Unmitigated Disasters? Risk Sharing and Macroeconomic Recovery in a Large International Panel*

Goetz von Peter[1] Sebastian von Dahlen[2] Sweta Saxena[3]

[1]Bank for International Settlements

[2]Federal Ministry of Finance, Germany

[3]United Nations

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Abstract

This paper examines the pattern of macroeconomic recovery following natural disasters. In a panel with global coverage from 1960 to 2015, data on insurer-assessed losses allows us to condition the dynamic growth response on risk transfer. We find that major disasters cause permanent output costs amounting to several percent of GDP, adding to the direct damage to property and infrastructure. It is the uninsured losses that drive this macroeconomic cost; insured losses leave no forgone output in the aggregate. By helping to finance the recovery, risk transfer mitigates the macroeconomic cost of disasters. Countries that lack the capacity to (re)insure themselves would benefit from greater international risk sharing.

JEL: G22, O11, O44, Q54.

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Introduction

Many results in macroeconomics depend on whether shocks have transitory or permanent effects. A growing literature maintains that wars, financial crises and other disasters have permanent effects: a weak recovery often leaves the economy below its pre-crisis trend (Cerra et al, 2023). The scarring effects of the 2008 global financial crisis long fuelled the perception that output losses are only partly reversed over time. Yet the endogenous nature of crises means that causality also runs the other way: economic slowdowns make crises more likely, and their singular impact is difficult to identify. This complication does not arise for natural disasters, which are exogenous over the relevant horizon, hence unambiguous in their causation.

The literature on the economic effects of natural catastrophes is quite disparate, reflecting the complexities of large-scale disasters and their multiple consequences. The survey by Cavallo and Noy (2011) provides a useful starting point. The burgeoning field has spawned many papers since; some focus on disasters of a specific physical type (e.g. cyclones) using dedicated databases, many others rely on the Emergency Events Database (EM-DAT) covering various types of disasters. Regarding method, in addition to case studies, most research applies panel regression analysis, while some papers apply an event study approach (Borensztein et al, 2017) or synthetic control methods (Cavallo et al. 2013). Papers also differ in sample size and the time horizon over which economic effects are examined: most regression studies measure the short-term impact, few allow for longer-term effects.[1] The selection of disasters also differs, based on physical intensity (e.g. Strobl, 2012, Felbermayr and Groeschl, 2014, Bakkensen and Barrage, forthcoming), or by the number or share of people killed (most other studies). While each approach has its merits, there is little consensus on the size and time-profile of disaster-related growth effects. Most authors find negative effects, though some find a qualified positive effect (e.g. Skidmore and Toya 2002).

In an effort to unify, our analysis is broader in scope and uses better loss data than previous research. First, our dynamic specification estimates the full time profile of economic growth in response to disasters, encompassing impact and longer-term effects. Second, we use direct economic losses to identify major disasters: damage to property and infrastructure is more informative for growth than physical intensity or the number of lives lost in a natural disaster. We rely on detailed statistics on disaster-related losses assessed by the insurance industry; they are more precise and complete than the loss data in EM-DAT and other public sources. Our dataset covers more than 200 countries and jurisdictions over a period of 55 years (1960-2015), merged with thousands of natural disasters of the four main physical categories.

We find that major disasters are predominantly harmful to growth. On top of the immediate losses from damage to property and infrastructure, major disasters leave behind a permanent macroeconomic cost in terms of forgone output. On impact, growth falls by 1 percentage point,

[1] For instance, Raddatz (2007), Noy (2009), Dermott et al (2014) and Felbermayr and Groeschl (2014) study the contemporaneous growth impact, other authors examine the level of GDP after five years (Hochrainer 2009), growth over five-year intervals (Loayza et al. 2012), long-term average growth in a cross-section (Skidmore and Toya 2002), or real GDP per capita over a ±6-year window around major disasters (Borensztein et al, 2017). Some papers also estimate separate effects for different physical types (Fomby et al. 2009, Loayza et al. 2012).

and output losses cumulate to reach an overall cost on the order of 2% to 4% of GDP. Such a harmful effect is not an obvious finding, since reconstruction investment is part of measured GDP, whereas the loss of physical capital (a stock) is not. Yet the consequences of natural disasters are substantial and play out over years, affecting populations and asset markets for an extended period. Similar to wars, political and financial crises, "unmitigated disasters" are macroeconomic shocks from which countries do not fully recover.

The second and more novel contribution is to make the growth response to disasters conditional on risk transfer. For lack of data, empirical research has ignored the role of insurance - even as policy work has long emphasised the importance of financial preparedness (Cummins and Mahul 2009, Kunreuther and Michel-Kerjan 2009, and World Bank and United Nations 2010). The growth effects we find are in fact driven by *uninsured* disasters – insured losses can be inconsequential or even growth-enhancing over time. Insured losses generally leave no foregone output in the wake of a disaster. These results hold for disasters of various physical types and at any stage of economic development. Incorporating risk transfer thus helps to reconcile conflicting findings in the literature, not least because insurance coverage differs systematically across physical types of disasters.

Risk transfer thus mitigates the macroeconomic cost of disasters. In the wake of a disaster, affected agents may be unable to mobilise funding for reconstruction, due to the financial imperfections at the heart of the literature on finance and growth (Levine and Zervos 1998). Insured disasters trigger insurance payouts and facilitate the replacement or repair of damaged productive assets and infrastructure. The timing of the growth spurts we find suggests that insured losses indeed help to finance reconstruction in the post-disaster years. Insurance also plays a mitigating role through disaster management and best practices for building codes. These channels add up to a measurable aggregate effect, which would be enhanced when inflows from abroad complement domestic transfers.

The macroeconomic value of risk transfer can be greatest for those countries that lack the capacity to (re)insure themselves against major natural catastrophes, resonating with the model of Borensztein et al (2017). In reality, however, the global catastrophe bond market remains small, and even with today's global reinsurance industry the extent of international risk sharing remains low. Using balance of payments data, Ito and McCauley (2022) find that losses from disasters are shared internationally to a very limited extent – compared to optimal risk-sharing in theory.

Our findings also put natural disasters on the map of the literature on rare disasters, which takes on new salience in the age of climate change. Historically, output contractions were large and frequent enough to explain asset-pricing puzzles in a standard asset pricing model (Barro 2006).[2] Barro (2009) further demonstrates that the permanent nature of rare disasters makes their welfare costs about 15 times as large as those Lucas (1987) had calculated for normal economic fluctuations. Are these models relevant for the 21st century? It was the wars and depressions of the 20th century that drove the empirical results in Barro and Ursúa's (2008)

[2] Allowing for time-varying severity of disasters, Gabaix (2012) accounts for a full ten asset-pricing puzzles in a unified and tractable macro-finance framework.

data. Today, natural disasters have emerged as a major threat to many countries around the world. Extreme weather events can increasingly be attributed to climate change (Scott, 2016). As such, they are expected to rise in frequency and severity to an unknown scale (Stern 2007, Weitzman 2009).

The paper proceeds as follows. Section 1 introduces direct loss statistics and describes the methodology for estimating the indirect output costs in the aftermath of disasters. Section 2 provides the baseline results on the macroeconomic cost of disasters, and the role of risk transfer in mitigating these effects. Section 3 nuances the results by controlling for financial development, aid flows and man-made crises, and expands the specification to estimate separate responses for different physical types of disasters. Section 4 concludes. The Appendix contains details on data sources and aggregations, and provides additional robustness tests.

1 Measuring the Effects of Natural Disasters

When catastrophe strikes, the immediate destruction and the tragic loss of life are plain to see in the media coverage following the event. *Direct* losses are widely assessed and reported. However, the aftermath of disasters also entails unseen consequences, where various forces – from the initial disarray to reconstruction efforts – shape economic activity. Assessing the macroeconomic cost of disasters therefore requires that we estimate those indirect effects, over and above the reported direct losses.

