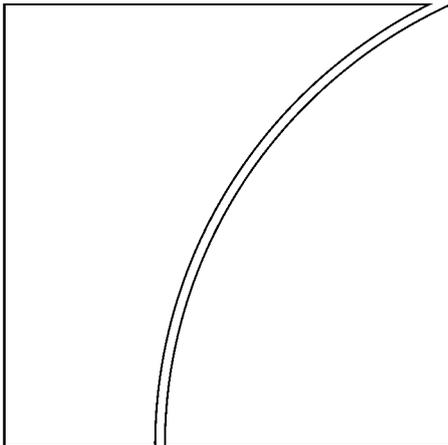




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Unmitigated Disasters? New Evidence on the Macroeconomic Cost of Natural Catastrophes

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Abstract

This paper presents a large panel study on the macroeconomic consequences of natural catastrophes and analyzes the extent to which risk transfer to insurance markets facilitates economic recovery. Our main results are that major natural catastrophes have large and significant negative effects on economic activity, both on impact and over the longer run. However, it is mainly the *uninsured* losses that drive the subsequent macroeconomic cost, whereas sufficiently insured events are inconsequential in terms of foregone output. This result helps to disentangle conflicting findings in the literature, and puts the focus on risk transfer mechanisms to help mitigate the macroeconomic costs of natural catastrophes.

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Keywords: Natural catastrophes, disasters, economic growth, insurance, risk transfer, reinsurance, recovery, development.

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1 Introduction

A series of tragic events in recent years has rekindled interest in the economic consequences of natural catastrophes. A growing literature studies whether disasters are harmful or conducive to economic activity. While the immediate destruction they cause triggers a range of adverse socio-economic consequences, natural disasters may also have growth-enhancing effects since investment for reconstruction is part of measured GDP (a flow), whereas the destruction of physical capital (a stock) is not. Replacing dated capital with more recent vintages might also raise long-term growth. Weighing against this optimistic view are the disarray and loss of productive capacity depressing output in the immediate aftermath of a major catastrophe. Existing studies differ widely in terms of sample size and the time horizon over which these effects are examined, and formal research disregards the role of risk transfer even as policy papers emphasize the importance of financial preparedness. The literature thus reaches no firm conclusions on disaster-related growth effects.

By using a novel and unique dataset, this paper measures the dynamic response of growth to major natural catastrophes, and examines the extent to which risk transfer to insurance markets facilitates economic recovery for a large cross-section of countries. With this aim, the paper makes three contributions to the literature. First, our analysis has a broader scope than other studies. We construct a large panel with 8,252 country-year observations, covering 203 countries and jurisdictions between 1960 and 2011, matched with 2476 major natural catastrophes of four different physical types. Importantly, we make use of the most detailed statistics available on total and insured losses, obtained from industry sources. These unique data are better suited for the analysis than the public CRED database used in the existing literature.¹ On the methodological side, we estimate the full time profile of economic growth in response to natural disasters in a dynamic specification. This allows us to present a more complete picture of growth dynamics than studies that focus on a particular time segment only.

Third, and most importantly, this is the first paper to make the link between natural catastrophes and economic growth conditional on risk transfer. This nuances the transmission channels, thereby helping to resolve the conflicting findings on catastrophe-related growth effects in the literature. In particular, we show that the *uninsured* part of disaster-related losses drives the subsequent macroeconomic cost in terms of foregone output. In focusing on economic activity, we recognize that disasters invariably diminish the wellbeing of affected populations even if growth rebounds.² That said, there is little evidence that countries rebound from natural catastrophes when uninsured. We find that a typical (median) catastrophe causes a drop in growth of 0.6-1.0% on impact and results in a cumulative output loss of two to three times this magnitude, with higher estimates for larger (mean) catastrophes. Well insured catastrophes, by contrast, can be inconsequential or positive for growth over the medium term as insurance payouts help fund reconstruction efforts.

These findings suggest that risk transfer to insurance markets has a macroeconomic value. This value may be particularly high for smaller nations that lack the capacity to (re)insure themselves against major natural disasters. The analysis thus contributes to the policy debate on different forms of post-disaster spending, as well as the balance between prevention *ex ante* and compen-

¹The Centre for Research on the Epidemiology of Disasters (CRED) collects the International Disaster Database (<http://www.cred.be>).

²Disasters affect social wellbeing through various channels, including health, education, and nutrition (World Bank and United Nations 2010).

sation ex post. Our finding that catastrophes have permanent output effects is also relevant for a growing literature that explains asset pricing puzzles through rare disasters. The extent to which risk transfer mitigates the macroeconomic cost of disasters is pertinent to the literature on finance and growth, which focuses on banks and stock markets but not on insurance. Considering the macroeconomic value of risk transfer could also enrich the macroprudential approach to the regulation and supervision of insurance companies.

The paper is structured as follows. Section 2 presents a case study contrasting Haiti and New Zealand, two island states that were struck by physically similar earthquakes in 2010, yet faced radically different economic consequences. Section 3 describes the construction of the dataset, offers stylized facts about natural catastrophes and introduces the methodology. The baseline results on the occurrence of natural disasters are presented in section 4, while section 5 extends the regressions to account for the severity of catastrophes. Section 6 conditions the estimates on insurance coverage and studies natural disasters of different physical types. Section 7 considers the role of development for insurance coverage and output losses, and section 8 concludes.

2 Two Islands, Worlds apart: Haiti vs. New Zealand

Physical similarities. In 2010, both Haiti and New Zealand were struck by powerful earthquakes. The two events were physically similar in many respects. Both earthquakes released energy equivalent to a moment magnitude of 7.0. In both cases, the epicenter was located near a major economic hub – Port-au-Prince, Haiti’s capital, and Christchurch, New Zealand’s second largest city. Furthermore, both countries are island states, subject to recurring natural catastrophes in the form of hurricanes, flooding and earthquakes. In light of these physical similarities, one might expect similar economic consequences to unfold on the two islands.

Devastation and the real economy. Haiti’s earthquake was one of the largest natural catastrophes affecting a developing country in history. The immediate destruction resulted in widespread disruption and 220,000 fatalities (2.25% of the population), and dislocated or affected another 40% of the population. Economic losses *directly* attributable to the catastrophe amounted to 8 billion US dollars, or 126% of 2010 GDP. A large share of private and public buildings, as well as manufacturing and transportation facilities, were destroyed, among them export-oriented farms and apparel production facilities. High on the list of damaged infrastructure were Haiti’s main airport and harbor.

The *indirect* macroeconomic effects resulting from the 2010 earthquake include a drop in real growth from 3.5% to -5.1% in 2010 alone, accompanied by a sharp decline in exports. It is too early for a comprehensive assessment of longer-term effects, but the extent of disruption can be gleaned from various signs. One year after the earthquake, just 20% of the rubble had reportedly been cleared from the Port-au-Prince (BBC News 2011). This was followed by an outbreak of cholera. The scale of human suffering made visible in the media worldwide triggered unprecedented aid flows. Aid to Haiti amounted to \$2.9 billion in 2010, a tenfold increase over the average inflow of \$0.35 billion between 1990 and 2009 (OECD 2012), with billions more committed.

In the case of New Zealand, the direct losses were of a similar order of magnitude in absolute terms. Losses *directly* attributable to New Zealand’s 2010 earthquake amounted to \$6.5 billion (5.3% of GDP). The event produced no fatalities, in a population of 4.3 million. Even so, infrastructure

disruptions included a major airport, different ports and essential roads. Hampered transportation facilities and damage to office buildings caused numerous businesses to close, including facilities for food processing, paper production, textiles, machinery, transportation equipment and service providers.

Indirect macroeconomic effects also started to unfold immediately after the quake due to widespread disruptions. At the same time, reconstruction, inventory adjustment and a large increase in local government spending on repairing public infrastructure induced positive growth effects. Local experts estimated that the immediate growth-enhancing effects of reconstruction add 0.4% to real growth, and projected similar gains over the medium term (Statistics New Zealand 2010; New Zealand Treasury 2010). The fourth quarter saw growth rise to 1.7% (third quarter 1.2%). Following a second earthquake in February 2011, growth remained positive but slightly lower in a band of 1.1 to 1.6%, before picking up to 2.0% by mid-2012 (Reserve Bank of New Zealand 2012; Statistics New Zealand 2012).

An important distinction. In view of the striking physical similarities between the earthquakes, what explains the different economic consequences in Haiti and New Zealand? The difference we emphasize here is that of financial preparedness for dealing with natural disasters, particularly the extent of risk transfer arranged for *ex ante*. When the 2010 earthquakes struck, 81% of the resulting direct losses in New Zealand were covered and subsequently reimbursed based on existing insurance contracts (coverage for the 2011 earthquake was likewise at 80%). By contrast, Haiti's insurance coverage was below 1%. This stark contrast also reflects the two countries' different stages of economic development. Unlike most countries, New Zealand had made earthquake insurance largely mandatory. As a result of the broad coverage, the 2010 earthquake in New Zealand triggered financial compensation in excess of \$5 billion from primary insurance companies. A large share of this amount was covered in turn by reinsurance contracts. Reinsurance companies headquartered outside New Zealand ultimately covered some \$3.5 billion of earthquake-related losses (Holborn 2011). Haiti, in stark contrast, had negligible insurance coverage and thus found itself dependent on the disbursement of foreign aid.

The case of New Zealand suggests that insurance coverage facilitates rebuilding even with a slow pace of reimbursement. In spite of extensive insurance coverage in New Zealand, only a small share of claims were reimbursed shortly after the event. Depending on the specific earthquake insurance arrangement, many reimbursements had to be transferred through the public Earthquake Commission (EQC). In the direct aftermath of the disaster it took the EQC and private carriers some time to cope with the surge in required resources, notably staffing. This initially resulted in a slow pace of reimbursement. The EQC category "urgent repairs" and privately processed claims saw swifter reimbursements, but overall the insured reportedly wanted faster payouts. Even so, on-site risk management experts indicated that many owners of businesses and private property started their reconstruction efforts immediately after the quake, since they knew that they would receive money based on their insurance contracts for several reasons. They could rely on the fact that private insurers operating in New Zealand typically reinsure their peak risk with reinsurance companies abroad. Furthermore, the EQC was known to spread risk by buying its reinsurance coverage only from global groups and was also backed by a government guarantee. In contrast to many other countries, New Zealand can be said to have a *de-facto* reinsurer of last resort – not all countries can shoulder the resulting contingent fiscal liability.

Channels. Insurance facilitates recovery through two main channels. Well insured natural disasters trigger various payments by insurers to reimburse individual losses. What is the transmis-

sion from this microeconomic level to economic activity in the aggregate? Compensation directs resources to agents who need them for the replacement and repair of damaged property and infrastructure. In the absence of such arrangements, capital may not flow to the affected agents for the same financial imperfections that inform the literature on finance and growth (e.g. Levine and Zervos 1998). An overall increase in the volume of reimbursements, especially in the form of inflows from abroad, helps to spur economic growth by funding building activity and facilitating investment in reconstruction, which is included in measured GDP. Extensive compensation is also likely to have second-round effects, as funded reconstruction activity spills over to other sectors through externalities and strategic complementarity. For instance, a business owner will be more willing to invest after a disaster if it is a known fact that many potential customers had bought insurance and will thus have money to spend as a going concern. Such measures on the microeconomic level plausibly add up to a macroeconomic effect. For such behavior to take effect, agents must have confidence that insurers will pay based on contractual obligations if compensation is not paid out immediately.

Beyond catastrophe-related payouts, a country can benefit from existing insurance coverage through the transfer of knowledge. We illustrate this channel with one example at the different stages of a catastrophe. *Ex ante*, (re)insurers provide incentives to establish advanced building codes. Making structures more resistant to earthquakes is in the interest of the country and the insurers alike, as it limits damage and facilitates recovery operations. Second, as a catastrophe unfolds, (re)insurers often send disaster management experts to catastrophe sites to provide specific expertise that helps to contain losses and speed up reconstruction. Finally, *ex post* (re)insurers have a vested interest in training their customers in catastrophe-prone regions with the aim of exposure mitigation and business continuity planning. Business interruption insurance compensates for income lost while a business is being rebuilt. By helping to limit losses and resume business, these initiatives also foster recovery and promote growth. Insurance payouts are automatically allocated to the repair or replacement of facilities deemed sufficiently important for agents to have insured them in the first place. Aid flows, and other forms of *ex post* relief, rarely come with such incentives and allocation mechanisms.

Related literature. Existing research focuses on the link between natural catastrophes and growth without taking into account the role of insurance in transferring risk. Within this limited focus, the literature varies along several dimensions. Many papers use relatively small samples with few countries or few disasters. Some articles focus on the contemporaneous impact (Murlidharan and Shah 2001, Noy 2009), others on five-year intervals (Loayza et al. 2012) or GDP after five years (Hochrainer 2009), and on long-term average growth (Skidmore and Toya 2002). Other research focuses on how the effects on economic growth differ according to physical type of natural catastrophes (Fomby et al. 2009, Loayza et al. 2012). Methods also vary: while most studies use classical regression analysis, Cavallo et al. (2010) employ synthetic control methods, and a vast literature uses descriptive case studies.

While each approach has its merits, the literature reaches no consensus on the sign and size of catastrophe-related growth effects. Some find a qualified positive effect (e.g. Skidmore and Toya 2002), others a negative effect (e.g. Rasmussen 2004, Fomby et al. 2009, Noy 2009) and some find no significant effect (e.g. Cavallo et al. 2010). The papers closest to ours are Noy (2009), Hochrainer (2009) and Loayza et al. (2012); all combine CRED data with World Bank statistics and include more macroeconomic covariates, at the expense of sample size. Noy estimates the contemporaneous impact of direct losses on growth in a sample of 109 countries over 1970-2003

(comprising 428 events) and finds a significant negative impact of 1% on average, and more for developing countries. Loayza et al. consider 5-year averages for 94 countries over 1961-2005, and show that growth effects over the medium term, although fairly small, differ by economic sector and physical type of catastrophe. Hochreiner uses non-parametric methods to examine 225 large disasters over 1960-2005, and finds that the level of GDP is on average 2 to 4% lower five years after catastrophes causing direct losses in excess of 1% of GDP.

