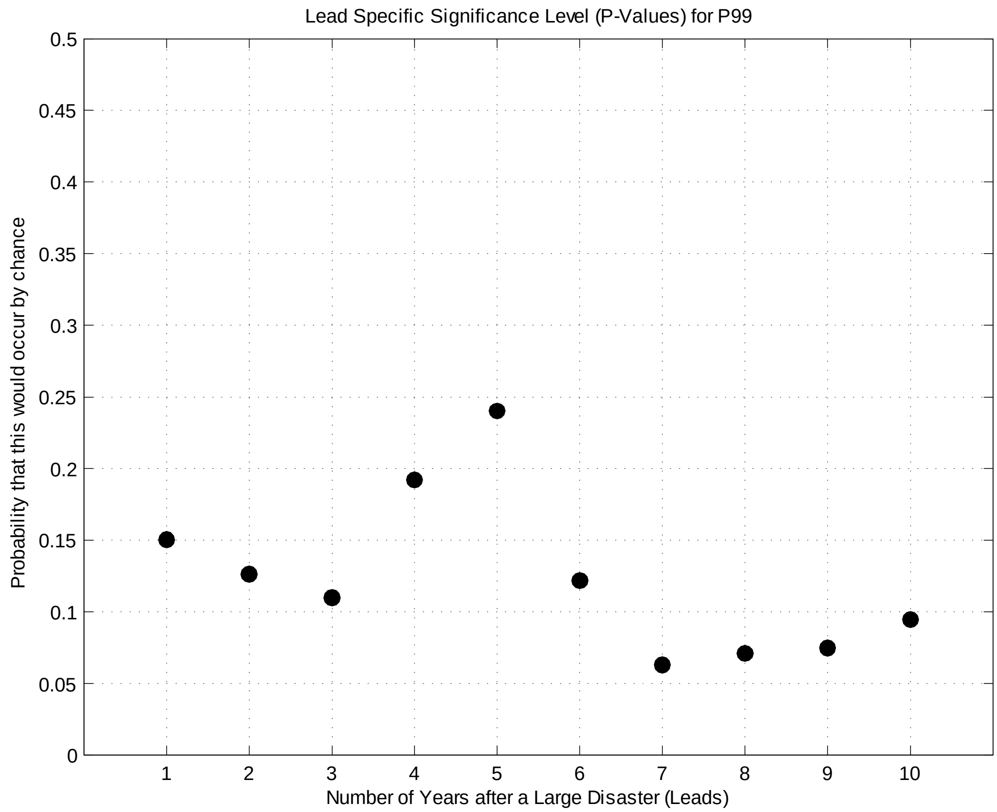


follow each other closely, not only before but also after the occurrence of the disaster. Finally when we consider our most lenient definition of large disaster using the 75th percentile (P75) we notice that, if anything, the results seem to be slightly positive, indicating that moderately large disasters somewhat stimulate growth.

In Figure 6 we present exact inference for the results in the P99 group.

Only the effects at leads t+7, t+8, t+9 and t+10 are significant at 90%. However, the above results are misleading, as we are including all the possible 4 disaster placebo averages. In particular, when computing placebo averages, we are including those placebo effects computed for placebo countries that do not have good pre-(placebo)

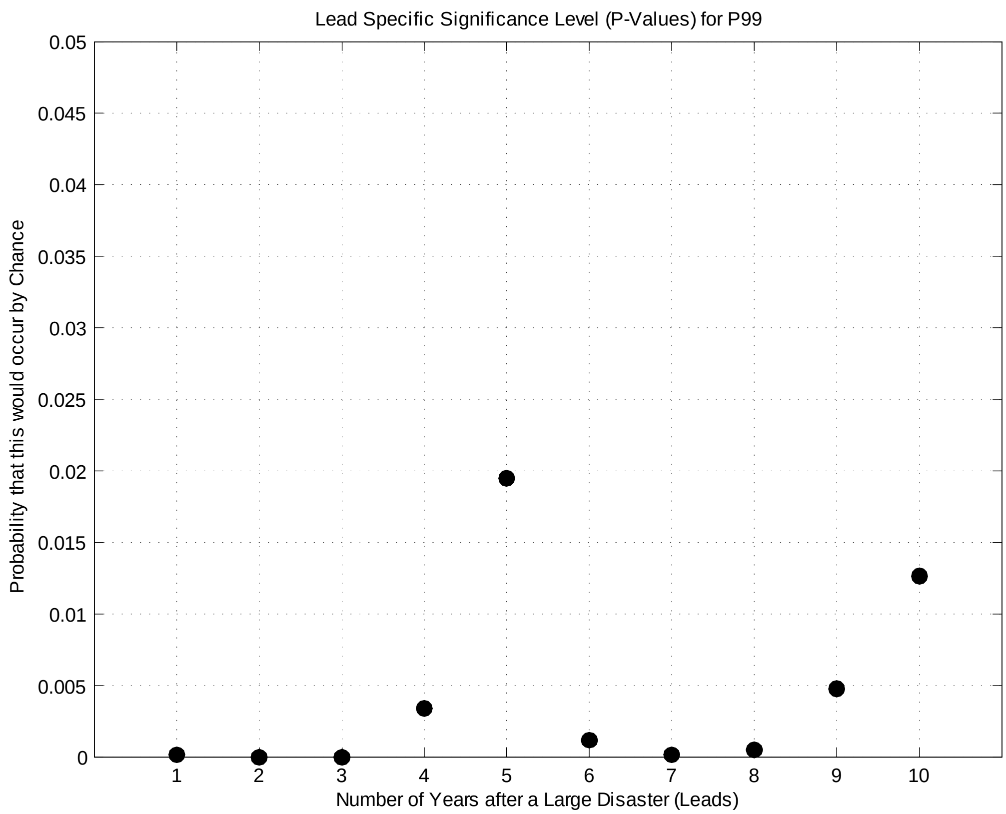
Figure 6: Unadjusted Significance Levels