Direct loss statistics from the insurance industry make clear that major disasters are sizable shocks that will have macroeconomic consequences. After introducing those statistics, the section presents our methodology for identifying the indirect effects on growth, contrasting the within-year *impact* and the cumulative *long-term effect* of a disaster in terms of GDP.[3] To do so, we match the reported loss data to macroeconomic panel data with broad coverage, and estimate the indirect costs separately for insured and uninsured losses.

1.1 Direct Losses from Natural Disasters

A critical input is comprehensive and reliable statistics on the date, location and severity of natural disasters. Economic losses are more informative for identifying growth effects than physical measures of intensity, or the number of lives lost or affected. Therefore, our starting point is a detailed quantitative database on damage to property and infrastructure.

Research to date mainly relied on the publicly available Emergency Events Database (EM-DAT).[4] Toya and Skidmore (2002, 2007), Noy (2009), Schumacher and Strobl (2011), Cavallo

[3]We focus on GDP as the most debated economic variable, and acknowledge that this approach does not capture many other important consequences that affect a nation's well-being (World Bank and United Nations 2010). The same method can be applied to other variables of interest, such as consumption or socio-economic measures.

[4]The EM-DAT is compiled by the Centre for Research on the Epidemiology of Disasters (CRED) in Belgium

et al (2013), Dermott et al (2014) and Borensztein et al (2017) have put those data to good use. But EM-DAT focuses on the humanitarian and epidemiological aspects of disasters - the coverage of economic losses is quite poor. An internal stock-take documented large data gaps in their loss data: of the 13,862 events recorded for 2000-2020, 80% were missing economic loss data altogether, and 95% lacked data on insured losses (CRED, 2021). Moreover, the economic loss data are systematically sparser for low-income countries (Jones et al 2022), possibly inducing selection bias (Felbermayr and Groeschl, 2014).

The missing-loss-data problem is hard to avoid. In an ingenious use of EM-DAT, Cavallo et al (2010) predict economic losses from the number of fatalities, and extrapolate to estimate the direct economic loss of the devastating earthquake in Haiti 2010, which killed more than 200,000 people. Their estimate of $8.1 billion is very close to the insurance assessment ($8.0). However, the R-squared of 40% in their regressions makes clear that fatalities and other public data are no reliable substitutes for missing data on economic losses. In the statistics we use, the correlation between economic losses and fatalities is as low as 20%.

The data in this paper are from Munich Re, a global insurance and reinsurance group whose Geo Risks Research unit has been collecting disaster-related data on a worldwide basis for more than 40 years (Munich Re 2011). Reinsurance companies are best placed to determine catastrophe-related losses - it is their core business. They track their own global insurance liabilities, and 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. Their data collection specialises in the assessment of economic losses, drawing extensively on industry sources to assess total and insured losses (www.munichre.com/geo).

As a result, the NatCat statistics have near-complete global coverage of economic losses, at least since 1980. They report *direct* losses from the immediate destruction of property and infrastructure, calculated on the basis of the cost of replacement or repair of affected homes, schools, other buildings, machinery, livestock, vehicles, other property and infrastructure. The statistics we received from Munich Re contain more than 22,000 detailed observations, covering direct losses to individual countries between 1950 and 2011 from disasters in four physical categories. During these 6 decades, natural disasters have claimed over 3.33 million lives, and caused $3.86 trillion in total direct losses giving rise to $914 billion in compensation from insurers worldwide (in constant 2011 US dollars). We focus on disasters since 1960, in line with our macroeconomic panel data.

Table 1 presents the data by physical type, with summary statistics on frequency, severity and insurance coverage. For 95% of all events, Munich Re reports positive economic losses. Overall, meteorological (storms) and hydrological events (flooding) are more frequent than geophysical and climatological events (row 1). Smaller events are more frequent and less consequential; all other rows thus focus on events where economic losses exceed 0.1% of the affected country's GDP. Scaling losses by the size of the economy gives due attention to disasters in poorer nations.[5] Frequencies are relatively high for earthquakes and flooding in Asia, storms in the

(www.emdat.be).

[5]Scaling economic losses by GDP also helps to offset the trend in losses induced by the rising value of

Americas, and droughts in Africa.

Clearly, major natural disasters amount to sizeable macroeconomic shocks. In terms of fatalities, the 1983 drought in Ethiopia and the 1970 storm surge in Bangladesh stand out, followed by earthquakes in China (1976) and Haiti (2010). Two earthquakes in Japan (2011 and 1995) and Hurricane Katrina in the United States (2005) saw the largest economic losses. The average disaster causes damage to property and infrastructure to the tune of 5% of a country's GDP - or more, for earthquakes and storms. At the same time, the devastation of major disasters is such that mean severity (5%) far exceeds median severity (0.5%). Our regression tables thus report results scaled by the typical (median) and average (mean) severity, respectively.

[**Table 1: Features of Natural Disasters (1960-2011)**]

For each disaster, insurance coverage is calculated as the share of insured losses in total direct losses. It is the effective compensation awarded by insurers ex post. Only 25% of major events over the 50 sample years had any insurance coverage (30% in the latest 10 years). At more than 90%, the proportion of uninsured events was particularly high for climatological events. When there is insurance, coverage varies substantially around the average share of 31%. For all 1,566 disasters in Table 1 combined, insured or not, the standard deviation of coverage is close to 20%.

There is enough variation in coverage across disasters to make use of the distinction between insured and uninsured losses in our empirical work. Figure 1 plots direct economic losses against insurance coverage, with thick dots representing disasters with damage exceeding 0.1% of GDP (as in Table 1). The spread of red dots conveys two points. First, scaling losses by GDP highlights some smaller disasters affecting poorer countries (there are red dots to the left) at the expense of costlier disasters in large economies (grey dots to the right). Second, severity and insurance coverage are almost unrelated. There are uninsured events all along the x-axis. And insured events, small and large, form a cloud.[6] This is helpful, for if coverage were systematically lower for costlier events, it would be hard to disentangle whether the macroeconomic costs are driven by greater severity or by lower coverage.

Each observation on insurance coverage results from the aggregation of many individual contracts that commit insurance companies to pay for damages. The insurance industry mainly comprises (local) primary insurers and (global) reinsurance companies. Policyholders arrange for coverage with a primary insurer offering various lines of business, such as property, automobile, business interruption, health and life insurance. In the event of a disaster, those lines will be jointly affected, leading to thousands of claims, with losses build up at the primary insurer. To limit their exposure, insurers commonly buy coverage from reinsurance companies, often in the form of "catastrophe excess of loss" contracts (CatXL). The reinsurance sector in turn retains the bulk of the underwritten risk, and transfers some peak risks to broader financial markets through retrocession and securitization (e.g. through catastrophe bonds).[7]

infrastructure and productive assets over time.

[6]A simple regression of coverage on the log of losses/GDP explains 6% for all events, and only 0.2% for major events (thick dots in Figure 1).