This paper departs from this literature in three respects. First, the scope is broader than in existing studies: we construct a large dataset that spans 52 years (1960-2011) across 203 countries and jurisdictions, comprising 2476 major events. This helps avoid the selection bias afflicting studies with incomplete cross-sections or short time-series. Second, we perform dynamic panel analysis to estimate the full time profile of economic growth in response to natural catastrophes. This presents a more complete picture of growth dynamics than existing studies that focus on five-year averages or on a particular time segment. Third and most importantly, existing empirical research disregards the role of risk transfer, due to data limitations, even as the policy literature emphasizes the importance of financial preparedness (e.g. Kunreuther and Michel-Kerjan 2009, Cummins and Mahul 2009, World Bank and United Nations 2010). Using a unique dataset on risk transfer via (re)insurance, our paper makes the link between natural catastrophes and economic growth and thus helps to disentangle some of the conflicting findings in the literature.

3 Data and Methodology

The NatCat data. The dataset employed here contains close to 21,768 observations on the direct costs of natural catastrophes to individual countries between 1960 and 2011. The coverage is very broad. Since 1960, natural catastrophes have claimed over 3.2 million lives, and caused \$3,800 billion in total losses giving rise to \$905 billion in insurance payouts. The data include *direct losses* from the immediate destruction of property and infrastructure. They exclude indirect costs – estimating these subsequent, macroeconomic costs is the objective of the paper. Direct losses are calculated based on the cost replacing or repairing affected homes, schools, other buildings, machinery, livestock, vehicles, and other property and infrastructure. The raw data are in original US dollars, whereby inflation exaggerates the upward trend in economic losses. To make losses comparable over time, we express nominal amounts in constant 2011 US dollars using the US CPI.

The data were obtained from the NatCatService of Munich Re, a global insurance and reinsurance group. These statistics specialize in economic losses and draw extensively on industry sources (see Appendix A for details). As such, they are better suited for our research questions than the CRED database commonly used in the literature. That said, there is considerable overlap between the two sources in terms of the physical events covered, and inconsistencies are eliminated by regular exchange between the data collecting institutions (Below et al. 2009).

The key difference for our purposes is the quality of the loss data, which is insufficient in CRED. Reinsurance companies are well placed to assess catastrophe-related losses: they not only track their own global insurance liabilities, but also have incentives to collect statistics on the entire universe of natural catastrophes in order to set appropriate terms and premiums on their (re)insurance contracts. As a result, the NatCat statistics provide the most accurate data on insured and total losses. Appendix 1 provides further detail and reports on data quality tests. Most importantly, since natural catastrophes do not respect national borders, it was important to confirm that supra-

national events (those affecting entire regions) come with sufficient information for allocating losses to individual countries as necessary for our macroeconomic analysis.³ The consistency between regional totals and country breakdowns speaks to the quality of the NatCat statistics.

Stylized facts. Most of our analysis focuses on *major* catastrophes between 1960 and 2011 (Table 1). This comprises the 2,476 known events with a severity of category 4 and above, a threshold defined by a minimum of 100 fatalities and/or \$250 million in losses in constant 2011 US dollars. These events jointly account for more than 90% of all reported losses and fatalities from natural catastrophes since 1960. Table 1 breaks down the frequency of major catastrophes by continent and by their physical properties, and provides summary statistics on their severity and insurance coverage. The relative frequency is particularly high for storms in North America, droughts in Africa, and flooding and earthquakes in Asia. Note that the severity of disasters is so skewed that the worst catastrophes pull the mean well above the median of the distribution, both for fatalities and for economic losses. We therefore distinguish between typical (median) disasters and larger average (mean) disasters when presenting empirical results. Normalizing losses by land area, population or GDP shows just how concentrated the damage from natural disasters can be, especially for storms, earthquakes and volcanic eruptions.

Table 1: Features of Natural Catastrophes

Insurance coverage. We compute effective coverage for each disaster by expressing insured losses as a share of total losses ex post. Over the sample’s span of 52 years, nearly 60% of major events were entirely uninsured (53% over the past decade). At close to 80%, the proportion of uninsured events is particularly high among hydrological and climatological events, while meteorological events are frequently insured, especially in North America. Insurance coverage goes broadly hand in hand with development. High-income countries contract more insurance for every physical type of catastrophe than lower-income groups; as a result, the bulk of losses reaching the global insurance market derives from catastrophes in North America, Europe, Japan and the Pacific region (von Dahlen and von Peter 2012). By comparison, low- and middle-income countries host less developed insurance markets (Cummins and Mahul 2009), although there are sufficient insured disasters in this group of countries to perform the regressions.

The same point holds for insurance coverage at different degrees of severity (Figure 1). The red dots represent major catastrophes of category 4 and above. The lack of insurance for a great number of events is apparent from the cluster along the x-axis. Yet there is a wide dispersion of insurance coverage at all levels of severity, which is important for identifying the role of insurance. In particular, coverage does not fall systematically with severity, which could have biased our estimates below – the quadratic line fitted through the scatter plot only declines moderately beyond disasters costing more than \$10 billion ($\10^{10}).

Our observations on insurance coverage result from the aggregation of a multitude of individual contracts that commit insurance companies to pay for damages in the wake of a natural catastrophe. Coverage is generally arranged between policyholders and a (local) primary insurance company. The individual insurer usually offers different lines of business, including property, automobile,

³A case in point is the Indian Ocean Tsunami of 26 December 2004. The event caused 220,363 fatalities and \$12.055 billion in direct losses overall, which are attributed to Indonesia (160,000 lives, \$4.5 billion in losses), Sri Lanka (35,300 lives / \$1.0 billion), India (16,300 lives / \$2.5 billion), Thailand (8,200 lives / \$2.0 billion) and 9 lesser affected countries.

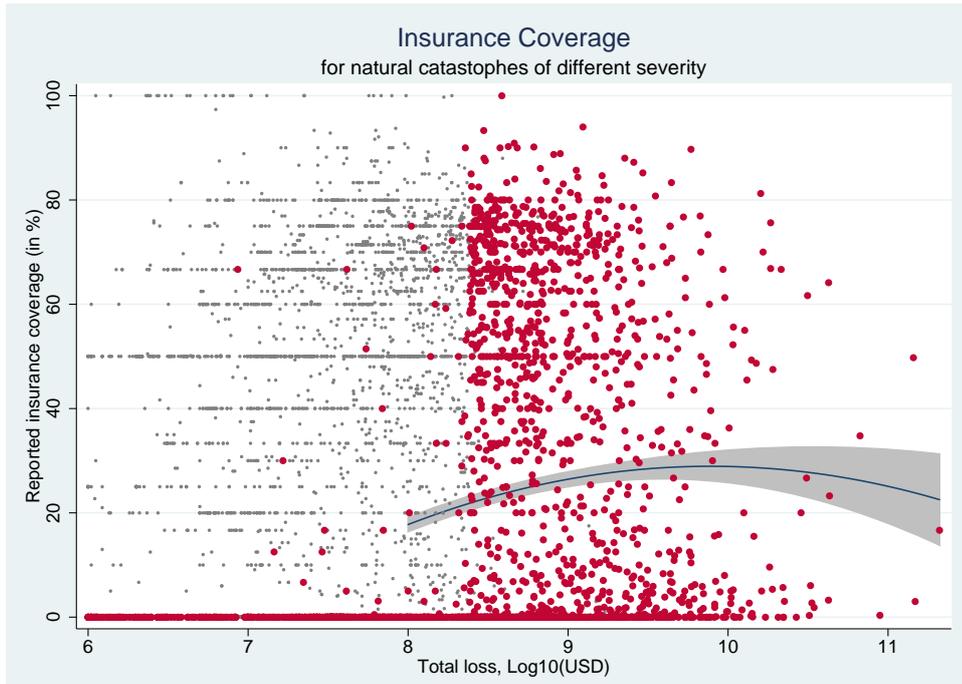


Figure 1: The Figure plots insurance coverage against the severity of natural catastrophes, as measured by direct economic losses. The quadratic fit is estimated for the set of natural catastrophes with severity category of 4 and above (thick dots), excluding events with reported losses below \$1 million. The shaded area represents the 95% confidence interval around the predicted curve.

business interruption and life insurance. Those different lines of business will be jointly affected by a natural catastrophe, leading to thousands of insured claims and an accumulation of losses at individual insurance companies. To limit their exposure, insurers commonly buy coverage from reinsurance companies, often in the form of "catastrophe excess of loss" contracts (CatXL).⁴ The reinsurance sector retains most of the underwritten risk, and transfers some peak risks to broader financial markets through retrocession and securitization (e.g. through catastrophe bonds), as described in von Dahlen and von Peter (2012).⁵ Natural disasters resulting in significant losses have become more frequent in recent decades, with insured losses peaking in 2005 (\$116 billion), and total losses reaching a record \$386 billion in 2011.

Constructing the panel dataset. To perform dynamic panel analysis, the NatCat data must be matched with macroeconomic time series. We proceed in two steps. Countries often suffer several catastrophes within a single year, yet their macroeconomic data are at the annual frequency.⁶ We

⁴An individual CatXL contract could typically come with the following caps: \$6 million for the primary insurer, plus \$8 million for the reinsurer. The aggregate exposure of any single reinsurer can reach billions in the event of a major catastrophe.

⁵Detailed analyses of the market for insuring catastrophe risk include Froot (2001), Kunreuther and Michel-Kerjan (2009), and Cummins and Mahul (2009) from a developing-country perspective. World Bank and United Nations (2010) place catastrophe insurance in a broader context of coping and prevention.

⁶Higher-frequency growth data are unavailable for most countries over any significant length of time. Similarly, regional (sub-national) data would also be better suited for measuring the effect of natural catastrophes. If we detect growth effects in annual and national data, they are even more likely to show in quarterly and sub-national data.

aggregate multiple disasters within each year to obtain a unique observation for each country-year pair. This step consolidates 2,476 disasters of category 4 and above into 1,319 observations at the country-year level while retaining the number and physical types of catastrophes occurring in each country-year pair by folding this information into additional variables. The second step matches the NatCat dataset with macroeconomic panel data (see Appendix 1). We draw on the World Bank’s *World Development Indicators* database, in line with related studies.⁷ We complement missing countries and jurisdictions with United Nations *National Accounts* data to obtain broader coverage, and add macroeconomic controls (Appendix Table A1 lists variables and data sources). This yields an (unbalanced) panel dataset spanning the period 1960-2011 comprising 8,252 growth observations and 2,381 natural catastrophes of category 4 and above (20,999 when including all categories). There are 203 countries and jurisdictions with more than 20 years of growth data. What follows uses the inflation-adjusted dataset on catastrophes of category 4 and above. Appendix 3 performs robustness tests for different thresholds of severity and timing to ensure that our results do not depend on the choices made in the construction of the panel dataset.

Methodology. Our point of departure is a simple dynamic stochastic growth model from which we generate impulse response functions to simulate the impact of natural catastrophes on a country’s growth path. This approach accounts for the nonstationarity of output (Nelson and Plosser 1982) and can be implemented using dynamic panel methods. Let y_{it} denote real GDP growth of country i in period t . The variable x_{it} measures severity if a natural catastrophe occurs in country i and period t , and equals zero otherwise. Growth dynamics can be described by an autoregressive model of the form

$$y_{it} = \alpha_i + \sum_n \beta_n y_{it-n} + \sum_n \lambda_n x_{it-n} + \varepsilon_{it}.$$

The coefficients on x_{it} and its lags translate natural catastrophes into growth outcomes. The *impact* of a disaster on the growth rate within the same year equals λ_0 . If negative, this drag on economic activity also affects next year’s growth through the autoregressive process, and may be further compounded (or attenuated) by a negative (or positive) λ_1 , and so forth. The perturbed path describes deviations from the long-term growth rate of $y_i^* = \alpha_i / (1 - \sum \beta_n)$.⁸ Over time, the *cumulative effect* of a disaster on growth converges to

$$\mathbb{E}(\Delta y_i) = \frac{\sum \lambda_n}{1 - \sum \beta_n} x_i. \quad (1)$$

The ratio in this expression is the multiplier that translates the impulse (a catastrophe of severity x_i) into the long-term cumulative effect on growth. The lag structure thus allows the data to identify how the effects of natural catastrophes work their way through to economic growth in stages. In contrast to impact studies (e.g. Noy 2009), we thus estimate a time profile of the growth response. To evaluate the hypothesis whether natural catastrophes are harmful or conducive to growth, we test the sign and significance of the coefficients λ_n . We then visualize the full growth response over time by simulating the recursive equation from a single impulse at $t = 0$. In doing so we focus on economic growth – the most debated economic variable – while acknowledging that GDP does not capture many important consequences of natural disasters that affect people’s wellbeing. That said, the method can be applied to other variables of interest, such as infrastructure investment, consumption or socio-economic measures.

⁷These include Barro (2009), Cerra and Saxena (2008), Noy (2009), and Loayza et al. (2012).

⁸Using lag polynomials, the equation becomes $B(L)y_{it} = \alpha_i + \Lambda(L)x_{it} + \varepsilon_{it}$. For stable stochastic difference equations of this form, the mean path describing the systematic dynamics is given by the expectation $\mathbb{E}(y_{it}) = B^{-1}(L)[\Lambda(L)x_{it} + \alpha_i]$ (e.g. Harvey 1990).