treatment fit. This adds substantial noise into the exact inference procedure. Below we refine our inference approach and include only the averages computed with placebos that had as good a pre-treatment fit as the country that they serve as donors for.

Note that the scale of the figure for the refined inference is much smaller. As can be seen, the natural disaster causes on average, a significant decline in GDP percapita in all the 10 years in its aftermath. The probability of observing such declines is close to zero in every period.

Figure 7: Adjusted Significance Levels



6 Conclusions

We examine the short and long run impact of natural disasters on GDP per capita by combining information from comparative case studies. We contribute to the literature by providing new evidence, based on an alternative methodology to estimate causal effects. We do not look at the relationship between disaster risk and long run growth. Rather we focus on the effects of specific, large unexpected disasters on domestic output. We find that large disasters have a negative effect on output both in the short and long run. Using exact inference methods we show that these results are statistically significant. Smaller disasters tend to not have a significant effect on output neither in the short nor in the long run.

References

[1] Albala-Bertrand J M. Political economy of large natural disasters. Oxford: Clarendon Press; 1993.

[2] Auffret, P. (2003). High Consumption Volatility: The Impact of natural Disasters? World Bank Policy Research Working Paper #2962.

[3] Abadie and Gardeazabal (2003), The Economic Costs of Conflict:A Case Study of the Basque Country, American Economic Review

[4] Abadie, Diamond and Hainmueller (2008), Synthetic Control Methods for Comparative Case Studies: Estimating the Effects of California's Tobacco Control Program.

[5] Caballero and Hammour (1994), The Cleansing Effect of Recessions, American Economic Review, Volume 84, No. 5, (December 1994), pp. 1350-1368

[6] Cuaresma, J.C., Hlouskova, J., and M.Obersteiner. Natural disasters as creative destruction? Evidence from developing countries. Economic Inquiry 2008; 46(2); 214-226.

[7] Easterly, Willliam, and Levine, Ross, (2001) "It's Not Factor Accumulation: Stylized Facts and Growth Models" World Bank Economic Review, Volume 15, Number 2

[8] Fomby, Thomas, Yuki Ikeda and Norman Loayza (2009). The Growth Aftermath of Natural Disasters. World Bank Policy Research Working Paper 5002.

[9] Hallegatte, Stéphane, and Patrice Dumas, 2009. Can natural disasters have positive consequences? Investigating the role of embodied technical change. Ecological Economics 68, 777-786.

[10] Heger, Martin, Alex Julca, and Oliver Paddison, 2008. Analysing the Impact of Natural Hazards in Small Economies: The Caribbean Case. UNU/WIDER Research paper 2008/25

[11] Hochrainer, Stefan (2009) Assessing the Macroeconomic Impacts of Natural Disasters: Are There Any ? , World Bank Policy Research Working Paper # 4968

[12] Jaramillo, Christian R. H., 2009. Do Natural Disasters Have Long-Term Effects On Growth? Universidad de los Andes, Manuscript.

[13] Kahn M E. The death toll from natural disasters: The role of income, geography, and institutions. Review of Economics and Statistics 2004;87(2); 271–284.

[14] Kellenberg, Derek K., and Ahmed Mushfiq Mobarak, 2008. Does rising income increase or decrease damage risk from natural disasters? Journal of Urban Economics 63, 788–802.

[15] Loayza, Norman, Eduardo Olaberría, Jamele Rigolini, and Luc Christiansen (2009). Natural Disasters and Growth – Going Beyond the Averages. World Bank Policy Research Working Paper 4980.