[7]Based on Munich Re statistics, von Dahlen and von Peter (2012) document trends in disaster coverage

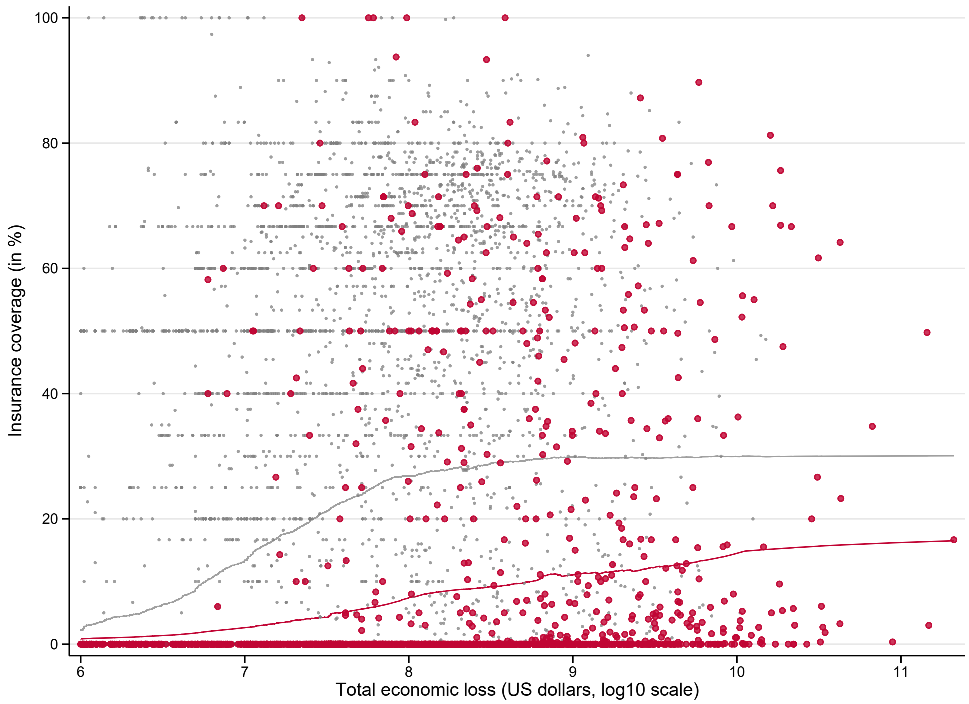

Figure 1: Direct Losses and Insurance Coverage, 1960-2011.
The scatter plot sets reported insurance coverage against the severity, measured by direct economic losses in constant 2011 US dollars. (On a log10 scale, x=9 corresponds to $1 billion.) The dots represent the natural disasters between 1960 and 2011 with reported losses of $1 million or more (9,876 events). The thick dots show the subset of disasters where direct losses exceeded 0.1% of GDP. The lines trace out the smoothed coverage ratios for the respective groups, using locally weighted regressions (bandwidth 0.5).

1.2 Identifying Indirect Macroeconomic Costs

We employ a methodology that allows us to estimate the dynamic profile of the growth response to natural disasters. Throughout, the purpose is not to identify the determinants of growth (as in the empirical growth literature), but to document the pattern of recovery from disasters. We estimate a simple stochastic growth model to generate impulse responses to a disaster. This approach accounts for the non-stationarity of output (Nelson and Plosser, 1982). Let y_{it} denote real GDP growth of country i at time t, and $\mathbf{z}_{it}$ represent a vector of macroeconomic controls described below, and consider an autoregressive model of the form

$$y_{it} = \underbrace{\alpha_i + \sum_{n=1}^{L_y} \beta_n y_{it-n}}_{\text{growth autoregression}} + \underbrace{\sum_{n=0}^{L_x} \lambda_n x_{it-n}}_{\text{disaster effects}} + \underbrace{\sum_{n=0}^{L_z} \theta_n \mathbf{z}_{it-n}}_{\text{macro controls}} + \varepsilon_{it}, \quad (1)$$

where x_{it} is a disaster variable: it is positive if a natural catastrophe occurs in country i at time t, and zero otherwise. The coefficients on x_{it} and its L_x lags translate natural disasters of a given severity x (direct losses) into growth outcomes (indirect effects).

and risk transfer in the global (re)insurance market. Other analyses of catastrophe risk markets include Froot (2001), Cummins and Mahul (2009), and Kunreuther and Michel-Kerjan (2009).

The signs of the estimates of λ_n, if significant, capture whether natural disasters are harmful or conducive to growth. We distinguish between the contemporaneous impact and longer-term effects. The *impact* of a disaster of severity x on growth in the year of the disaster amounts to

$$\text{Impact:} \qquad \lambda_0 x, \tag{2}$$

and is expected to be negative. Disasters may have growth effects in the years after the disaster, captured by the lags λ_n. A positive λ_1 represents extra growth in the year after a disaster, e.g. if reconstruction investment boosts GDP. At the same time, the autoregressive process carries any growth effects forward: a positive β_n compounds the effects on economic activity over time. The dynamics governed by β_n and λ_n thus describe a perturbed path around a country's average growth rate given by $y_i^* = \alpha_i/(1 - \Sigma\beta_n)$.[8] Over time, the macroeconomic effect of a disaster x cumulates to the following *long-term effect*,

$$\text{Long-term effect:} \qquad \frac{\sum_{n=0}^{L_x} \lambda_n}{1 - \sum_{n=1}^{L_y} \beta_n} x. \tag{3}$$

If negative, this effect represents the *macroeconomic cost* of a disaster, measured in percent of GDP. Its magnitude is governed by three factors. First, the *severity* of a disaster (x) scales the growth responses in equations (2) and (3). Second, the coefficients λ_n measure the *sensitivity* of growth to a given severity, from impact to the long-term effect. Third, greater *persistence* in the growth process (β_n) compounds the long-term effect as deviations from trend growth are carried forward in time.

Estimating a time profile presents a fuller picture of growth dynamics than earlier studies, which limit their focus on one segment of the growth response (see Introduction). However, the most novel aspect studied here is the role of *risk transfer*. To test whether insurance coverage helps to mitigate the macroeconomic cost in the wake of a disaster, we make the growth response conditional on the extent of insurance in place. For each disaster in country i at time t, the direct loss x_{it} can be decomposed into a part that is *transferred* to insurance markets (τ_{it}), and the residual (υ_{it}) that remains *uninsured*. Extending equation (1), we estimate distinct coefficients for the two types of losses,

$$\begin{aligned} y_{it} &= \underbrace{\alpha_i + \sum_{n=1}^{L_y} \beta_n y_{it-n}}_{\text{growth autoregression}} + \underbrace{\sum_{n=0}^{L_z} \theta_n \mathbf{z}_{it-n}}_{\text{macro controls}} \\ &+ \underbrace{\sum_{n=0}^{L_x} \mu_n \upsilon_{it-n}}_{\textbf{uninsured}\text{ catastrophe losses}} + \underbrace{\sum_{n=0}^{L_x} \sigma_n \tau_{it-n}}_{\textbf{insured}\text{ losses}} + \varepsilon_{it}. \end{aligned} \tag{4}$$

The advantage of this specification is that there is no need to split the sample or specify an arbitrary threshold at which disasters are deemed insured. Equation (4) allows us to identify *separate* impacts and long-term effects for insured and for uninsured losses, by plugging the respective loss severities (τ_{it} or υ_{it}) and estimated sensitivities (σ_n or μ_n) into equations (2)

[8] Macroeconomic controls are ignored for ease of exposition; the variables are centered in the empirical specification.

and (3). There is sufficient heterogeneity in observed coverage across catastrophes to make the distinction in (4) operational. Importantly, if the sensitivities to insured and uninsured losses differ systematically from each other, then the presence of insurance alters the macroeconomic cost of disasters.

1.3 Estimation with Panel Data

To estimate the macroeconomic cost of disasters, we merge direct losses with a panel dataset. Aiming for global coverage dictates the use of annual data at the national level.[9] Our dependent variable is the rate of growth in real GDP. In line with related studies, we take growth from the World Bank's *World Development Indicators (WDI)* database.[10] The panel also includes macroeconomic variables and development controls (Appendix 1 lists definitions and sources). The resulting dataset is an unbalanced panel covering more than 200 countries and jurisdictions between 1960 and 2015 with close to 9,000 country-year pair observations.