4 Occurrence of Natural Catastrophes

Baseline. This section focuses on the occurrence of natural catastrophes, regardless of their severity. This follows Cerra and Saxena’s (2008) study on financial and political crises. For natural catastrophes, this approach benefits from strict exogeneity: their occurrence does not depend on economic conditions in the years preceding them. After testing down the lag structure, we settle on the following baseline regression,

$$y_{it} = \alpha_i + \sum_{n=1}^2 \beta_n y_{it-n} + \sum_{n=0}^4 \delta_n N_{it-n} + [\text{Macro controls}] + \varepsilon_{it}, \quad (2)$$

where the indicator variable N_{it} equals 1 if natural catastrophe(s) occur in country i in year t , and zero otherwise, focusing on catastrophes of category 4 and above.⁹ Guided by the Hausman test, we estimate (2) using panel fixed effects with robust standard errors.¹⁰ This is a natural choice, since virtually all countries are in the sample, and their growth rates differ for structural reasons.

The baseline result suggests that major natural catastrophes are harmful to economic activity (Table 2). At the time of impact, a catastrophe reduces growth by an estimated 0.64 percentage points within the first year on average ($\hat{\delta}_0$ in column 1). This impact persists through the growth process (the autoregressive lags are positive), and is compounded two years after the event by a further drag on growth (lag 2 of the indicator equals -0.55%). In this specification, the estimated cumulative effect amounts to -1.65% of GDP and passes the significance test at the 1% level. The response of growth to natural catastrophes thus exhibits a rich dynamic profile.

Table 2: Natural Catastrophes and Economic Growth

Impulse response. Simulating the response of economic growth shows that the adverse effects of natural catastrophes are significant, both in the statistical and in the economic sense. Figure 2 generates the full time-profile of growth, from the impact to the long-run response to a disaster. The central path traces out the average growth response relative to the long-run growth path, which would remain constant at a rate of 4.60% in the absence of catastrophes and other shocks (the actual sample average is 3.94% per annum). Following a natural catastrophe, real growth declines by 0.64% on impact, briefly recovers and slumps again before converging back to the long-run growth rate (left panel). This perturbed path is embedded in a confidence band that excludes the x-axis for the most part, indicating statistical significance. The tentative rebound in the year after the disaster presumably reflects the contribution of reconstruction activity to measured GDP.

Interpretation. Does this growth pattern represent a recovery? The answer depends on the way one defines the term. Countries affected by a catastrophe may not see the *level* of GDP fall, since growth, albeit subdued, remains positive on average. Over time, the economy regains its *long-run growth rate* as the perturbed path approaches zero (Figure 2, left panel). However, countries generally do *not* recover their *previous growth path*. This would require that growth overshoot its long-term average (and jump into the positive quadrant of the Figure). Instead, the years

⁹This excludes a large number of small and moderate natural catastrophes (see Appendix 1). Other thresholds are tested in Appendix 3.

¹⁰In this regression, the country fixed effects are correlated with the lagged dependent variables. However, Nickell (1981) has shown that the estimation bias is of order $1/T$, which is small for this dataset, and smaller than in Cerra and Saxena (2008) who also follow this approach. Moreover, in the context of positive autocorrelation, the bias is negative and leads the persistence of growth to be underestimated.

of sluggish growth in the aftermath of a natural catastrophe leave behind a measure of foregone output. The growth effects dissipate but leave a level effect. In this sense, countries never fully recover the output lost in the wake of a natural catastrophe. This pattern of incomplete recovery is also observed for man-made disasters (Cerra and Saxena 2008). Likewise, in so-called consumption disasters the initial decline is not fully reversed by the partial recovery (Gourio 2008). It is the permanent effects that make the welfare cost much larger than in Lucas’s (1987) estimates. Such permanent effects are also necessary for explaining asset pricing puzzles through rare disasters (Barro 2009, Gabaix 2012).

Consequently, natural catastrophes leave behind a permanent macroeconomic cost, over and above the direct loss from the destruction of property and infrastructure. The right panel of Figure 2 sums the growth deviations over a ten-year period to show that the cumulative effect converges to -1.65% , as estimated in Table 2 (column 1) and derived from equation (1).¹¹ The cumulative effect thus exceeds the short-term impact by a factor of more than two. This underlines that the consequences of natural catastrophes play out over several years. Attention to affected populations and areas should therefore not be limited to the immediate aftermath of a disaster. Long-term effects on health, nutrition and education illustrate the social dimension of the problem (World Bank and UN 2010).

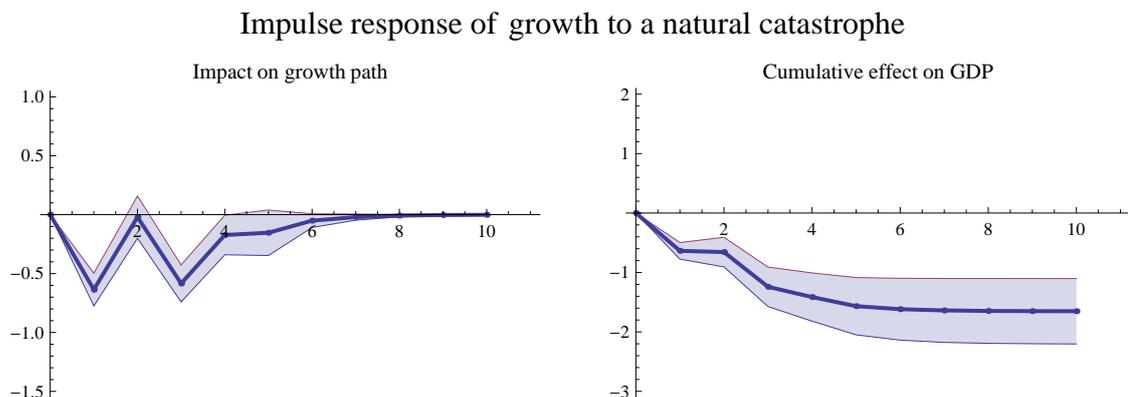


Figure 2: The impulse response function traces out the path of GDP growth over time by simulating the recursive equation (2) with the estimated coefficients of Table 2 (column 1) in response to a disaster triggering the dynamics, relative to the long-run growth rate. The catastrophe occurs between year 0 and 1, such that observation $t = 1$ represents growth in the impact year, observation $t = 2$ the year after, etc. The confidence band is derived from Monte Carlo realizations perturbing each of the estimated coefficients by a disturbance with a variance proportional to its estimated standard error (s). Specifically, we compute 10,000 realizations for each coefficient ($\hat{\alpha}'_r = \hat{\alpha} + s * e_r$) to produce as many paths from the recursive equation (2), and identify point-wise for every period t the realization that lies ± 1 standard deviation away from the central path (see also Sims and Zha 1999).

¹¹We chose to use the growth of real GDP (not per capita) as the dependent variable. If GDP slows or declines, so does GDP/capita, unless the decline in population is even sharper. Disasters rarely decrease a population to any significant extent, and it would be inappropriate in such cases to associate higher GDP/capita with greater wellbeing.

Man-made disasters. Natural catastrophes may coincide with man-made disasters that also have persistent negative effects on growth (Cerra and Saxena 2008). In 11% of country-year pairs with major natural catastrophes, a banking, currency, debt or political crisis or civil war starts in the same year. Ignoring these crises strengthens the estimated effect of natural catastrophes (Table 2, column 2). But this estimate is biased, since the regression excluding macroeconomic controls attributes some consequences of man-made crises to natural catastrophes. It is thus necessary to control for man-made crises, as confirmed by the likelihood ratio and Wald tests, and we do so throughout.¹² When estimated jointly (column 1), the macroeconomic costs of man-made crises are larger than those of natural catastrophes (see Table A2). Indeed, the impact of all five types of man-made crises exceeds 2% of GDP within the same year, and further costs arise in the case of civil wars, banking and debt crises. If countries could avoid man-made crises, their long-term growth would be 0.5% higher on average (comparing $\hat{\alpha}/(1 - \Sigma\hat{\beta}_n)$ in columns 1 and 2).

On robustness and exogeneity. The baseline regression is robust with respect to lag structure, estimation methods and subsamples – indeed, several departures from column 1 strengthen the estimated effects of natural catastrophes (see Appendix Table A2). While this baseline is not our preferred regression, it does have the virtue that the explanatory variables are truly independent, which should make the estimates reliable. The occurrence of natural catastrophes is completely exogenous over the relevant horizon, and the events themselves are identified by their physical characteristics.¹³ Natural catastrophes such as earthquakes materialize regardless of the prevailing economic environment. In this sense, the finding that natural catastrophes are followed by subdued growth plausibly reflects a causal link, since the regression is not subject to the endogeneity that plagues many other panel studies.

5 Severity of Natural Catastrophes

Log-loss specification. We now take advantage of the availability of data on the severity of natural catastrophes in terms of damage to property and infrastructure. Such a cost measure is likely to be more informative about economic activity than physical measures would be.¹⁴ In the panel regression measuring the dynamic response of GDP growth, we replace the NatCat indicator variable in (2) first by total direct losses L in constant 2011 US dollars expressed in logarithms,¹⁵

$$y_{it} = \alpha_i + \sum_{n=1}^2 \beta_n y_{it-n} + \sum_{n=0}^4 \lambda_n \log(L_{it-n}) + [\text{Macro controls}] + \varepsilon_{it}. \quad (3)$$

When using measures of severity, it is important to report the estimates λ_n scaled to convey a meaningful scenario. The distribution of losses is so skewed that the mean loss is an order of magnitude larger than the median loss (recall Table 1). Table 2 first reports coefficients scaled

¹²In order to maximize sample size and to avoid introducing potentially endogenous variables, we do not include further macroeconomic controls beyond the five types of man-made crises and country-fixed effects (as well as GDP per capita as a proxy for the stage of development in section 6).

¹³By comparison, the literature on consumption disasters, for instance, defines these events as a decline in the macroeconomic series of interest (Barro and Ursúa 2008).

¹⁴The cost measure will differentiate according to whether an earthquake with moment magnitude of 8.0, for example, releases its energy near Tokyo or in Siberia.

¹⁵As losses are close to log-normally distributed, the log-transform of losses (and of related severity measures) is approximately normal.

by the median loss, to show the growth response to a typical catastrophe at the center of the loss distribution. To complement, the shaded rows report coefficients scaled by the mean ($\hat{\lambda}_n \log(\bar{L})$), as the response to a mean loss is more relevant when assessing a country’s *expected* costs from a major natural catastrophe.

Results. The log-loss specification strengthens the estimated effects of natural catastrophes. The output cost of a typical (median) catastrophe amounts to 0.75% in the impact year and cumulates to 2.1% over time, slightly more for a mean catastrophe (Table 2, column 3).¹⁶ The hypothesis of a zero impact, and that of zero permanent effects of disasters on growth, can both be rejected at the 1% significance level. The impact and lag 2 coefficients are both more negative and estimated with greater precision than in the baseline regression (column 1). These results hold regardless of the exact threshold of severity used for including natural catastrophes in the sample (see Appendix Table A3). In sum, the quantitative information on damage to property and infrastructure is useful for identifying how catastrophes affect countries’ growth prospects.

An alternative measure of severity is the number of lives lost in a natural catastrophe. Using the logarithm of fatalities as a regressor puts more weight on catastrophes with higher death tolls, such as the droughts in Africa in the early 1980s. It also includes observations with unknown economic losses, such as the 1975 dam failures in China claiming 26,000 lives. This specification leads to smaller estimates (column 4), although the impact of a mean disaster remains similar (-0.77%). As Noy (2009) observes, property damage predicts growth better than the number of fatalities does – this is not surprising given that the median number of lives lost is low in all but the worst catastrophes (Table 1). Perhaps this is why Loayza et al. (2012), using the share of affected population as a severity measure, also find small effects of disasters on overall GDP growth over the medium term.

Concentration. We explore whether more concentrated losses come with higher macroeconomic costs in the remaining columns of Table 2. One would expect natural catastrophes to have a greater effect on smaller countries. There it is more likely that a disaster with a given physical scope affects a substantial share of output at the observed national level – small islands, such as Montserrat, face the highest exposure. Running the log-loss regression for small countries and jurisdictions, defined as those with land area at or below the median of 111,890 km² (the size of Honduras), yields an elevated impact and cumulative loss of 0.9% and 2.9% following average catastrophe.

The size effect becomes more apparent when expressing the cost of destruction relative to land area. With this measure (column 5), the impact and the cumulative effects are comparable to the log-loss results (column 3) for a typical (median-sized) disaster. Following a larger (mean) disaster, however, growth falls by 1.16% on impact and leaves a cumulative output loss of 3.7%. The macroeconomic costs are clearly visible in Figure 3. Normalizing losses by land area puts more weight on small nations and costly disasters when computing the correlations between growth and NatCat losses that determine λ_n . For example, while Grenada suffered \$3.16 million/km² in losses in 2004 (Hurricane Ivan), the same measure of geographic concentration never exceeded \$227/km² in Russia. Based on column (5), the predicted output loss for the 2011 Great East Japan Earthquake (with \$582,700/km² in direct losses) equals 1.39% on impact and 4.41% overall.

Similar results hold when scaling losses by the population of each affected country. This normalization emphasizes cases in which the consequences of a natural catastrophe have been shouldered by

¹⁶The Log_{10} transform takes the edge off larger catastrophes. To illustrate, when the actual loss grows tenfold from \$10 to \$100 billion, the log-loss variable increases by just one unit, from 10 to 11.