[16] Martin, Philippe, and Carol Ann Rogers, 1997, "Stabilization Policy, Learning-By-Doing, and Economic Growth," Oxford Economic Papers, Vol. 49, No. 1, pp. 152–66.

[17] Noy, Ilan, 2009. The Macroeconomic Consequences of Disasters. Journal of Development Economics, 88(2), 221-231.

[18] Noy, Ilan and Tam Vu, 2009. The Economics of Natural Disasters in Vietnam. University of Hawaii Working Paper 09.

[19] Noy, Ilan, and Nualsri, Aekkanush, 2008. Fiscal Storms: Public Spending and Revenues in the Aftermath of Natural Disasters. University of Hawaii Working paper 08-09.

[20] Raddatz C., 2007. Are external shocks responsible for the instability of output in low-income countries? Journal of Development Economics 84; 155-187.

[21] Raddatz, Claudio, 2009. The Wrath of God: Macroeconomic Costs of Natural Disasters. Manuscript.

[22] Rasmussen T N. Macroeconomic implications of natural disasters in the Caribbean. IMF working paper WP/04/224; 2004.

[23] Rodriguez-Oreggia, Eduardo, Alejandro de la Fuente, Rodolfo de la Torre, Hector Moreno, and Cristina Rodriguez (2009). The Impact of Natural Disasters on Human Development and Poverty at the Municipal Level in Mexico. Manuscript.

[24] Solow, Robert M. (1956): "A Contribution to the Theory of Economic Growth." Quarterly Journal of Economics, 70:65-94.

[25] Skidmore M, Toya H., 2002. Do natural disasters promote long-run growth? Economic Inquiry 40(4); 664-687.

[26] Strobl, Eric (2008). The Economic Growth Impact of Hurricanes: Evidence from US Coastal Counties. IZA discussion papers series.

Table 1 : Disasters by Country

Country	Years without Disasters	Disaster Years	Total Years		Years without Disasters	Disaster Years	Total Years
Afghanistan	12	29	41	Latvia	11	6	17
Albania	27	14	41	Lebanon	35	6	41
Algeria	15	26	41	Lesotho	27	14	41
American Samoa	36	5	41	Liberia	28	13	41
Angola	24	17	41	Libyan Arab Jamah	40	1	41
Anguilla	37	4	41	Lithuania	11	6	17
Antigua and Barbuda	35	6	41	Luxembourg	36	5	41
Argentina	7	34	41	Macau	39	2	41
Armenia	12	5	17	Macedonia FRY	8	10	18
Australia	4	37	41	Madagascar	14	27	41
Austria	17	24	41	Malawi	23	18	41
Azerbaijan	11	6	17	Malaysia	19	22	41
Bahamas	32	9	41	Maldives	36	5	41
Bahrain	40	1	41	Mali	18	23	41
Bangladesh	3	38	41	Marshall Is	39	2	41
Barbados	33	8	41	Mauritania	18	23	41
Belarus	9	8	17	Mauritius	25	16	41
Belgium	20	21	41	Mexico	3	38	41
Belize	30	11	41	Micronesia Fed States	35	6	41
Benin	16	25	41	Moldova Rep	9	8	17
Bermuda	36	5	41	Mongolia	30	11	41
Bhutan	35	6	41	Morocco	20	21	41
Bolivia	12	29	41	Mozambique	12	29	41
Bosnia-Hercegovenia	10	7	17	Myanmar	18	23	41
Botswana	30	11	41	Namibia	28	13	41
Brazil	5	36	41	Nepal	8	33	41
Brunei Darussalam	40	1	41	Netherlands	22	19	41
Bulgaria	26	15	41	Netherlands Antilles	39	2	41
Burkina Faso	16	25	41	New Caledonia	34	7	41
Burundi	29	12	41	New Zealand	11	30	41
Cambodia	26	15	41	Nicaragua	17	24	41
Cameroon	19	22	41	Niger	16	25	41
Canada	6	35	41	Nigeria	19	22	41
Cape Verde Is	31	10	41	Northern Mariana Is	40	1	41
Cayman Islands	38	3	41	Norway	34	7	41
Central African Rep	26	15	41	Oman	36	5	41
Chad	19	22	41	Pakistan	7	34	41
Chile	11	30	41	Palestine (West Bank)	40	1	41
China P Rep	6	35	41	Panama	20	21	41
Colombia	4	37	41	Papua New Guinea	14	27	41
Comoros	27	14	41	Paraguay	23	18	41
Congo	29	12	41	Peru	4	37	41
Costa Rica	17	24	41	Philippines	2	39	41
Cote d'Ivoire	29	12	41	Poland	22	19	41
Croatia	10	8	18	Portugal	21	20	41
Cuba	12	29	41	Puerto Rico	25	16	41
Cyprus	31	10	41	Romania	18	23	41
Czech Rep	6	10	16	Russia	1	16	17
Czechoslovakia	19	6	25	Rwanda	23	18	41
Denmark	30	11	41	Samoa	34	7	41
Djibouti	23	18	41	Sao Tome et Principe	38	3	41
Dominica	31	10	41	Saudi Arabia	33	8	41
Dominican Rep	18	23	41	Senegal	19	22	41
Ecuador	13	28	41	Serbia Montenegro	8	7	15