The main regressor is the *severity* of a disaster, measured as the direct loss from the immediate destruction of property and infrastructure (Section 1.1). Reported losses exclude all indirect costs to the economy (Wirtz et al. 2012). Conversely, the WDI growth series are free of disaster-related losses.[11] Nor do insurance payouts affect measured growth, since capital transfers are not part of GDP. Therefore, the loss and GDP series do not overlap, ensuring that equations (1)-(4) measure nothing more than the indirect, macroeconomic costs.

For our panel regression we aggregate and scale the disaster severity variable as follows:

Aggregation. Since countries can experience multiple events in some years, we aggregate losses within each year to obtain a single observation for each country-year pair. This step consolidates more than 22,000 individual disaster events into 1,954 yearly panel observations with disasters. For each observation, we split total losses into their insured and uninsured parts. Appendix 1 describes the process further, including the attribution of losses for disaster affecting several countries.

Scaling. Following Noy (2009), we scale direct losses by the size of the economy, i.e. express losses as a percentage of GDP to obtain our measure of severity x_{it}. This variable has a heavy-tailed distribution: using the methods of Clauset et al (2009), we find that the tail of the distribution (where losses exceed 1.45% of GDP) follows a power law with scaling parameter of 1.8; the power law fits better than an exponential distribution, but is not distinguishable statistically from the log-normal distribution for this sample. We thus apply a natural-log

[9]Higher-frequency and subnational growth data would make it easier to detect disaster-related effects, but they are available only for few countries over any long period.

[10]These include Barro (2009), Cerra and Saxena (2008), Noy (2009), and Loayza et al. (2012). Using WDI growth data also avoids known problems with growth regressions based on the GDP series from the Penn World Tables (Johnson et al. 2013).

[11]The real GDP growth series are based on constant domestic prices, "calculated without making deductions for depreciation of fabricated assets" (WDI release notes); the series thus exclude disaster-related direct losses which could have exaggerated the estimated indirect effects.

transform to obtain our measure of severity: $x = \ln(Loss/GDP + 1)$. The unit shift ensures that the severity measure is positive if and only if losses are, and the log transform has the property that $x \approx Loss/GDP$ for small disasters (Mercator series). Having split losses into their insured and uninsured parts, we apply the same procedure to obtain the corresponding severity measures τ_{it} and υ_{it} for equation (4).

Threshold. We impose a minimum severity threshold of 1% of GDP for including disasters in the panel. Including all recorded disasters would introduce too much noise: smaller events are more frequent but inconsequential on the macroeconomic scale of interest. The 1% cut-off leaves 460 event-years in the panel; hence 5% of the 8,921 panel observations are event-years. Empirical results for some alternatives (a 0.5% threshold and other scaling options) are reported in the robustness Table A2.

Estimates. To make results comparable across different samples and disaster types, we scale estimated coefficients in all regression tables. Instead of showing the sensitivity coefficient λ_n by itself, we report sensitivity times severity, since it is this product that shapes the macroeconomic response (e.g. $\lambda_n x$ in equation (1)). When scaling the coefficient by the *median* loss, we obtain the estimated effect of a typical disaster; scaling by the *mean* loss instead yields the effect of a disaster of average size. Due to the presence of large rare disasters in the data, the average disaster (with mean loss of 15.4% of GDP) far exceeds the median disaster (3.19%). The mean loss may be more relevant for policymakers concerned with the expected cost of disasters.

Our regression tables Tables 2-4 and A2 thus report all the estimates of interest in equations (1) to (4). Guided by the Hausman test, we use panel fixed effects with Huber-White robust standard errors - a natural choice, given the heterogeneity in growth across countries for various structural reasons.[12] After testing down the lag structure, we include four autoregressive lags on growth ($L_y = 4$), the contemporaneous impact and four lags on the disaster variables ($L_x = 4$), and two lags on the man-made crises controls ($L_z = 2$, see equations (1) to (4)).

2 The Role of Risk Transfer in Mitigating Disasters

Our empirical analysis starts with a parsimonious specification (Table 2), to minimise the selection bias that may arise when missing data eliminate poorer or smaller countries that may be most vulnerable to natural disasters. The next section adds macroeconomic variables and controls for financial development (Table 3), to control for (1) access to banking, insurance, and credit, (2) aid flows and official development assistance, and (3) five types of man-made crises: wars, political crises, as well as banking, currency, and debt crises. Table 4 further expands the specification to estimate separate macroeconomic effects for different physical types of disasters.

[12] In 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 to the persistence of growth being underestimated.

2.1 Baseline Response to Disasters

We first focus on the growth effects of natural disasters while ignoring risk transfer, in line with other studies. The first specification maximises coverage by using only two autoregressive lags and country fixed effects (Table 2, column 1). The panel contains 8,921 growth observations matched with 460 country-year observations with natural disasters causing at least 1% of GDP in direct losses to property and infrastructure ("event-years"). The first row reports the typical (median) severity x, and subsequent rows present estimates of *indirect* macroeconomic costs as measured by the scaled coefficients $\lambda_i x$. The shaded rows report the estimates scaled by the *mean* severity of disasters instead. In both cases, equations (2) and (3) define the impact and long-term effects (LT-effect, in bold font), respectively.

On impact, the typical disaster (which causes 3.19% of GDP in direct losses) reduces growth by an estimated 1.0% in the disaster year alone.[13] Across all countries, decades and types of disasters, real growth within the year of a disaster is typically one percentage point lower than it would have been in the absence of the disaster. The lagged coefficients identify further negative effects on growth two years after the event. Both effects are carried forward and compounded by the autoregressive lags ($\widehat{\beta}_n > 0$). The estimated cumulative effect on GDP implies a permanent macroeconomic cost of 2.1%. The statistical significance of the long-term effect is obtained from a non-linear Wald test on the ratio of estimated coefficients in equation (3).

The results are slightly weaker when using four lags and basic controls (Table 2, column 2). The richer lag structure extends that of Noy (2009), Dermott et al (2014) or Felbermayr and Groeschl (2014), for instance, who focused only on the growth impact *during* the disaster year, based on an AR(1) growth model. The basic controls include a time trend and the log of GDP per capita to account for the stage of development (Toya and Skidmore, 2007). The estimated impact remains close to -1.0%, but the macroeconomic cost falls to 1.9% of GDP due to lower estimated sensitivities ($\widehat{\lambda}_n$). GDP per capita is not significant in this basic specification, but the role of development is explored further with extended controls and interactions in Section 3.[14]

These results refer to the effects of a median (typical) disaster; scaling the sensitivities by the larger *mean* loss yields greater estimated costs.[15] Mean disasters reduce growth by nearly 2% on impact, and produce a long-term loss near 4% of GDP (shaded rows in Table 2). The estimates can also be scaled by severities beyond the mean loss in order to predict the effects of extreme disasters.

[**Table 2: The Macroeconomic Cost of Natural Disasters - Baseline Results**]

The baseline results confirm that major natural disasters are harmful for growth, in line with earlier research (surveyed in Cavallo and Noy, 2011). Our estimated impact matches Noy's

[13] From equation (2), the median impact is the product of estimated contemporaneous sensitivity, $\widehat{\lambda}_0 = -0.698$, and median severity $x = \ln(3.19 + 1)$.

[14] The time trend hints at a weak growth slowdown over time, albeit insignificant. Table A2 also controls for time-varying global factors estimated by yearly fixed effects.

[15] After the log transform, the mean is nearly twice as large as the median disaster, and the estimated macroeconomic costs rise accordingly, see equations (2)-(3).

(2009) short-run response for developing countries (-1%), while the long-term effect aligns with Hochrainer's (2009) estimated GDP drop of 2-4% by year 5 after the event, respectively. Cavallo et al (2013) and Borensztein et al (2017) have found such marked responses only for extreme disasters, while our estimates are based on hundreds of major disasters; the difference may be down to the selection of which disasters are in the sample: it is based on economic losses in our case, and the number of fatalities in theirs. Our rich lag structure also reveals a distinctive time profile, whereby growth dips again in year two after the event ($\widehat{\lambda}_2 < 0$), thereby compounding the macroeconomic cost. The estimated effects are so persistent that the cumulative output loss is about twice the size of the within-year impact.