Impulse response to a catastrophe of average severity (loss/km²)

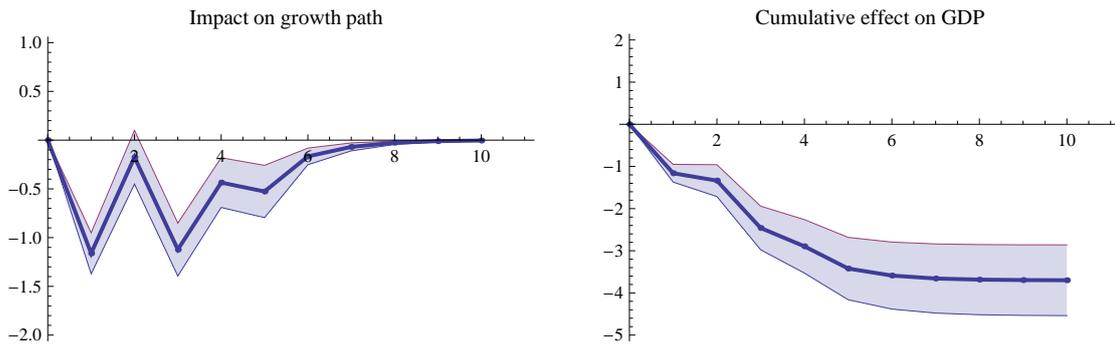


Figure 3: The impulse response function traces out the path of GDP over time by simulating the recursive equation (3), as described under Figure 2, with the estimated coefficients from Table 2 (column 5) associated with the regressor $\text{Log}_{10}(\text{Loss}/\text{km}^2)$, following a catastrophe of mean severity.

smaller populations – losses often exceed \$1,000 per head on Caribbean and Pacific islands. (By way of comparison, China’s losses peaked at \$88/head with the devastating 2008 Sichuan earthquake.) The estimates continue to be negative and significant (column 6), ranging from -0.56% (-1.26%) on impact to -1.96% (-4.41%) in the long run for median (mean) catastrophes, respectively. The effects are so persistent in this specification that the cumulative output loss reaches nearly four times the size of the impact.

The final column assesses losses in relation to the size of the economy when estimating growth effects. When using loss/GDP as a regressor, the estimated impact is still close to -0.7% for a typical (median) disaster, but the growth effects appear less persistent in this specification. Larger (mean) disasters again pose greater macroeconomic costs.¹⁷ Up to this point, the results are comparable with Noy’s (2009) short-run response for developing countries (-1%), and Hochreiner’s (2009) estimated GDP drop of 2-4% of GDP, respectively. The predicted output loss of Haiti’s 2010 earthquake (126% of GDP) equals 5.3% in this specification. Setting losses in relation to GDP in the regression gives less weight to the major economies, where the effect of a localized catastrophe may not show up at the national level. The only year in which the United States suffered catastrophe losses exceeding 1% of GDP was in 2005 when the Gulf Coast was struck by hurricanes (including Katrina). That said, the estimates become somewhat weaker when lowering the disaster threshold for direct losses (from 1% of GDP to 0.5% or 0.1%).¹⁸ An alternative interpretation is that richer countries are better able to cope with the consequences of natural catastrophes (Toya and Skidmore 2007, Kellenberg and Mobarak 2008). In what follows, we pursue one particular angle on why an advanced stage of development can mitigate the macroeconomic cost of natural catastrophes.

¹⁷However, the mean loss (15.4% of GDP) is influenced by 21 observations where smaller countries suffered losses above 100% of GDP in a single year.

¹⁸Perhaps the Log_{10} transform of what is already a ratio (loss/GDP) becomes too clustered in the estimation and scaling of the coefficients. It is also possible that endogeneity becomes an issue, since the numerator of loss/GDP is a result of prior growth.

6 The Role of Risk Transfer

Specification. We now make the link between natural catastrophes and economic growth conditional on risk transfer. To do so, we employ detailed statistics on insurance coverage obtained from industry sources. For each catastrophe in country i at time t , we decompose the total loss L_{it} into the *uninsured* part (U_{it}) and the part that was *transferred* to insurance markets (T_{it}). The extended regression allows us to estimate distinct coefficients for insured and uninsured losses,

$$y_{it} = \alpha_i + \sum_{n=1}^2 \beta_n y_{it-n} + \sum_{n=0}^4 \mu_n \log(U_{it-n}) + \sum_{n=0}^4 \tau_n \log(T_{it-n}) + [\text{Macro controls}] + \varepsilon_{it}. \quad (4)$$

This specification effectively treats insured and uninsured losses as separate events occurring jointly in space and time.¹⁹ There is sufficient heterogeneity in insurance coverage across catastrophes to make this separation operational across the full sample (Figure 1). Significant differences between the estimated coefficients μ_n and τ_n constitute evidence that the macroeconomic costs of natural catastrophes depend on whether damages to property and infrastructure were insured or not.

Results. The estimates in Table 3 suggest that uninsured losses bring about significant macroeconomic costs, whereas insured losses are inconsequential or positive for growth. Columns 1 and 3 show *uninsured* losses to have a stronger negative effect on growth than was the case when no such distinction was made (Table 2, columns 3 and 5). The same holds for the growth response to mean losses ($\hat{\mu}_n \log(\bar{U}) < \hat{\lambda}_n \log(\bar{L})$ for $n = 0, 2$), even though the uninsured loss coefficients are scaled by a smaller number ($\bar{U} < \bar{L}$). Moreover, the tentative rebound in year one ($\hat{\lambda}_1 > 0$) is even smaller and less significant than in all previous specifications.

By contrast, *insured* losses appear to be largely inconsequential. All lags from year one to year three point to positive growth effects, although the signs are not reliable when lacking statistical significance (column 1). Therefore, the growth response to insured losses is likely close to zero while that to uninsured losses was clearly negative (a cumulative 2.3% or more). Hence it is the uninsured part of catastrophe-related losses that drives the macroeconomic cost.

Table 3: The Role of Risk Transfer

Small countries suffer more when uninsured but also recover faster when insured (column 2). Following an uninsured event, the impact estimate rises to 0.93%, and sluggish growth in each subsequent year brings the cumulative output loss to nearly 4% of GDP. The converse holds for insured losses: they can be growth-enhancing, especially in the year following the catastrophe (lag 1 is significant at +1.27%), and the cumulative output gain comes to 2.4%. Higher geographic concentration again strengthens the estimated growth responses both ways. Normalising losses by land area (column 3) yields stronger responses than those in column 1, for both insured (+) and uninsured (-) losses.²⁰ By this measure, the consequences of an average disaster are also twice as large as those of a median disaster, owing to the skewed distribution of losses per km². Uninsured losses again have

¹⁹This allows for full-sample estimation with all loss observations decomposed into their insured and uninsured parts. It is not necessary to split the sample or to specify an (arbitrary) threshold of insurance coverage at which an event is said to be insured.

²⁰Land area is our preferred scaling variable, as it is more exogenous with respect to growth than GDP and the other scaling variables used in Table 2.

a substantial impact and trigger a large cumulative output loss (1.25% and 4.03%, respectively), whereas insured losses are inconsequential or growth-enhancing.

The comparison between insured and uninsured disasters suggests that insurance plays a *mitigating* role: while it cannot guarantee positive growth, sufficient coverage helps avert the adverse growth response that typically follows a major natural catastrophe. Figure 4 traces out these differential growth paths, where we simulate the growth responses to an entirely uninsured event (top row) and to a fully insured event (bottom row). While events with no insurance are frequent in reality, the case of 100% coverage is more hypothetical in nature. The experiment can be thought of as the purest form of the distinction we made between Haiti and New Zealand in the case study.

These extreme differences in coverage yield starkly different growth paths in the wake of a major catastrophe. An uninsured catastrophe leads to the negative growth response observed earlier, but the opposite holds for the fully insured case. For the first time we observe a full recovery that sets in after a muted impact, whereby the growth rate overshoots its long-run average. Whereas the growth spurt is on the margin of statistical significance and therefore possibly nil, the contraction following an uninsured catastrophe is economically and statistically significant.

This finding does not imply that any insurance coverage delivers growth-enhancing effects in due course. Figure 5 parametrizes various coverage ratios to examine the degree to which insurance mitigates the contractionary effects of a mean-sized catastrophe. The lower and upper bounds represent the responses under 100% and 0% insurance from Figure 4. The simulated growth paths for intermediate cases mirror the shapes of these bounds in line with the insurance coverage ratio.²¹

Judging by these simulations, what would constitute adequate insurance coverage? One criterion could be a desire for zero output loss. If one takes these estimates at face value, it would take 91% insurance coverage for the central path to settle on zero (red line).²² Allowing for estimation error, the cumulative loss turns statistically insignificant (the confidence band includes zero) once insurance coverage exceeds 60%. Whether it is efficient for countries to contract high coverage depends, of course, on the frequency of disasters as well as on the pricing of insurance contracts.

Dynamics. The paths in Figures 4 and 5 show that the strongest growth-enhancing effects from insured losses appear in the three years following a catastrophe. What explains this particular time profile? Anecdotal evidence suggests that this is the horizon over which investment and reconstruction efforts concentrate. Loayza et al. (2012) document that the growth-enhancing effects of earthquakes and storms work through capital formation over a five-year horizon. Relatedly, the bulk of insurance payouts accrues within three years of the event, with 83% reimbursed in the first 8 quarters (Figure 6). To the extent that insurance payouts facilitate the financing of reconstruction, it is plausible that economic activity should share a similar time profile.²³ About 10 quarters after the catastrophe, insurance payouts typically slow down, having reached 87% of the ultimate paid loss. Perhaps it is this decline in funding that explains why early output gains are partly reversed

²¹This need not hold by construction, since each intermediate path is not a mixture of the paths in Figure 4, but the simulated response to a mixed event of insured and uninsured losses.

²²The same would occur at 86% if one takes the estimates in column 3 as a basis (instead of column 1 from Table 3). The required coverage falls further for small countries for their positive response to insured losses (column 2).

²³Both survey evidence and randomized field experiments point to the importance of insurance for recovery. Runyan (2006) finds that in the wake of Hurricane Katrina (August 2005), firms with insurance quickly replaced destroyed assets whereas those without insurance did not; in the context of the Asian Tsunami (December 2004), De Mel et al. (2011) use random allocations of cash grants to firms to show that providing additional capital sped up the recovery.

The role of risk transfer

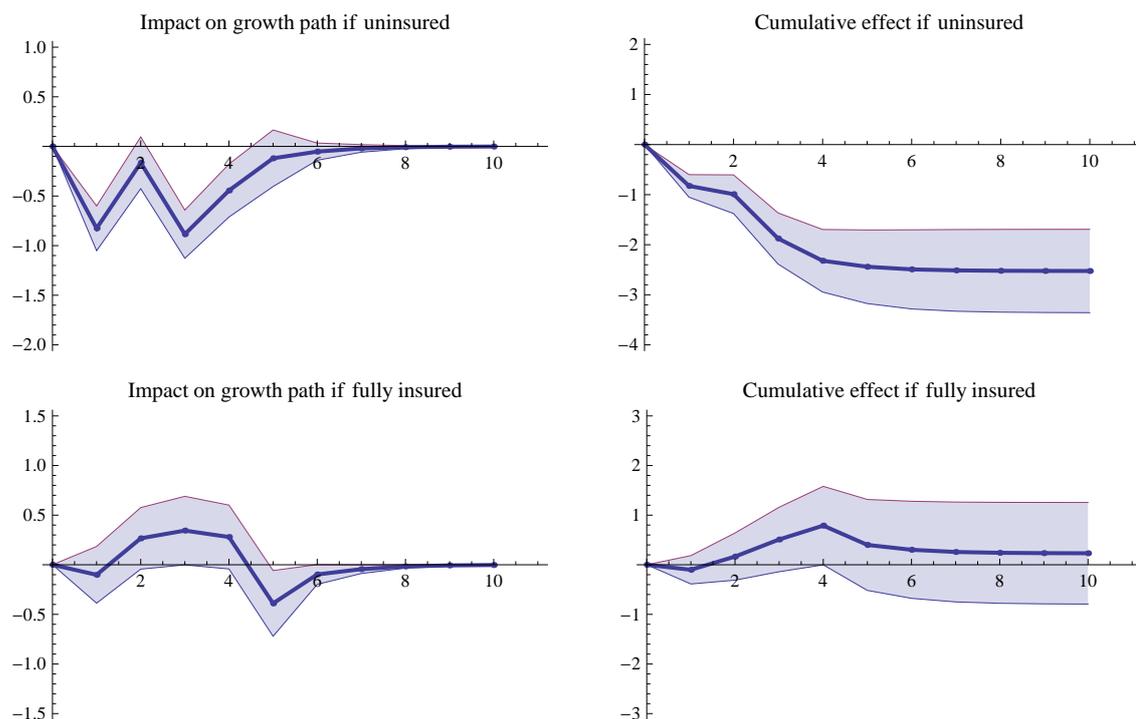


Figure 4: The impulse response function traces out the path of GDP growth over time by simulating the recursive equation (4) using the regressor $\text{Log}_{10}(\text{Loss})$, with the estimated coefficients from Table 3 (column 1), as described under Figure 2 (10,000 realizations). The upper panels simulate the growth response to a completely uninsured event of severity equal to the mean size of uninsured losses in the sample. The lower panels simulate a hypothetical fully (100%) insured event of severity equal to the mean size of insured losses.

in the fourth year (the dip in Figure 4 due to lag 4 of Table 3). This may be compounded by fiscal constraints that are more likely to bind when smaller countries are affected by major catastrophes (column 2).

It is perhaps more surprising that the *contemporaneous* impact also appears to be smaller for insured events. One would expect a catastrophe to cause a certain amount of destruction, with insurance at best speeding up the subsequent recovery as payouts help fund reconstruction. However, insurance arrangements also contribute to prevention and disaster management *ex ante*. As outlined in the case study, insurance companies may insist on sound building codes, for instance, and help establish (or provide incentives for) best practices in disaster management – not least to limit their own liabilities. This form of assistance is difficult to quantify as it works through the pricing of premiums and transfer of knowledge.²⁴

²⁴This may explain why Crespo et al. (2008) find little evidence of technological transfer following natural catastrophes when looking for imports of technology-related goods.