Egypt	27	14	41	Seychelles	37	4	41
El Salvador	21	20	41	Sierra Leone	26	15	41
Equatorial Guinea	40	1	41	Singapore	38	3	41
Eritrea	36	5	41	Slovakia	30	11	41
Estonia	15	2	17	Slovenia	13	5	18
Ethiopia	10	31	41	Solomon Is	26	15	41
Fiji	15	26	41	Somalia	17	24	41
Finland	39	2	41	South Africa	12	29	41
France	8	33	41	Soviet Union	10	14	24
French Polynesia	38	3	41	Spain	12	29	41
Gabon	35	6	41	Sri Lanka	8	33	41
Gambia The	23	18	41	St Kitts and Nevis	34	7	41
Georgia	8	9	17	St Lucia	30	11	41
Germany	1	17	18	St Vincent and The Gr	30	11	41
Germany Dem Rep	21	2	23	Sudan	17	24	41
Germany Fed Rep	14	9	23	Suriname	39	2	41
Ghana	24	17	41	Swaziland	30	11	41
Greece	13	28	41	Sweden	33	8	41
Grenada	35	6	41	Switzerland	17	24	41
Guam	34	7	41	Syrian Arab Rep	34	7	41
Guatemala	14	27	41	Taiwan (China)	18	23	41
Guinea	26	15	41	Tajikistan	0	17	17
Guinea Bissau	25	16	41	Tanzania Uni Rep	10	31	41
Guyana	33	8	41	Thailand	11	30	41
Haiti	17	24	41	Timor-Leste	36	5	41
Honduras	10	31	41	Togo	26	15	41
Hong Kong (China)	14	27	41	Tonga	33	8	41
Hungary	26	15	41	Trinidad and Tobago	34	7	41
Iceland	32	9	41	Tunisia	32	9	41
India	2	39	41	Turkey	8	33	41
Indonesia	4	37	41	Turkmenistan	15	2	17
Iran Islam Rep	7	34	41	Tuvalu	36	5	41
Iraq	32	9	41	Uganda	19	22	41
Ireland	27	14	41	Ukraine	4	13	17
Israel	32	9	41	United Kingdom	14	27	41
Italy	8	33	41	United States	2	39	41
Jamaica	20	21	41	Uruguay	27	14	41
Japan	3	38	41	Uzbekistan	12	5	17
Jordan	32	9	41	Vanuatu	21	20	41
Kazakhstan	6	11	17	Venezuela	18	23	41
Kenya	18	23	41	Viet Nam	9	32	41
Kiribati	38	3	41	Virgin Is (US)	36	5	41
Korea Dem P Rep	26	15	41	Yemen	19	22	41
Korea Rep	7	34	41	Yugoslavia	15	9	24
Kuwait	39	2	41	Zaire/Congo Dem Rep	17	24	41
Kyrgyzstan	5	12	17	Zambia	22	19	41
Lao P Dem Rep	22	19	41	Zimbabwe	27	14	41

Note: 7669 country-years. 3323 disasters

Table 2: Disasters by Year

	Countries without Disasters	Countries with Disasters	Countries
1968	179	1	180
1969	174	6	180
1970	137	43	180
1971	142	38	180
1972	140	40	180
1973	147	33	180
1974	142	38	180
1975	140	40	180
1976	133	47	180
1977	114	66	180
1978	120	60	180
1979	118	62	180
1980	113	67	180
1981	117	63	180
1982	114	66	180
1983	89	91	180
1984	108	72	180
1985	103	77	180
1986	103	77	180
1987	89	91	180
1988	95	85	180
1989	101	79	180
1990	91	89	180
1991	91	91	182
1992	105	92	197
1993	113	84	197
1994	109	88	197
1995	98	99	197
1996	94	103	197
1997	88	109	197
1998	77	120	197
1999	61	136	197
2000	68	129	197
2001	76	121	197
2002	69	128	197
2003	70	127	197
2004	73	124	197
2005	62	135	197
2006	82	115	197
2007	65	131	196
2008	136	60	196
Total	4,346	3,323	7,669