Finding negative growth effects is not a foregone conclusion: direct disaster losses do not enter measured GDP, while investment for reconstruction boosts output - yet, the disruptive effects of disasters are sufficient to curb growth instead. This finding does not support the view that natural disasters promote growth - at least not in the short and medium run. The case has been made by Skidmore and Toya (2002), arguing that disasters fuel human capital accumulation and update the capital stock. Instead, we find that major natural disasters harm economic growth, over and above the direct losses from the destruction of property and infrastructure.

2.2 Distinguishing Insured from Uninsured Losses

We now test whether insurance coverage helps to mitigate the macroeconomic cost of natural disasters. The coefficients in equation (4) identify separate responses to insured and uninsured losses, which are estimated in column 3 of Table 2. *Uninsured* losses continue to have a negative effect on growth. The mean uninsured disaster reduces growth by 1.63% on impact ($\widehat{\mu}_0 \upsilon$ in equation (4)), and by a cumulative 2.75% over time. By contrast, *insured* losses turn out to be insignificant in their growth effects ($\widehat{\sigma}_n \approx 0$).[16] This stands in sharp contrast with the negative response to uninsured losses, which was statistically significant and economically large.

This finding suggests that uninsured losses cause substantial macroeconomic costs, whereas insured losses appear inconsequential for growth. Risk transfer may not reduce the the direct loss (severity); but by shifting the balance toward insured losses, it mitigates the adverse macroeconomic effects following a disaster of a given severity.

These results may well depend on a country's the stage of development. Column 4 excludes high-income countries, and column 5 also removes upper-middle income countries, keeping only the two lowest income groups in the sample. Both columns show that uninsured losses are more harmful to poorer countries, echoing Noy's (2009) findings. Interestingly, this is not because poorer countries experience more severe disasters relative to the size of their economies: uninsured losses to GDP are similar to those of the full sample. Instead, poorer nations appear to be more *sensitive* to a given loss/GDP: the estimated $\widehat{\mu}_0$ and $\widehat{\mu}_2$ are more negative in columns 4-5 than in the full sample (column 3). For a mean disaster, the impact (-1.7% to -1.9%) and long-term effect (-3.0% to -3.6%) of uninsured losses are greater for poorer countries than for all countries combined. And the bulk of disaster losses in poorer countries were uninsured

[16] The significance of coefficients is based on sensitivity; severity merely scales the estimated coefficients.

(Table 1). Insured losses have a negative impact too (marginally significant), but their long-term effect is indistinguishable from zero (p-values in brackets).

Case study: Haiti vs New Zealand. A comparison of similar events across different countries makes clear why it will be necessary to further control for the stage of development. In 2010, Haiti and New Zealand were both struck by powerful earthquakes sharing similar physical features. Both were of moment magnitude 7.0, with epicentres near a major economic hub (Haiti's capital, and New Zealand's second largest city). Both events produced immediate destruction ($8.0 billion US dollars in direct losses in Haiti, $6.5 billion in New Zealand), and disrupted manufacturing and transportation facilities. Both countries are island states exposed to recurring natural catastrophes.

In spite of these physical similarities, the macroeconomic consequences on the two islands were worlds apart. The direct losses, though similar in absolute value, amounted to 120% of Haiti's GDP, compared to 4.4% of New Zealand's - which makes the case for scaling losses by GDP. Haiti faced a death toll of 222,570 (more than 2% of the entire population), and saw real growth plummet from 5.9% in 2009 to -5.7% in 2010 alone. New Zealand, by contrast, saw no fatalities in this event and experienced little impact on the aggregate economy (New Zealand Treasury, 2010; Doyle and Noy, 2015).

The extent of risk transfer may account some of this divergence. Haiti was largely uninsured and found itself dependent on foreign aid, whereas New Zealand had 81% of losses covered and reimbursed as a result of a mandatory add-on to residential insurance.[17] The 2010 earthquake triggered $5 billion in payments from primary insurance companies, backed by an inflow of $3.5 billion from reinsurance companies outside New Zealand. That said, the two countries are at different stages of development in many other respects that could also affect the response to disasters.

[17] We are grateful to a referee for correcting us on which part of insurance was mandatory at the time.

3 Risk Transfer and the Stage of Development

Are the mitigating effects identified so far really due to insurance, or a by-product of other aspects of development? Less developed countries find it harder to cope with natural disasters. More people die when natural disasters strike low- and middle-income countries (Kahn 2005, Toya and Skidmore 2007, Noy 2009, Loayza et al. 2012); our data confirm that the number fatalities tends to decline with measures of development. The same does not hold for direct economic losses in our sample. Richer countries have more infrastructure and productive assets exposed to natural disasters, even if they can also take more preventive measures (Schumacher and Strobl, 2011).

What about the indirect, macroeconomic costs estimated in this paper? Advanced economies may be less sensitive to natural disasters, and better insured at the same time. To disentangle the role of risk transfer from confounding factors, this section incorporates a host of regressors controlling for financial development and other institutional factors. We then refine the analysis by estimating separate growth responses to four different physical types of disasters. These enhancements help sharpen the finding that risk transfer helps to mitigate the adverse growth effects of natural disasters.

3.1 Nuancing the Role of Development

All our specifications scale direct losses by GDP, which ensures that the measure of severity covers the costliest disasters at any stage of development - including many disasters that affected poor countries. In the interest of country coverage, Table 2 only accounted for development in a basic way, using GDP per capita alongside country fixed effects and a time trend. Yet countries differ in various institutional features that determine their ability to recover from disasters, such as differential access to financial resources that help countries finance the recovery (Cummins and Mahul, 2009, Noy, 2009, Loayza et al, 2012).

The extended specification now adds a battery of controls (Table 3). We focus on measures of financial development and factors that might substitute for (re)insurance transfers, e.g. foreign aid and development assistance. We also control for man-made crises that may coincide with natural disasters. We do not control for fiscal and monetary policies, which are part of the response of the economy to shocks - like other endogenous macroeconomic variables.[18]

We first control for financial development and foreign assistance (Table 3, column 1). Foreign assistance includes aid flows and official development assistance (both in % of GDP); it is separate from the reinsurance transfers a country receives after incurring losses on insured assets.[19]

[18] If an economy has the means to offset the effect of disaster through fiscal stimulus, for instance, then this is part of the measured response to disasters. In reality, the amounts are often relatively small and disbursement slow. Worse, middle and low-income countries exhibit procyclical dynamics, where lower spending and higher revenues exacerbate disaster effects (Noy and Nualsri, 2011). Controlling for endogenous macroeconomic variables and domestic policy responses would also decimate the sample.

[19] That said, well-insured countries would not attract major aid flows - the two forms of relief rarely coincide.

These external sources may all help finance the recovery and mitigate the macroeconomic cost of disasters over time. For financial development, we include access to bank branches, non-life insurance penetration, and access to credit proxied by the credit-to-GDP ratio (definitions and sources are in Table A1). Adding development controls reduces the sample from 212 to 162 countries, and from 8,459 to 6,812 observations with 355 event-years.[20]

The development variables enter on a stand-alone basis, and as interactions to test whether they matter specifically in years when natural disasters strike. Richer countries grow more slowly in normal years (as poorer countries catch up); but higher GDP/capita may help growth in a disaster if it reflects better institutions or preparedness. Noy (2009) and Dermott et al (2014) employed an interaction to examine how development affects growth in the impact year; we further add interaction lags to match the dynamic profile we estimate. The interactions with the disaster indicator identify separate effects in the year of, and the two years after, major disasters.