Growth responses for various insurance coverage ratios

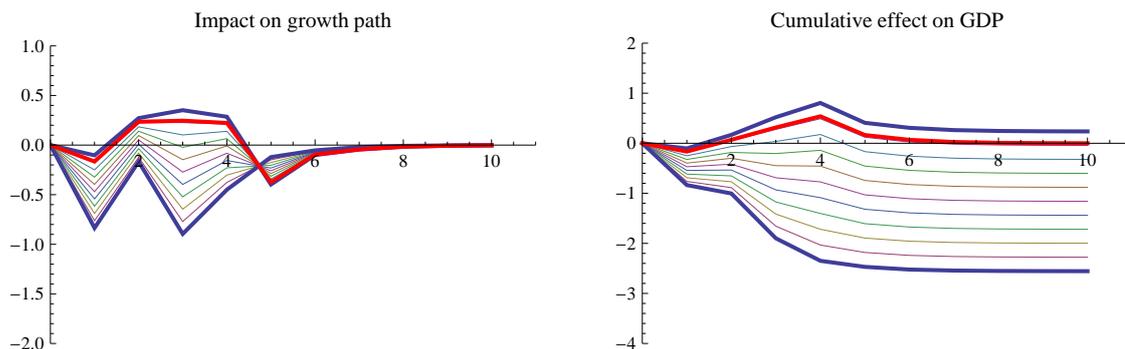


Figure 5: The lines represent the impulse responses to events with different insurance coverage. The lower (upper) bound represents the central path of growth in response to a completely uninsured (fully insured) event shown in the upper (lower) panel of Figure 4, without confidence bands. The interior paths show the responses to a catastrophe where the same (log) total loss is split into insured and uninsured parts according to coverage ratios of c %, where $c = 10, 20, \dots, 90$, that are then simulated using equation (4) with the estimated coefficients from Table 3 (column 1). The red line shows the response to the insurance coverage that sets the estimated cumulative effect equal to zero.

Physical types. To test for the role of risk transfer in greater detail, we allow for different economic growth responses according to the physical type of natural catastrophes. In Table 3 (column 4), we expand regression (4) to distinguish geophysical (earthquakes, volcanos), meteorological (storms), hydrological (flooding) and climatological events (extreme temperatures) as in Table 1. In spite of considerable variation across types, it continues to be case that uninsured losses drive the macroeconomic costs of disasters. The impact estimates of uninsured losses are all negative, with consequences unfolding over years, in line with the same regularity observed in more aggregated regressions. For three physical types, the cumulative output loss following a typical (median) disaster equals 2-3% of GDP, only hydrological events appear weakly expansionary even if insured. Due to the skewed distribution of losses, larger (mean) disasters are two to three times as harmful on average as median events: earthquakes and volcanic eruptions causing $\$60,000/\text{km}^2$ in losses can produce additional macroeconomic costs amounting to 6% of GDP.²⁵ By these estimates, even full insurance coverage would just reduce, but not overturn, the adverse consequences of geophysical events. For storms, flooding and climatological events, by contrast, insured losses appear to induce growth effects sufficient to turn the cumulative output losses into gains, though this finding lacks statistical significance.²⁶ The estimates still show that insurance coverage supports growth at least by mitigating the macroeconomic costs that would follow uninsured disasters.

Our decomposition into insured and uninsured losses helps disentangle some conflicting findings in the literature. Loayza et al. (2012) and other studies (e.g. World Bank and United Nations 2010)

²⁵Haiti's 2010 earthquake caused direct losses worth $\$299,677/\text{km}^2$. Since the damage was essentially uninsured, the predicted output loss can be revised here to 7.0%. In our linear regression framework, the log transform curbs the effects of even the largest disasters.

²⁶The estimates in column 4 are not as robust to changes in specification as earlier results and should therefore be interpreted with caution.

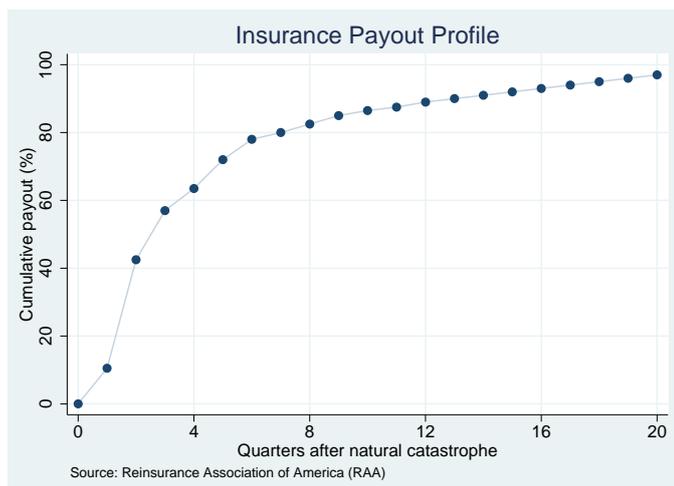


Figure 6: Cumulative percentage of ultimate payout on "catastrophe excess of loss" contracts, based on worldwide observations with respect to the historical paid loss development until 2011.

find storms to be inconsequential for growth on average. We suspect that studies ignoring the role of insurance may confound positive and negative effects and estimate the average to be insignificant. By conditioning on risk transfer, we identify opposite effects for meteorological events: rather than being inconsequential, storms are harmful when uninsured (-2.67%) but growth-enhancing when highly insured (+1.35%). The unconditional approach just observes a mixture of effects, since over 70% of storms are insured against with coverage ratios in excess of 50% (Table 1).²⁷ By contrast, 85% of climatological events, including droughts in Africa, are entirely uninsured (Table 1). This may explain why Loayza et al. (2012) find negative growth effects to be stronger for droughts than for any other type of catastrophe, and why their estimate (-3% compounded) is close to our result for *uninsured* climatological events (-3.8%).²⁸ With better availability of insurance coverage, the macroeconomic cost could likely have been mitigated or offset.

7 The Role of Development

Can the growth-enhancing effects we find really be attributed to insurance, or are the macroeconomic costs of disasters largely determined by a country's stage of development? It is well documented that many more people are affected in disasters striking low- and middle-income countries; the number of fatalities generally declines with measures of development (Toya and Skidmore 2007, Strömberg 2007, Noy 2009, Loayza et al. 2009). This suggests that more developed countries are

²⁷For flooding, Loayza et al. (2012) estimate positive effects, and Fomby et al. (2009) find zero long-term costs – in this case, both findings are consistent with the mildly positive (insignificant) effects of hydrological events in column 4. Raddatz (2007, 2009) and Loayza et al. (2012) also find no systematic impact of geophysical disasters on real GDP per capita and medium-term growth, respectively. It is possible that the countries in their (smaller) sample mainly includes better-insured developed nations at the expense of less developed countries and small island nations.

²⁸Dell et al. (2012) also find that high temperature shocks substantially reduce growth, mostly in developing countries.

in principle better able to cope with the consequences of natural catastrophes. If so, is it possible that development drives both output loss and insurance coverage, with no causal link between the latter?

Let us again distinguish between the direct effects of a disaster (on which there are statistics) and the subsequent macroeconomic costs that this paper estimates. Regarding the *direct effects*, it is true, also in the NatCat statistics employed here, that the number of lives lost in natural disasters falls as countries develop. However, what holds for fatalities need not hold for the destruction of property and infrastructure. Indeed, direct losses tend to rise as a function of income per capita.²⁹ The value of infrastructure and capital that countries accumulate on the path to development implies greater exposure that is only partially offset by preventive and mitigating measures.

Hence it is not a foregone conclusion that developed countries face milder *macroeconomic consequences* in the aftermath of natural catastrophes. Table 4 explores this relationship in two steps. The first estimates the growth response for high-income and lower-income countries separately (column 2) to assess whether there are systematic differences in their growth responses. Although catastrophe insurance markets are underdeveloped in low- and middle-income countries (Cummins and Mahul 2009), there are sufficient insured events for estimating the coefficients τ_n . Uninsured catastrophes come with negative growth effects on both income groups. While the impact is larger for lower-income countries, the subsequent drag on growth (years 2 and 3) is greater for high-income countries. This is partly due to their coefficients being scaled by higher loss severity; at least lower-income countries are more sensitive to a given loss on impact ($\mu_0^{lo}/\mu_0^{hi} = 1.69$). Moreover, disasters on average have a negative impact on low- and middle-income countries even when insured ($\mu_0^{lo} < \tau_0^{lo} < 0$); but this impact is outpaced by the recovery in the years after the catastrophe. For both income groups, the growth effects of reconstruction in the years after a disaster are positive and significant only in the insured case; once insurance payouts taper off, growth effects dissipate (lag 4). The most telling difference occurs in the impact year, when only lower-income countries first witness negative growth whether insured or not. This was not the case for high-income countries, nor for countries with small land area (Table 3, column 2).³⁰ In less developed financial markets it is more difficult to obtain credit for reconstruction, while mature markets may allow agents to receive bridge loans while awaiting insurance payouts, as in the case of New Zealand (section 2).

Table 4: Stages of Economic Development

In the second step, we directly control for the stage of development in a full-sample estimation (columns 3-4). Income groups are based on a discrete time-invariant classification – for a sample that spans 60 years it is preferable to use a continuous measure.³¹ Insurance coverage clearly correlates with the stage of development, as proxied by GDP per capita; yet there is sufficient dispersion in coverage at any stage of development to disentangle the two factors empirically (Figure 7). Controlling for development leaves the estimated growth effects largely unchanged though slightly smaller in magnitude, suggesting that there may be a role for development in mitigating

²⁹A simple regression on catastrophes of category 3 and above (5617 events) shows that a 10% increase in GDP/capita goes with 6% fewer fatalities ($R^2=35\%$), but entails 8% higher losses in terms of damage to property and infrastructure ($R^2=27\%$).

³⁰This is consistent with Noy's (2009) separate estimates for developing countries (-1.09%) and OECD members (+1.58%), although his estimates measure only the impact (year 0) and are not conditioned on insurance. Based on five-year averages, Loayza et al. (2012) also find that growth in developing countries is more sensitive to natural disasters.

³¹In addition, constant structural differences are captured in the country-specific fixed effects.

the macroeconomic costs (column 3). The development proxy itself enters with a negative (and insignificant) coefficient reflecting the forces of convergence in growth rates.

The final regression (column 4) separately takes development into account at the time catastrophes strike. Interestingly, this raises the estimated cost of uninsured catastrophes while leaving the effects of insured events largely unchanged. The interaction term is significantly positive, and represents an add-on growth effect enjoyed more by richer countries. Specifically, a developed country can mute the impact of natural catastrophes by 0.3 percentage points *more* than a country whose GDP/capita is ten times lower, holding everything else equal.³² According to this crude measure, which does not take into account targeted efforts in prevention and mitigation, it would take long-lasting general development to offset the macroeconomic costs of natural catastrophes in the way that insurance coverage appears to do. Taking these results at face value thus suggests that development tends to support growth whenever disasters strike, but it is the degree of insurance coverage that ultimately determines whether the macroeconomic effects in their wake are positive or negative.

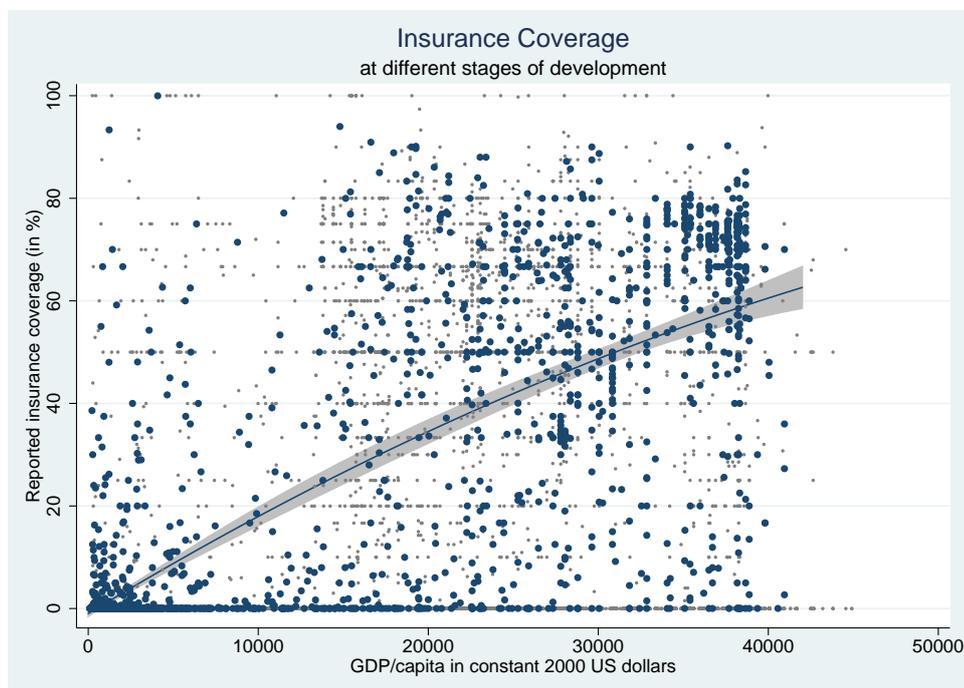


Figure 7: The Figure plots insurance coverage against the stage of development, as proxied by the log of GDP per capita at constant 2000 US dollars. The quadratic fit and other aspects are as in Figure 1.

Aid vs. insurance. We end this section with the observation that other forms of financial relief could also help mitigate the macroeconomic cost of natural catastrophes. Large disasters often entail increased government spending or foreign aid flows not contained in our statistics. While

³²The interaction term equals 1.03% at the median stage of development (with GDP/capita of \$2,079, such as Guatemala), so the impact of an uninsured catastrophe comes to -0.7% (down from -1.7%). This term adds an additional 0.3% in growth for countries with ten times the median GDP/capita (\$20,790, such as Taiwan), leaving an impact of -0.4%. This coincides with the difference in the separate impact estimates for high-income and lower-income countries (column 2).

these forms of compensation serve important purposes, we would not expect their inclusion to affect our results. Aid disbursements can be slow and small in relation to the affected economies; Becerra et al. (2012) document that the median aid increase following large natural disasters covers only 3% of the overall damage. Aid flows are also based on humanitarian motives, responding to the immediate exigency of saving lives and reducing human suffering. As such, they respond to the number of killed and displaced people, with some distortion arising from the extent of news coverage, common language and colonial ties (Strömberg 2007).³³ Taken together, these flows are not primarily geared toward financing a major reconstruction effort.

Furthermore, most forms of ex post compensation do not come with the incentive and allocation mechanisms provided by insurance arrangements. Insurance payouts automatically target the repair or replacement of those facilities that private agents had deemed important enough ex ante to warrant insurance coverage, often ones that serve a productive purpose. From this perspective, we would expect insurance coverage to contribute more toward economic recovery than ex post compensation in the form of aid or government relief programs. The effectiveness of different forms of post-disaster spending, ranging from aid and insurance payouts to fiscal expenditure, is an important area for future research.

8 Conclusions

This paper shows that major natural catastrophes are harmful for economic growth in addition to causing human suffering and broader destruction. In panel regressions on a large cross-section of 203 countries and jurisdictions over 52 years, we identify a significant impact as well as a cumulative output loss unfolding over several years. Most specifications share the regularity that the initial impact on growth gives way to a tentative rebound in the year after the disaster, followed by a further drag on growth in the second year after the event. This rich dynamic pattern goes unnoticed in studies that focus only on a particular time segment, be it the impact (e.g. Noy 2009), 5-year intervals (e.g. Loayza et al. 2012) or long-term averages (e.g. Skidmore and Toya 2002). With some variations in terms of how losses are normalized, we find that growth falls by some 0.65 percentage points on impact in a typical median disaster (and 1% in a mean disaster), and estimate the cumulative output loss to be 1.7% (2.6%). The permanent loss thus exceeds the initial impact by a factor of two or three. This macroeconomic cost is in addition to direct losses from the immediate destruction of property and infrastructure which often make up several percent of GDP already.

Our main and novel finding is that it is the uninsured part of catastrophe-related losses that drives macroeconomic costs, whereas well insured catastrophes can be inconsequential or even positive for economic activity. The strongest growth-enhancing effects from insured losses appear in the three years following a catastrophe, in line with the average timing of insurance payouts. This suggests that insurance facilitates the financing of the reconstruction effort that contributes to measured GDP. Distinguishing the effects by physical type of catastrophe shows that insurance coverage at best neutralizes the contractionary effects of earthquakes and volcanic eruptions, while the growth effects of storms, flooding and climatological events can be weakly positive when insured.

³³Relatedly, since donors usually respond after disasters strike, not enough is being done for prevention (World Bank and United Nations 2010).

Insurance can therefore play an important role in mitigating the macroeconomic costs arising from major natural catastrophes. This form of risk transfer can be useful at any stage of development. Splitting the sample by land area and income group shows that small and low- to middle-income countries suffer more when uninsured but also recover faster when insured against catastrophes. Hence the mitigating role of insurance appears to be more pronounced for this group, especially in the year after a disaster when reconstruction takes place. Whether it is desirable for countries to seek high coverage depends, of course, on the frequency of disasters and on the terms and cost of insurance. Not enough data are available on the pricing of contracts to enable a cost-benefit analysis. In this respect, by providing the first evidence that risk transfer alters the effects of catastrophes on growth, the paper seeks to contribute to the broader debate on the effectiveness of different forms of compensation (aid, insurance, fiscal spending) and the right balance between prevention ex ante and compensation ex post.

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Appendix

1. Constructing the dataset. The NatCat statistics were provided by Munich Re, a global insurance and reinsurance group. Our query for data on major natural catastrophes resulted in a list of 22,033 entries on natural catastrophes since 1950 (and 21,768 since 1960). Each entry comes with an identifier and event description, and states the catastrophe type, time period, affected country, number of fatalities, as well as insured losses and total losses in millions of US dollars. To express reported dollar losses in terms of constant 2011 US dollar values, we use the standard US CPI index (all consumers, all items, city average). Events are divided into four physical types (geophysical, meteorological, hydrological and climatological) and six levels of severity as defined in Table A3. As explained in the text, the NatCat statistics are a proprietary dataset; being compiled by a global reinsurance company that relies on these statistics for monitoring and pricing reinsurance contracts worldwide, the information on insured and total losses is the most comprehensive and accurate in existence (Munich Re 2011, Kron et al. 2012).³⁴ The scope of the statistics covers most natural catastrophes since 1950, including uninsured events and events insured by other insurance companies; coverage since 1980 is almost exhaustive as it includes virtually all events that entailed fatalities or property damage.

We performed several tests to ensure that the data are adequate for the analysis. One concern was that there might be insufficient detail on losses for earlier events (1950-1979). Less than 5% out of 21,768 observations contain no information on economic losses. For the 2,476 observations in the severity range of interest (category 4 and above), this share falls to 3.5%. One might suspect that (known) insured losses are often used to proxy for unknown total losses, yet there are only a few cases (with just one major event of category 4) for which total losses fall within 1% of insured losses that were probably used as a proxy. A further concern was that country-specific breakdowns of losses might not be consistent with the region totals reported for regional events affecting several countries, as the data provider possibly obtains information at the national and regional levels from different sources. Country-level breakdowns account for over 15% of observations in the dataset, while the remaining observations represent catastrophes affecting a single country. To check for consistency between these two levels, we compare a sample of 331 major regional events for which we have *both* the regional loss totals and 1,383 further observations detailing how the countries in the region were affected. Reassuringly, for the bulk of regional events (75%), the region total falls within $\pm 10\%$ of the losses aggregated across the affected countries. This holds for both total and insured losses. We detect potential under-reporting in only 8% of regional events, in that the country breakdowns account for less than 80% of the region totals.

Table A1 lists variable definitions and data sources. The macroeconomic panel data are taken from the World Bank's *World Development Indicators* (WDI), with missing countries and jurisdictions complemented by data from the United Nations *National Accounts* (SNA). The GDP series are "calculated without making deductions for depreciation of fabricated assets" (WDI release notes): this ensures that the GDP series do not reflect catastrophe-related damage to enhance our results. The man-made crisis data are from Laeven and Valencia (2010). In line with the statistics on

³⁴Munich Re has been collecting data on losses from natural catastrophes for four decades, drawing on information from (1) the insurance industry, (2) science and research, (3) UN, EU, administrations, governmental and non-governmental organizations, (4) meteorological, geological, and other services, (5) news agencies, and (6) other sources (Kron et al. 2012). In addition, Munich Re relies on 60 offices worldwide and on client relations in 150 countries, and uses tried and tested algorithms to estimate losses where official and industry sources are incomplete (Munich Re 2011).

natural catastrophes, the crisis dummies indicate the year in which a crisis started (rather than the years a crisis lasted). As explained in the text, we match aggregated versions of the NatCat statistics with the macroeconomic data to form an (unbalanced) panel comprising 213 countries and jurisdictions over the period of 1960-2010. More than 20 years of real growth data are available for 203 countries.

Table A1: Variables and Data Sources

Variable definition	Source
y_{it} = annual growth rate of real GDP, in %	World Bank (WDI), UN (SNA)
pop_{it} = country population in thousands	Penn World Table 7.0, UN (SNA)
$land_{it}$ = land area in km ²	World Bank (WDI)
GDP in current and constant 2000 US dollars, respectively	World Bank (WDI), UN (SNA)
Country classification by income groups	World Bank (WDI)
BC = 1 in year banking crisis starts, 0 otherwise	Laeven-Valencia (2010)
CC = 1 in year currency crisis starts, 0 otherwise	Laeven-Valencia (2010)
DC = 1 in year debt crisis starts, 0 otherwise	Laeven-Valencia (2010)
EC = 1 in year regime becomes authoritative, 0 otherwise	Polity IV Dataset (executive constraint)
War = 1 in year war starts, 0 otherwise	Correlates of War Dataset
$life_{jit}$ = total number of fatalities for event j	NatCat Service, Munich Re
$loss_{jit}$ = total loss per event (in \$ millions) for event j	NatCat Service, Munich Re
ins_{jit} = total insured loss per event (in \$ millions) for j	NatCat Service, Munich Re
N_{it} = 1 if a catastrophe occurred in country-year pair (i, t)	Constructed from event data
L_{it} = total losses from catastrophes in country-year pair (i, t)	$\sum_j loss_{jit}$ (separable by type)
T_{it} = insured part of total losses	$\sum_j ins_{jit}$ (separable by type)
U_{it} = uninsured part of total losses	$\sum_j [loss_{jit} - ins_{jit}]$
Total losses per km ² of land area	$L_{it} * 10^6 / land_{it}$
Total losses in US dollars per capita	$L_{it} * 10^6 / (pop_{it} * 10^3)$
Total losses in % of GDP	$L_{it} * 10^6 / GDP_{it} * 100$

2. Specification of the baseline regression. The baseline regression estimating equation (2) was reported in Table 2 (column 1) and is reproduced in full here in Table A2 (column 1). The F-test rejects the null hypothesis that constant terms are equal across countries, indicating that pooled OLS would produce inconsistent estimates. Equation (2) is thus estimated using panel fixed effects, with Huber-White robust standard errors. Using random effects instead (column 2) also produces significant results, though with slightly smaller coefficients on the catastrophe indicator: the impact and lag 2 are not as negative, and lag 1 picks up a modest rebound (+0.37%). However, the Hausman specification test strongly rejects the null hypothesis that random effects delivers consistent estimates.

Column 3 thus reverts to fixed effects and includes additional autoregressive lags. Testing down from 8 lags confirms those beyond lag 2 are small and insignificant at the 5% level. Since each

additional lag costs 200 observations early in the sample, we settle for a parsimonious lag structure with two autoregressive lags. Experimenting with lags also demonstrates that the drag on growth we regularly observe in year 2 (significant catastrophe lag 2) is not an artifact of having chosen an AR(2) growth process. The growth series contains a few outliers that appear doubtful. Dropping the 18 observations outside the band of $\pm 40\%$ accentuates catastrophe lags and strengthens their cumulative effect (column 4). Excluding the 90 observations outside the $\pm 25\%$ band leads to similar results. We prefer to retain all growth observations and account for extreme observations by including five types of man-made crises as macroeconomic controls.

In all specifications, the natural catastrophe indicator and its (second) lags are individually and jointly significant. The likelihood-ratio test rejects the restricted model excluding the catastrophe variables. The same is true for the macroeconomic controls and their lags. The estimated effects of natural catastrophes are stronger when excluding macroeconomic controls, as shown in Table 2 (column 2), but the Wald and likelihood-ratio tests show that they should be included. The five types of crises are all significant on impact and some up to lag 1, but not thereafter. Adding lags beyond lag 2 worsens both the AIC and BIC criteria. This is also the case for the NatCat indicator, but we still prefer to show four lags to allow this key regressor to exhibit its full time profile.

Table A2: Robustness of the Baseline Regression

The baseline results also remain consistent across subsamples. To rule out that individual countries drive the results, we exclude the United States, Japan and China, the top three countries in terms of reported losses. This raises the long-term cumulative response while leaving other estimates largely unchanged. Excluding only the United States (home to numerous costly storms) slightly strengthens the estimates or impulse responses. Similarly, no single continent drives the results: excluding countries from one of the six continents at a time does not qualitatively change the results on the remaining sample (not reported); growth falls at least 0.5% on impact, leaving a cumulative output loss of at least 1.5% in each of the six regressions. The same holds when excluding countries of one of the four World Bank income groups: only when excluding lower-middle income countries do the estimated impact and cumulative loss fall (to 0.5% and 1.1%, respectively) compared to the full sample results (0.64% and 1.65%).³⁵

Next we split the sample in 1980, the year Munich Re expanded coverage in its NatCat statistics. Results and impulse responses become slightly less pronounced after 1980 (column 6). Before 1980, the estimated macroeconomic costs were larger, albeit estimated with lower precision in part due to fewer growth data being available in 1960-1980. When excluding the years since the global financial crisis, when poor growth performance coincided with a number of natural catastrophes, the estimated impact and cumulative effect both strengthen, to -0.77% and -1.86%, respectively (not reported).

The final column reports the Arellano-Bover and Blundell-Bond linear dynamic panel data estimator to address possible concerns over endogeneity by differencing and using lags as instruments. This raises all disaster indicator variables in magnitude, especially those on man-made crises, and leads to a stronger estimated cumulative output loss of 2.25%. Estimates using resampling (bootstrap and jackknife) are virtually indistinguishable from the baseline results in column 1 and are not reported.

³⁵A regression on the subsample of lower-middle income countries suggests that the growth effects of natural catastrophes appear to be strongest for this group of countries (-1.1% on impact, and -3.2% cumulatively in this specification).

3. Robustness to thresholds in severity and timing. This section examines whether the results are robust to different ways of aggregating disaster-related losses. Table A3 estimates the log-loss specification (3) for different versions of the dataset which successively include only events that exceed a certain threshold of severity (all datasets include the "great disasters" of category 6). The thresholds follow the categorization that Munich Re attaches to each event based on the number of fatalities and total economic losses (Munich Re 2011). The body of the paper uses the threshold of category 4 and above – the results of column 4 here are therefore familiar from Table 2 (column 3). Table A3 shows that stepping through thresholds of increasing severity leaves the coefficients on the AR process (as well as on the macro controls) virtually unaffected. More importantly, the contemporaneous impact, lag two and the cumulative output loss following natural catastrophes all remain highly significant throughout. The impact estimates and cumulative effects are more significant and larger in magnitude for datasets excluding small-scale and moderate events in categories 1 and 2. Such small events, frequent and inconsequential as they are, introduce noise in the growth regressions because under the log transform they appear nearly as large as much costlier catastrophes. On the other side of the spectrum, results do get uniformly stronger when including only the worst catastrophes (column 6) as the number of disasters in the sample becomes rather small. For intermediate thresholds (columns 3 to 5), the estimates are comparable to those quoted in the body.