The use of controls strengthens the estimated growth effects of natural disasters. Column 1 shows larger impacts and long-term effects than Table 2 column 3, even as the mean and median severities are held constant for comparison.[21] The output loss following a typical uninsured disaster is greater than before, both on impact (-1.0%) and over time (-1.95% of GDP); the effects are again larger for a mean disaster (impact -1.96% and long-term cost -3.81%).

At the same time, insured losses are found to spur growth in the year after a disaster. The estimated growth spurt is significant in statistical and economic terms: $+0.58\%$ following a median disaster, and $+3.67\%$ for a mean disaster - about as large as the direct insured loss caused by the disaster.[22] This boost is partly offset by slower growth in years 3 and 4, leaving the long-term response to insured losses statistically insignificant overall.

Among the development controls, access to banking and aid flows appear to help the most. In normal years, the access variables tend to correlate with lower growth overall (convergence). However, access to banking supports growth in a disaster year and the following two years: the number of bank branches per 100,000 adults is consistently significant in the interaction terms. With a two year lag, credit-to-GDP also goes with higher growth. So do foreign aid and official development assistance in the year after a disaster. But aid flows are associated with negative growth in the year of a disaster; this may reflect cases where aid has been mobilised in response to major disasters to meet humanitarian needs (eg Haiti 2010).[23] Other financial access variables are not significant across countries and time, but their influence on the disaster

[20] The credit-to-GDP ratio is more widely available than access to credit in the form of bank loans or credit lines. Using the former helped limit the drop in sample size without changing any results.

[21] Disaster severity (losses per GDP) is held constant across all columns of Table 3; the differences across estimates thus reflect changes in the *sensitivity* to losses.

[22] This number corresponds to $\widehat{\sigma}_1\tau$ from equation (4), the product of the estimated sensitivity (2.0) and severity $\tau = \ln(Loss/GDP + 1)$ with a mean uninsured loss of 5.28%.

[23] A separate reason for the outsized estimate is that aid flows are relatively small. Becerra et al. (2014) document that the median aid increase following large natural catastrophes covers only 3% of the overall damage.

coefficients suggests that the stage of development does matter when disasters strike.

[Table 3: Controlling for the Stage of Development]

Another aspect of development is institutional quality and stability, or its absence in the form of crises. We next control for five types of crises: wars, political crises, as well as banking, currency, and debt crises.[24] These "man-made disasters" also depress output, and sometimes occur in natural-disaster years: for 11% of country-year pairs with major disasters, a crisis starts in the same year. In Cavallo et al (2013), the two disasters with the largest output costs in their sample were followed by political revolutions. Hence, Table 2 may have overestimated the effect of natural disasters on growth.

When controlling for crises, the estimated growth effects of natural disasters continue to be negative when uninsured, and positive when insured (Table 3, column 2). The impact and long-term effects continue to be stronger than in Table 2 where no development controls were used. An uninsured mean loss slows growth by 1.75% in the disaster year; by contrast, an insured mean loss has no significant impact at first, and boosts growth by 3.57 percentage points the year after. Over time, forgone output from uninsured losses is 3.43% of GDP, whereas fully insured losses entail no such cost.[25]

The man-made crises themselves are associated with large macroeconomic costs. All five types reduce growth by between 1.7 and 4.1 percentage points at the onset of the crisis. The impact is highly significant for every type of crisis, and some also spell negative effects in the year after. Over the longer term, the typical costs of banking crises, debt crises and wars range from 5.0% to 9.5% in terms of foregone output (Table 3, last column). This echoes the findings of Cerra and Saxena (2008), who documented that financial and political crises entail large and permanent output losses. Compared side-by-side on the same methodology, our results show that major natural disasters can spell long-term costs comparable to, but somewhat smaller than, those following political or economic crises.[26]

By controlling for crises we may understate the effects of natural disasters to the extent that recessions are attributed to the crisis coinciding with a disaster. If a drought fuels a war, say, then part of its cost is really due to the initial drought. There is growing evidence that natural disasters can fuel political crises and make conflict more likely. Rahman et al (2022) document that major storms in island economies erode political institutions and often lead to a more

[24] The five types of enter coded as dummy variables equal to one in the year a disaster begins, for banking, currency and debt crises (based on Laeven and Valencia 2012 and updates) as well as wars and political crises (based on the Correlates of War and Polity IV datasets). See Table A1.

[25] The long-term effect of uninsured losses (+4.46%) suggests an expansionary effect overall, but the sign is not reliable since the effect is marginally insignificant. The non-linear Wald test of the long-term effect (equation (3)) returned a p-value of 0.11.

[26] The direct loss estimates for natural disasters benefited from expert assessments of damage to capital and infrastructure (Section 1.1); no comparable severity information is available for political and economic crises. To compare crises and natural disasters on identical terms, we recode disasters the same way as crises: using an indicator equal to 1 if a disaster occurs in country i in year t, and 0 otherwise. By this estimate, a typical disaster reduces growth by more than one percentage point on impact, and costs nearly 2% in terms of foregone GDP overall (Appendix Table A2, column 1).

autocratic regime. Burke et al (2015) find that deviations from normal precipitation and mild temperatures systematically increase the risk of conflict, and survey the growing literature on climate and human conflict.

3.2 Discussion: Partial Recovery and Risk Transfer

Whether shocks have transitory or permanent effects makes a crucial difference in many macroeconomic settings. Our work extends a line of research that finds wars, political and financial crises to have permanent effects, in the sense that output losses are only partly reversed over time (Cerra and Saxena, 2008, Cerra et al, 2023). It takes about eight years on average to reach the pre-crisis level of income following financial crises (Reinhart and Rogoff, 2014), not to mention the previous trend. For man-made crises, however, identification is complicated by the endogenous forces at work: economic slowdowns make crises more likely in the first place. For natural disasters, on the other hand, the direction of causality is clear: the occurrence of disasters is exogenous, and therefore the probable cause of the observed growth effects.[27] We thus interpret the results so far as follows.

First, our findings suggest that major natural disasters can spell substantial macroeconomic costs, over and above the direct losses from the destruction of property and infrastructure. Figure 2 traces out the growth responses to mean-sized natural disasters, contrasting uninsured losses (top row) with insured losses (bottom row). The left panels show simulated growth rates as deviations from zero (representing the absence of disasters). The right panels cumulate the growth responses over time, to obtain the overall macroeconomic cost. The top panels underline that natural disasters, most of which are uninsured, can harm growth for years.

Second, the macroeconomic cost in terms of foregone GDP is permanent. In response to mean uninsured losses, real growth declines almost 2% on impact and slumps again in year 2 after the disaster (Figure 2, top left panel).[28] This impulse response bears all the signs of a partial recovery. Even if the growth rate eventually recovers, the disaster leaves behind a measure of forgone output: the economy does not recover to its previous growth path.[29] Countries never fully recoup the output lost in the wake of a major disaster. This is evident in the top right panel, which cumulates the top left panel over a ten-year period, approaching the cumulative effect defined in equation (3). It represents a permanent macroeconomic cost of more than 4% of GDP, about twice the initial impact on growth. The effects of major disasters play out over several years; hence, attention to affected areas or populations should not be limited to the immediate aftermath of a natural catastrophe. Important social consequences also include adverse effects on health, nutrition and education (World Bank and United Nations 2010).

[27] Granted, the *magnitude* of direct losses can be endogenous: countries that had grown faster prior to a disaster tend to have greater exposure in terms of infrastructure and productive assets. But that does not make the *occurrence* of a disaster more likely, except around the inclusion cutoff (set at 1% of GDP in all regressions, and varied in Table A2).

[28] Double dips are quite common in recessions following financial crises (Reinhart and Rogoff, 2014).

[29] Given the negative impact, a full recovery would require that the growth rate overshoot its long-term average, jumping into the positive half of the figure.