Table A3: Results by Severity Threshold

A series of smaller natural catastrophes could be as costly as a major event. The last column in Table A3 examines this possibility by applying the severity cut-off after aggregation (column 7). This modified dataset comprises country-year pairs for which all disasters combined within a year caused more than 100 fatalities or \$250 million in losses (the criteria for single events of category 4). The number of disasters entering this aggregation is correspondingly higher (13,452 events). The results differ marginally from those of category 4 and above (column 4), with slightly weaker impact and cumulative effects as might be expected from an aggregation that includes many smaller, possibly inconsequential, events.

A further test considers the match between the event date and the impact year. Throughout, we had merged the NatCat statistics with macroeconomic data by the year the event occurred. Yet events that occur late in the year, such as the Indian Ocean Tsunami (December 26, 2004), may affect growth only the following year. Noy (2009) deals with this issue by scaling down overall losses in proportion with the months remaining before year-end. Doing so sets the impact of the Indian Ocean Tsunami effectively to zero. By using the lag structure, we can avoid the loss of data: we examine whether associating late events with growth data of the following year alters the results. We observe no major changes when testing threshold months 10 and 9. When events after month 6 are allocated to the next year, the estimated negative impact becomes weaker without strengthening subsequent lags. Most likely the carried-over negative impact is now confounded with reconstruction activity in the year after the event. Conceptually, imposing earlier thresholds raises the risk of missing an early impact with no corresponding gain – we prefer to work with the original-year match, knowing that the four-year lag structure will take care of any delay in growth effects over time.

Further results on the robustness of our findings on risk transfer are available from the authors upon request.

Table 1 – Features of Natural Catastrophes

Properties	All types	(----- Weather-related events -----)			
		Geophysical ^A	Meteorological ^B	Hydrological ^C	Climatological ^D
<i># Events overall (types in %)</i>	21768	12%	42%	34%	12%
Frequency					
# Events category 4+	2,476	212	980	739	545
Africa	240	10	20	49	161
Asia	949	114	284	418	133
Europe	364	33	125	110	96
Latin America & Caribbean	307	36	110	103	58
North America	539	9	413	41	76
Pacific	77	10	28	18	21
Severity					
<i>Maximum fatalities</i>	300,000	242,769	300,000	26,000	300,000
<i>Mean fatalities</i>	1,275	6,056	833	359	1,362
<i>Median fatalities</i>	22	246	10	117	0
Maximum loss (\$ mn)	210,000	210,000	144,201	43,000	28,567
Mean loss (\$ mn)	1,420	4,661	1,346	1,066	774
per land area (\$ /km ²)	34,367	56,800	70,734	2,567	3,365
per head (\$ /capita)	190	652	305	20.9	36.2
per unit income (% of GDP)	2.5	7.5	3.1	1.0	1.7
Median loss (\$ mn)	338	454	474	239	89
Coefficient of variation (\$ mn)	4.9	4.2	3.9	3.3	2.9
Risk transfer					
Uninsured events (%)	57.7	59.4	29.0	75.4	84.6
Median coverage (if >0)	50.0	6.6	58.3	19.3	47.4
High income countries	55.0	8.7	62.5	30.0	49.5
Low & middle income c.	6.9	5.0	10.0	5.0	25.0
Mean coverage (if >0)	44.3	15.2	52.2	28.4	42.8
High income countries	50.2	19.5	56.5	34.1	44.0
Low & middle income c.	16.3	11.0	19.3	13.7	32.3

Notes: The table shows summary statistics on natural catastrophes between 1960 and 2011. Apart from the first row, the numbers relate to catastrophes of category 4 and above, defined as events causing major property, infrastructure and structural damage with total losses exceeding \$250 million in constant 2011 US dollars and/or more than 100 fatalities. Coverage is computed over observations with positive insured losses. (Unconditional median coverage is zero when more than half of the events are entirely uninsured, as for types A, C and D). The physical types are grouped as follows:

A Earthquakes, volcanic eruptions and dry mass movement (rock falls, landslides, subsidence)

B Storms (tropical storms, extratropical storms, local windstorm)

C Flooding (river floods, flash floods, storm surge), wet mass movement (rock falls, landslides, avalanches, subsidence)

D Extreme temperatures (heatwave, freeze, extreme winter conditions), droughts, and wildfires.

Source: Calculations based on Munich Re Statistics (NatCatService).

Table 2 – Natural Catastrophes and Economic Growth

Estimated coefficients	Indicator regression		Measures of severity					
	(1) NatCat indicator	(2)	(3) Loss	(4) Life	(5) Loss/km ²	(6) Loss/cap	(7) Loss/GDP	
AR process	Lag 1 (β_1)	0.282*** (9.64)	0.299*** (10.23)	0.282*** (9.61)	0.283*** (9.66)	0.282*** (9.60)	0.281*** (9.58)	0.268*** (9.03)
	Lag 2 (β_2)	0.043** (2.10)	0.049** (2.35)	0.043** (2.08)	0.044** (2.16)	0.042** (2.06)	0.042** (2.06)	0.049** (2.41)
	Constant α	3.105*** (19.31)	2.725*** (17.98)	3.140*** (19.63)	2.993*** (19.64)	3.151*** (19.84)	3.142*** (20.10)	3.089*** (20.04)
Natural catastrophes	Median severity Impact (δ_0 or λ_0)	1 -0.636*** (-4.53)	1 -0.706*** (-4.73)	\$397 mn -0.748*** (-5.12)	177 lives -0.492*** (-2.90)	\$852 /km ² -0.704*** (-5.56)	\$14.0 /cap -0.561*** (-5.78)	3.19 % -0.671*** (-4.25)
	Lag 1	0.158 (0.91)	0.153 (0.86)	0.125 (0.72)	0.178 (0.94)	0.092 (0.57)	0.066 (0.52)	0.105 (0.75)
	Lag 2	-0.550*** (-3.69)	-0.619*** (-4.12)	-0.636*** (-4.20)	-0.432** (-2.54)	-0.621*** (-3.95)	-0.516*** (-3.86)	-0.387 (-1.62)
	Lag 3	-0.007 (-0.04)	-0.088 (-0.53)	-0.073 (-0.44)	0.123 (0.65)	-0.068 (-0.47)	-0.095 (-0.84)	0.115 (0.84)
	Lag 4	-0.079 (-0.43)	-0.023 (-0.13)	-0.108 (-0.56)	0.179 (0.82)	-0.216 (-1.41)	-0.217* (-1.82)	-0.019 (-0.14)
	Cumul. effect, % GDP	-1.652***	-1.966***	-2.134***	-0.660	-2.244***	-1.958***	-1.252**
	Mean severity	1	1	\$2,859 mn	3,247 lives	\$68,286/km ²	\$379 /cap	15.4 %
	Growth impact, % GDP	-0.636***	-0.706***	-0.823***	-0.769***	-1.161***	-1.264***	-1.584***
Cumul. effect, % GDP	-1.652***	-1.966***	-2.347***	-1.031	-3.702***	-4.410***	-2.956**	
Macroeconomic controls	2 lags	excluded	2 lags	2 lags	2 lags	2 lags	2 lags	
Number of observations	8,252	8,252	8,252	8252	8,252	8,252	8,164	

Notes: The dependent variable is real GDP growth (%), as specified in regressions (2) and (3) in the text, estimated on an unbalanced panel covering 203 countries and jurisdictions between 1960 and 2011. All columns use the fixed effects panel estimator with two autoregressive lags, macro controls with the number of lags indicated, and Huber-White robust standard errors.

Significance levels: *** 1% ** 5% * 10% (t-values in parentheses). The R² is 16.8% with minor variations across columns.

(1)-(2) "NatCat Indicator" equals 1 when natural catastrophes of category 4 and above occur, and 0 otherwise.

(3) equals total direct losses due to natural catastrophes (constant 2011 US dollars), in logs of base 10.

(4) equals the number of fatalities, in logs.

(5) equals losses per square kilometer of land area, in logs of constant 2011 US dollars.

(6) equals losses per capita (total population), in logs of constant 2011 US dollars.

(7) equals losses as a percentage the country's GDP, in logs.

The sample includes 2,381 natural catastrophes of category 4 and above, aggregated into 1,188 country-year pairs, except for column (7) which uses the GDP-based threshold of total losses exceeding 1% of GDP (452 country-year pairs with 1,922 catastrophes).

To make estimates comparable, the reported coefficients in columns (3)-(7) have been scaled by *median severity*. E.g. in column "Loss", the estimated coefficient of log loss (-0.0870) is scaled by the log of the median loss \$397 mn (8.599) to yield the reported impact of -0.748.

The shaded rows show coefficients scaled by *mean severity*, which exceeds median severity due to the skewed distribution of losses.

T-values relate to the original unscaled coefficients λ_n .

To test for cumulative GDP effects, the non-linear Wald test (delta method) is applied to $\Sigma \lambda_n / (1-\beta_1-\beta_2) = 0$.

Macroeconomic controls include banking, currency and debt crises, as well as political crises and wars; coefficients are reported in Table A2.

Table 3 – The Role of Risk Transfer

Estimated coefficients	(1)	(2)	(3)	(4)				
	Loss	Small countries	Loss/km ²	Geo-physical	Meteoro-logical	Hydro-logical	Climato-logical	
AR(2) coefficients	(not reported)			(not reported)				
Uninsured natural catastrophes	Impact (μ_0)	-0.751*** (-3.66)	-0.928** (-2.06)	-0.766*** (-4.14)	-0.487 (-2.28)	-1.052*** (-6.24)	-0.096 (-0.28)	-1.185*** (-14.76)
	Lag 1 (μ_1)	0.062 (0.27)	-0.301 (-0.59)	-0.006 (-0.03)	-0.676* (-2.38)	0.022 (0.16)	0.550 (2.33)	-0.086 (-0.22)
	Lag 2 (μ_2)	-0.731*** (-3.49)	-0.784 (-1.37)	-0.734*** (-3.26)	-0.254 (-1.85)	-0.769* (-2.70)	-0.222 (-0.99)	-0.489 (-1.41)
	Lag 3 (μ_3)	-0.171 (-0.74)	-0.317 (-0.62)	-0.145 (-0.68)				
	Lag 4 (μ_4)	0.040 (0.16)	-0.228 (-0.57)	-0.013 (-0.06)				
	Median severity	\$319 mn	\$317 mn	\$698 /km ²	\$44.6 /km ²	\$1,651 /km ²	\$116 /km ²	\$440 /km ²
	Cumul. effect, % GDP	-2.299***	-3.755*	-2.463***	-2.105**	-2.672**	+0.345	-2.613*
	Mean severity	\$2,198 mn	\$908 mn	\$45,285 /km ²	\$59,166 /km ²	\$119,021 /km ²	\$3,946 /km ²	\$6,860 /km ²
	Growth impact, % GDP	-0.825***	-0.978**	-1.254***	-1.402	-1.659***	-0.167	-1.719***
	Cumul. effect, % GDP	-2.525***	-3.957*	-4.032***	-6.056**	-4.215**	+0.601	-3.791*
Insured natural catastrophes	Impact (τ_0)	-0.092 (-0.35)	0.151 (0.25)	0.077 (0.32)	-0.598 (-0.61)	0.438 (0.76)	-0.310 (-0.32)	0.884 (2.32)
	Lag 1 (τ_1)	0.268 (0.99)	1.271** (2.01)	0.297 (1.10)	0.497 (0.30)	0.580 (1.13)	-0.747 (-1.52)	0.191 (0.15)
	Lag 2 (τ_2)	0.249 (0.82)	0.276 (0.42)	0.293 (1.05)	-0.213 (-0.47)	-0.110 (-0.22)	1.402*** (8.96)	0.215 (0.53)
	Lag 3 (τ_3)	0.156 (0.56)	0.986 (1.55)	0.146 (0.54)				
	Lag 4 (τ_4)	-0.439 (-1.54)	-1.061** (-2.01)	-0.574** (-2.25)				
	Median severity	\$265 mn	\$218 mn	\$452 /km ²	\$636 /km ²	\$1,880 /km ²	\$79.7 /km ²	\$77.6 /km ²
	Cumul. effect, % GDP	+0.209	+2.38	+0.355	-0.466	+1.348	+0.512	+1.916
	Mean severity	\$1,831 mn	\$420 mn	\$63,790 /km ²	\$54,133 /km ²	\$253,854 /km ²	\$1,571 /km ²	\$10,691 /km ²
	Growth impact, % GDP	-0.101	+0.156	+0.140	-1.009	0.723	-0.520	1.879
	Cumul. effect, % GDP	+0.230	+2.464	+0.642	-0.787	+2.225	+0.858	+4.073
# Country-years with NatCats	1,188	254	1,188	134	304	236	196	
# NatCats in sample	2,381	290	2,381	357	751	646	272	
Macroeconomic controls	2 lags	2 lags	2 lags		1 lag			
Number of observations	8,252	4,145	8,252		8,252			

Notes: The dependent variable is real GDP growth (%), as specified in regression (4) in the text. All columns use the fixed effects panel estimator with 2 autoregressive lags, macro controls with the lags indicated, and Huber-White robust standard errors.

Significance levels: *** 1% ** 5% * 10% (t-values in parentheses). The R² lies between 16.3% and 17.0% in all columns.

(1) Full sample estimation (1960-2011, 203 countries and jurisdictions) using as regressors the logs of uninsured vs insured losses.

(2) As column (1), on subsample of small countries with land area at or below the median of 111,890 km², the size of Honduras.

(3) As column (1), using as regressor losses per square kilometer of land area, in logs of constant 2011 US dollars.

(4) As column (3), where losses/km² are broken down by the physical type of natural catastrophes (see Table 1) before taking logs.

The sample includes 2,381 natural catastrophes of category 4 and above, aggregated into country-year pairs as indicated in row counts.

For column (4), the sample uses the GDP-based threshold of total losses exceeding 1% of GDP (as Table 2, column 7) for higher precision.