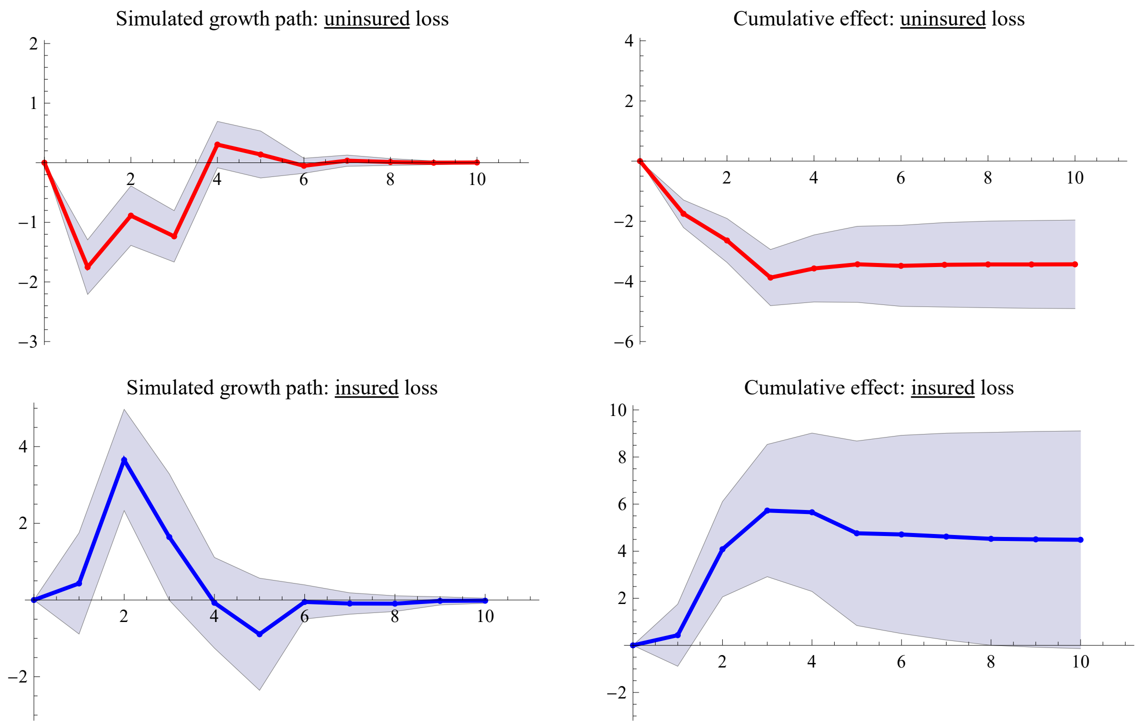

Figure 2: The growth response to insured vs uninsured losses.
The figure contrasts the effects of mean-sized uninsured losses (top row) and mean-sized insured losses (bottom row), by simulating the recursive equation (4) using the estimated coefficients from Table 3 (column 2). The left panels trace out the path of real growth over time, relative to its long-run average. The right panels cumulate the growth rates into the long-term responses defined in equation (3). The first observation ($t = 1$) refers to the growth drop in the impact year, $t = 2$ the year after, etc. The confidence band is derived from Monte Carlo simulations perturbing each of the estimated coefficients by a disturbance with a variance proportional to its estimated standard error (s). We run one million realizations for each coefficient ($\widehat{\alpha}'_r = \widehat{\alpha} + s * e_r$) to produce as many paths from equation (4), and identify point-wise for every period the realization that lies ± 1 standard deviation from the central path (see also Sims and Zha 1999).

Third, the "unmitigated disaster" (top panels) stands in sharp contrast with the response to fully insured losses (bottom panels). Insured losses turn out to be inconsequential, if not expansionary, in the aggregate. The bottom left panel highlights the growth spurt in the year after an insured disaster. If a country receives the average insured loss (5% worth of GDP) as insurance payouts, it tends to grow more than 3 percentage points faster in the following year than a country suffering the same uninsured mean loss with no insurance (see Table 3, column 2). Over time, the positive growth effects reverse and the confidence interval widens. The cumulative growth response (bottom right panel) is surrounded by a confidence band that includes the x-axis: the growth-enhancing effects eventually turn insignificant.

The differential responses in Figure 2 illustrate the *mitigating* effect of insurance. This effect plays a role even if insured losses do not deliver a positive growth spurt: since insured losses are less damaging to the economy than uninsured losses, insurance coverage helps mitigate the adverse macroeconomic effects by shifting the balance from uninsured to insured losses.

Fourth, the mitigating effect likely reflects the role of insurance in financing reconstruction. Insurance payouts help finance reconstruction investment, which contributes to measured GDP growth. Property insurance automatically targets the repair or replacement of those facilities that private agents had deemed important enough to insure, often those that serve a productive purpose. These incentives ex ante provide the mechanism that allocates funds for rebuilding ex post. As such, insurance payouts are more geared toward economic recovery than other forms of ex-post compensation. Aid disbursements or emergency spending by the government primarily respond to the humanitarian exigencies of saving lives and reducing human suffering.[30]

The time profile in Figure 2 also suggests that insurance helps the economic recovery. The bottom left panel shows that the growth-enhancing effects accrue mostly from the time of impact through year 2 after the disaster. This is the horizon over which investment and reconstruction efforts take place, as documented in numerous case studies. Insurance compensation is paid out over a slightly shorter horizon: typically about two thirds of catastrophe-related payouts are reimbursed within the first year of the disaster, with a peak in payouts in the second quarter after the disaster (Figure 3). To the extent that insurance payouts help finance reconstruction, it is plausible that economic activity shares similar dynamics (comparing Figures 2 and 3). The estimated growth effects match the time profile not only as funds come in; they also subside once insurance payments start to peter out in year 3 after the disaster.

The mitigating effect of insurance suggests that financial constraints often hold back the recovery of economies affected by disasters. The role of insurance in funding the rebuilding effort has been identified in randomised field experiments and case studies. Runyan (2006) finds that in the wake of Hurricane Katrina (August 2005), firms with insurance promptly replaced destroyed assets whereas those without insurance did not; in the context of the December 2004 Asian tsunami, De Mel et al. (2011) use random allocations of cash grants to firms and find that providing additional capital accelerated the recovery. Whether a country can grow its way out of a disaster by repairing infrastructure and productive assets often depends on the financing available (Cummins and Mahul 2009, World Bank and United Nations 2010).

More surprising is that the *contemporaneous* impact of insured losses is found to be insignificant (Table 3, column Impact). One would expect a disaster to cause a certain amount of destruction, with insurance at best speeding up the subsequent recovery as payouts finance reconstruction. Yet, the year-0 impact of losses is lower when insured. Perhaps owners of insured assets can more easily borrow to rebuild when they (and their banks) know that compensation will be paid out.[31] Insurance arrangements also contribute to prevention and preparedness ex ante. Insurance companies may insist on solid building codes as a condition for coverage, and promote best practice in disaster management - not least to limit their own liability.[32] There is consensus

[30] Aid flows respond to the number of killed and affected people as well as media coverage (Eisensee and Strömberg 2007). However, since donors respond after a catastrophe strikes, not enough is being done for prevention (World Bank and United Nations 2010).

[31] This channel is also consistent with the positive interactions on banking and lagged credit-to-GDP in Table 3.