To make estimates comparable, the reported coefficients in columns (3)-(7) have been scaled by *median severity* as described in Table 2.

The shaded rows show coefficients scaled by *mean severity*, which exceeds median severity due to the skewed distribution of losses.

T-values relate to the original coefficients μ_n and τ_n . Insured loss severity is computed over observations with positive insurance coverage.

To test for cumulative GDP effects, the non-linear Wald test (delta method) is applied to $\Sigma \mu_n / (1-\beta_1-\beta_2) = 0$ (with low power in column 4).

To limit the number of coefficients to be estimated, we use the Wald test to reduce the five types of crises to two types: financial crises

(banking, currency and debt crises) and other (political crises and wars). In column (4), the lags are tested down to one significant lag.

Table 4 – Stages of Economic Development

Estimated coefficients	(1)	(2)		(3)	(4)	
	Loss	Low-middle income	High-income countries	Development (GDP/cap)	Development (interaction)	
AR(2) coefficients	(not reported)			(not reported)		
Uninsured natural catastrophes	Impact (μ_0)	-0.751*** (-3.66)	-0.780*** (-3.46)	-0.506 (-1.56)	-0.729*** (-3.55)	-1.716*** (-3.35)
	Lag 1 (μ_1)	0.062 (0.27)	0.046 (0.18)	0.300 (1.34)	0.094 (0.41)	0.103 (0.44)
	Lag 2 (μ_2)	-0.731*** (-3.49)	-0.720*** (-3.12)	-0.896*** (-2.81)	-0.728*** (-3.44)	-0.716*** (-3.40)
	Lag 3 (μ_3)	-0.171 (-0.74)	-0.096 (-0.38)	-0.666** (-2.33)	-0.147 (-0.63)	-0.134 (-0.58)
	Lag 4 (μ_4)	0.040 (0.16)	0.019 (0.07)	0.093 (0.21)	0.063 (0.25)	0.068 (0.27)
	Median severity	\$319 mn	\$154 mn	\$970 mn	\$319 mn	\$319 mn
	Cumul. effect, % GDP	-2.299***	-2.165***	-2.895**	-2.118**	-3.509***
	Mean severity	\$2,198 mn	\$1,367 mn	\$4,103 mn	\$2,198 mn	\$2,198 mn
	Growth impact, % GDP	-0.825***	-0.870***	-0.541	-0.801***	-1.885***
	Cumul. effect, % GDP	-2.525***	-2.415***	-3.096**	-2.326**	-3.855***
Insured natural catastrophes	Impact (τ_0)	-0.092 (-0.35)	-0.696* (-1.74)	0.225 (0.62)	-0.053 (-0.20)	-0.182 (-0.68)
	Lag 1 (τ_1)	0.268 (0.99)	0.902** (2.12)	-0.401 (-1.56)	0.304 (1.15)	0.281 (1.05)
	Lag 2 (τ_2)	0.249 (0.82)	0.325 (0.71)	0.420 (1.06)	0.285 (0.94)	0.281 (0.93)
	Lag 3 (τ_3)	0.156 (0.56)	0.105 (0.30)	0.687** (2.05)	0.203 (0.73)	0.194 (0.71)
	Lag 4 (τ_4)	-0.439 (-1.54)	-0.302 (-0.67)	-0.477 (-1.02)	-0.375 (-1.30)	-0.395 (-1.37)
	Median severity	\$265 mn	\$105 mn	\$435 mn	\$265 mn	\$265 mn
	Cumul. effect, % GDP	+0.209	+0.472	+0.785	+0.532	+0.262
	Mean severity	\$1,831 mn	\$337 mn	\$2,571	\$1,831 mn	\$1,831 mn
	Growth impact, % GDP	-0.101	-0.741*	+0.245	-0.058	-0.200
	Cumul. effect, % GDP	+0.230	+0.502	+0.855	+0.585	+0.289
Development	Log(GDP/cap)			-0.460 (-0.73)	-0.476 (-0.75)	
	Log(GDP/cap)*NatCat				0.311** (2.33)	
# Country-years with NatCats	1,188	831	357	1,180	1,180	
# NatCats in sample	2,381	1,383	998	2,373	2,373	
Number of observations	8,252	5,629	2,623	8,059	8,059	

Notes: The dependent variable is real GDP growth (%), as specified in regression (4) in the text. All columns use the fixed effects panel estimator with 2 autoregressive lags, macro controls with 2 lags, and Huber-White robust standard errors. Significance levels: *** 1% ** 5% * 10% (t-values in parentheses). The R^2 lies between 13.7% and 26.7% across columns. (1) Full sample estimation (1960-2011, 203 countries and jurisdictions), reproducing Table 3 column 1. (2) Separate regressions for low to middle versus high income countries, using the World Bank country classification. (3) Controlling for the stage of development by adding the regressor Log(GDP/capita), full sample estimation. (4) Controlling for development by interacting the regressor Log(GDP/capita) with the NatCat indicator variable, full sample. Scaling and testing is carried out as detailed under Table 3.

Table A2 – Robustness of the Baseline Regression

Estimated coefficients	(1) Baseline	(2) Random effects	(3) FE with AR(4)	(4) Exclude outliers	(5) Exclude big three	(6) Since 1980	(7) Panel IV estimates
AR process	Lag 1 (β_1)	0.282*** (9.64)	0.327*** (11.96)	0.261*** (8.58)	0.271*** (11.04)	0.281*** (9.56)	0.293*** (10.41)
	Lag 2 (β_2)	0.043** (2.10)	0.083*** (3.77)	0.040* (1.94)	0.055*** (3.10)	0.046** (2.20)	0.038 (1.59)
	Lag 3 (β_3)			0.033* (1.88)			
	Lag 4 (β_4)			-0.015 (-0.82)			
	Constant α	3.105*** (19.31)	2.567*** (18.40)	3.096*** (18.78)	2.750*** (20.04)	3.075*** (19.14)	2.860*** (16.88)
Natural catastrophes	Impact (δ_0)	-0.636*** (-4.53)	-0.416*** (-2.78)	-0.573*** (-3.94)	-0.723*** (-4.80)	-0.636*** (-4.43)	-0.654*** (-4.36)
	Lag 1 (δ_1)	0.158 (0.91)	0.373** (2.20)	0.150 (0.86)	0.184 (1.05)	0.158 (0.89)	0.281 (1.57)
	Lag 2 (δ_2)	-0.550*** (-3.69)	-0.358** (-2.33)	-0.474*** (-3.16)	-0.631*** (-4.11)	-0.545*** (-3.58)	-0.430*** (-2.71)
	Lag 3 (δ_3)	-0.007 (-0.04)	0.196 (1.23)	0.087 (0.53)	-0.059 (-0.37)	-0.014 (-0.09)	0.026 (0.15)
	Lag 4 (δ_4)	-0.079 (-0.43)	0.143 (0.78)	-0.153 (-0.85)	0.018 (0.10)	-0.131 (-0.69)	0.061 (0.30)
Macro controls	Banking crisis	-2.154***	-2.091***	-2.225***		-2.217***	-2.028***
	Lag 1	-2.550***	-2.485***	-2.903***		-2.528***	-2.466***
	Lag 2	0.319	0.416	0.348		0.413	0.420
	Currency crisis	-2.355***	-2.095***	-2.262***		-2.350***	-2.180***
	Lag 1	-0.105	0.211	-0.256		-0.100	0.053
	Lag 2	0.000	0.266	0.148		0.010	0.105
	Debt crisis	-4.009***	-3.921***	-4.089***		-4.014***	-3.856***
	Lag 1	-1.362	-1.174	-1.392		-1.361	-1.175
	Lag 2	-0.395	-0.160	-0.473		-0.399	-0.223
	Political crisis	-2.107***	-1.915***	-2.004***		-2.099***	-2.544***
	Lag 1	-0.332	-0.087	-0.473		-0.238	-0.437
	Lag 2	-0.212	0.074	-0.341		-0.145	-0.442
	War	-3.603***	-3.394***	-3.581***		-3.840***	-3.298***
Lag 1	-1.915**	-1.508**	-2.197***		-2.072***	-2.933***	
Lag 2	-0.144	0.387	-0.250		-0.228	-0.348	
Regression R ² in %	16.8	17.2	16.3	15.2	16.7	19.0	.
Number of observations	8,252	8,252	7,819	8,234	8,107	6,660	8,525
# country-years with NatCats	1,188	1,188	1,167	1,188	1,071	1,107	1,188
# NatCats in sample	2,381	2,381	2,353	2,381	1,579	2,281	2,381
Growth impact, % GDP	-0.636***	-0.416***	-0.573***	-0.723***	-0.636***	-0.654***	-0.653***
Cumul. effect, % GDP	-1.652***	-0.106	-1.414***	-1.799***	-1.737***	-1.072*	-2.253**

Notes: The table examines the robustness of the indicator regression of Table 2 using the specifications indicated in the column headings.

- (1) reproduces the baseline fixed effects specification shown in Table 2, column 1.
- (2) presents the estimates from the random effects panel estimator with robust standard errors.
- (3) implements the fixed effects estimator with four autoregressive lags on the growth process.
- (4) drops observations for which growth exceeds 40% in absolute value.
- (5) excludes the United States, Japan and China from the sample.
- (6) runs the baseline regression from 1980 onward, the year the NatCat statistics improved their data coverage.
- (7) implements the Arellano-Bover/Blundell-Bond linear dynamic panel data estimator.

As the indicator variable does not capture the severity of catastrophes, the reported coefficients show the original estimates (unit scaling).

Significance levels: *** 1% ** 5% * 10% (t-values in parentheses).

Table A1 lists definitions and data sources for the five crisis variables.

Table A3 – Results by Severity Threshold

Estimated coefficients	(1) All categories	(2) cat. 2 & above	(3) cat. 3 & above	(4) cat. 4 & above	(5) cat. 5 & above	(6) cat. 6 only	(7) cat. 4 aggregate	
AR process	Lag 1 (β_1)	0.279*** (9.49)	0.280*** (9.54)	0.281*** (9.57)	0.282*** (9.61)	0.281*** (9.60)	0.283*** (9.65)	0.282*** (9.59)
	Lag 2 (β_2)	0.043** (2.06)	0.043** (2.10)	0.043** (2.08)	0.043** (2.08)	0.044** (2.13)	0.045** (2.16)	0.044** (2.11)
	Constant α	3.381*** (19.35)	3.283*** (19.39)	3.226*** (19.33)	3.140*** (19.63)	3.084*** (19.96)	2.994*** (20.46)	3.130*** (20.14)
Natural catastrophes	Median severity Impact (δ_0 or λ_0)	\$10.5 mn -0.296** (-2.04)	\$27.3 mn -0.374** (-2.50)	\$127 mn -0.648*** (-4.57)	\$397 mn -0.748*** (-5.12)	\$1,428 mn -0.785*** (-4.09)	\$2,604 mn -0.769*** (-2.86)	\$602 mn -0.667*** (-4.13)
	Lag 1	-0.054 (-0.40)	-0.035 (-0.25)	-0.009 (-0.06)	0.125 (0.72)	0.037 (0.17)	-0.001 (-0.00)	0.024 (0.13)
	Lag 2	-0.649*** (-4.01)	-0.583*** (-3.81)	-0.604*** (-3.99)	-0.636*** (-4.20)	-0.610*** (-3.00)	-0.944*** (-3.57)	-0.751*** (-4.60)
	Lag 3	-0.104 (-0.70)	-0.027 (-0.18)	0.053 (0.40)	-0.073 (-0.44)	-0.329 (-1.39)	0.105 (0.48)	-0.081 (-0.45)
	Lag 4	0.127 (0.79)	0.113 (0.71)	-0.020 (-0.11)	-0.108 (-0.56)	-0.291 (-1.25)	-0.134 (-0.43)	0.053 (0.27)
	Cumul. effect, % GDP	-1.439***	-1.341***	-1.815***	-2.134***	-2.933***	-2.591***	-2.106***
	Mean severity	\$962 mn	\$1,155 mn	\$1,825 mn	\$2,859 mn	\$5,116 mn	\$8,337 mn	\$3,199 mn
	Growth impact, % GDP	-0.378**	-0.456**	-0.740***	-0.823***	-0.832***	-0.810***	-0.722***
	Cumul. effect, % GDP	-1.842***	1.634***	-2.074***	-2.347***	-3.110***	-2.730***	-2.280***
# country-years with NatCats	3,911	3,269	2,025	1,188	590	229	1,227	
# NatCats in sample	20,999	13,836	5,509	2,381	1,010	273	13,452	

Notes: The table shows the estimated coefficients of regression (3) in the text using the same specification for each column, the fixed effects panel estimator with robust covariance estimation, with 2 AR lags on growth and macro controls with 2 lags. The number of observations in each column is 8,252. The R^2 lies between 16.7% and 16.9% in all columns.

Significance levels: *** 1% ** 5% * 10% (t-values in parentheses).

To make estimates comparable, the reported coefficients have been scaled by median *severity* (mean in shaded columns), as explained in Table 2. T-values relate to the original unscaled coefficients λ_n .

The severity categories are defined by Munich Re, when expressed in constant 2011 US dollars:

- (1) Small-scale loss event with property damage exceeding \$1.4 million and/or 1-10 fatalities.
- (2) Moderate property and structural damage with losses exceeding \$11 million and/or 11-20 fatalities.
- (3) Severe catastrophe with property, infrastructure and structural damage exceeding \$64 million and/or 21-100 fatalities.
- (4) Major catastrophe with major property, infrastructure and structural damage exceeding \$250 million and/or 100-500 fatalities.
- (5) Devastating catastrophe, with losses within the affected region exceeding \$650 million and/or more than 500 fatalities.
- (6) Great natural catastrophe, interregional/international assistance necessary thousands of fatalities and/or hundreds of thousands homeless, substantial economic losses (UN definition).
- (7) Aggregation of catastrophes exceeding the threshold for category 4 within year.

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