[32] This form of assistance works primarily through the transfer of knowledge. This may explain why Crespo

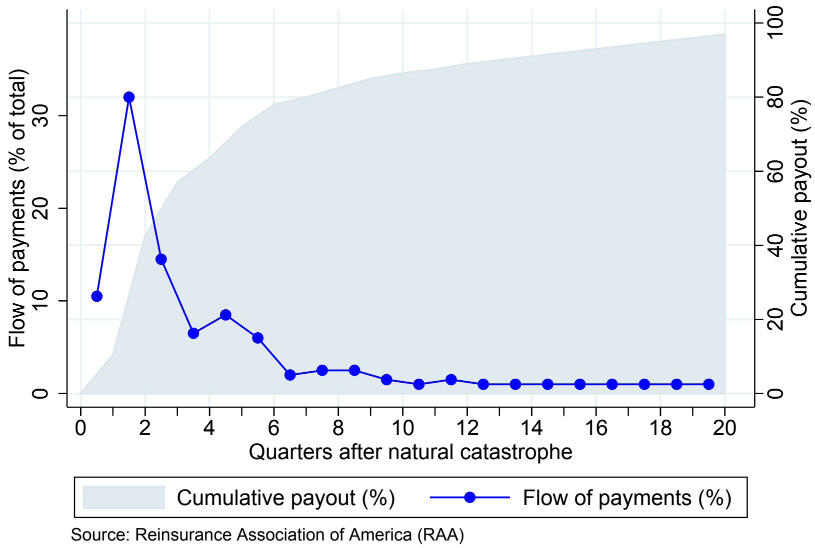

Figure 3: The Profile of Insurance Payments.
The figure shows the average flow of insurance payments (line, left axis) and the cumulative payout (shaded area, right axis), as shares of the total ultimate payout on "catastrophe excess of loss" contracts, based on worldwide observations. Point "0" represents the date of the natural disaster. Several factors contribute to the payout pattern following a disaster, including varying reporting timelines by the insured vis--vis the insurer and demanding damage analysis undertaken by the insurer; the balance between immediate payouts vs additional payments after the full damage has been assessed; specific timing provisions in certain contracts, such as business interruption insurance. Source: Reinsurance Association of America (RAA).

that various forms of disaster prevention and preparedness have potential, but too little is done in practice (World Bank and United Nations 2010).

3.3 Refinement: Physical Types of Disasters

So far we estimated lag structures for insured and uninsured losses regardless of their type. Yet natural disasters differ in their physical characteristics: earthquakes bring instant destruction, whereas droughts build up over months or years. The macroeconomic response will differ accordingly. Some physical types also tend to be well insured (e.g. storms), while others are largely uninsured (e.g. droughts, see Table 1).

To nuance the role of risk transfer in the light of such heterogeneity, Table 4 estimates regression (4) expanded to include separate lag structures for each of the four main physical types.[33]

et al. (2008) find little evidence of technological transfer following natural disasters when looking for imports of technology-related goods.

[33]Insurers face challenges when classifying losses by physical type. Multi-type catastrophes are generally coded by the triggering event (Wirtz et al. 2012). Accordingly, Japan in March 2011 first suffered an earthquake,

We maintain the un/insured distinction, fixed effects, and development controls with interactions (as in Table 3, "All controls"). To preserve degrees of freedom, we reduce the number of lags; lags in years 3 and 4 after the disaster (or crisis) tend to be insignificant or small.

Geophysical events register the largest growth effects (Table 4, full sample). A typical earthquakes or volcanic eruption in the sample (causing 4.43% in direct losses) entails a macroeconomic cost of 6.36% of GDP, curbing growth by 2.07% in the first year alone. By contrast, insurance turns negative into positive growth effects yielding a cumulative expansion of 2.08% of GDP. The growth response to mean disasters is much larger, to the point of being implausible (blue shaded results).[34] The analysis by type comprises only 48 major geophysical events, and includes extreme earthquakes and volcanic eruptions - such as the destruction of Montserrat Island in 1995-1997, a direct loss reported at 800% of GDP.

The other three physical types, with more than 100 observations each, produce growth responses in line with earlier estimates. Uninsured losses generally harm growth: mean uninsured losses from meteorological disasters (storms) and climatological events (droughts, wildfires, and extreme temperatures) reduce growth on impact and cost nearly 5% of GDP in cumulative terms. The growth slowdown we identified in year two after a disaster (Table 3) apparently stems from climatological events, which include long-lasting droughts. The only physical type for which we find no significant growth effects is hydrological, which includes flooding, storm surges and wet landslides, although specific events will differ from average estimates.

By contrast, insured losses tend to be expansionary for most physical types - albeit with distinct dynamics. Geophysical, meteorological and climatological disasters see positive long-term effects on growth when insured. The opposite holds for hydrological events, though with fewer observations and marginal significance. The timing of the growth responses largely reflects the physical type of the disaster. Positive growth effects within the year of a disaster only occur for geophysical events, perhaps because the damage can be assessed and paid out sooner (Table 4, row "Impact"). For meteorological and climatological events, on the other hand, the growth-enhancing effects of insurance materialise later, in the year after the disaster (row "Lag 1"). These differences may explain why the impact of insured losses appeared insignificant when all physical types were pooled in Tables 2 and 3.

These findings are not limited to rich countries, which tend to be better insured. The growth effects, both positive and negative, remain largely unchanged when excluding the countries in the top income group (Table 4, column 2). Controls and interactions capturing development have been carried over from Table 3. As before, uninsured losses cause significant macroeconomic costs, whereas insured losses tend to fuel growth over time as countries rebuild - only hydrological events appear to harm growth even when insured.

[**Table 4: The Cost of Disasters of Different Physical Types**]

Our disaggregated analysis helps disentangle conflicting findings in the literature. Papers that

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even as the flooding (tsunami) and the nuclear incident added to recorded losses.

[34] Table 4 implies a 12% contraction following uninsured mean losses, even larger than that following Haiti's 2010 earthquake, where growth dropped by 10 percentage points within the year (and recovered shortly after). More questionable sill is the 20% expansion estimated for a fully insured disaster.

estimate separate growth effects by physical type do not distinguish insured from uninsured losses. Most notably, Loayza et al (2012) study medium-term growth effects of the same four physical types included here; they usefully distinguish sectors (agriculture, industry, and services), but estimate coarser dynamics (5-year growth averages) and use the share of population hurt rather than data on economic losses or insurance. They find storms to be inconsequential for overall growth (except for severe storms). Using Caribbean hurricane track data, however, Strobl (2012) estimates an output loss of 0.83%. When conditioning on risk transfer, our results suggest that **storms** are typically harmful when uninsured (-2.17%) but growth-enhancing when insured ($+1.97\%$), with responses as large as $\pm 5\%$ for mean storms (Table 4, meteorological). Ignoring insurance confounds the positive and negative effects and produce an estimate near zero, since about 50% of storms have been insured (Table 1).

Loayza et al. (2012) also find **droughts** to be costlier than any other type of disaster. This may reflect relatively poor insurance coverage for droughts: 85% of climatological events - including droughts in Africa - are entirely uninsured (Table 1). The macroeconomic cost could likely have been mitigated with better risk transfer, judging by the results for insured climatological losses. For **flooding**, the positive effects found by Loayza et al. (2012) and Fomby et al. (2009) are not iconsistent with our estimate of an (insignificant) response, since floods disrupt activity but also deposit nutrient-rich silt and increase hydroelectric power boosting industrial growth (World Bank and United Nations 2010). Finally, for **geophysical** catastrophes, Loayza et al. (2012) and Raddatz (2007) find no systematic impact on GDP, perhaps because their (smaller) samples exclude many poorer countries that appear to drive our results for this physical type.

The results in Table 4 are informative, but also less stable than earlier results since we estimate many more coefficients on fewer disasters per physical type. The results for all types combined (Tables 2-3) are rather robust. Appendix 2 reports specific tests to examine whether our findings hold up to various changes in specification (Table A2). These include changes to the scaling of losses, the cutoffs used to define disasters, accounting for a break in the quality of loss data, and the use of GDP per capita as the main dependent variable. These experiments change the point estimates of impact and long-term costs, but do not alter any of our main findings.

4 Concluding Remarks

This paper shows that major natural catastrophes harm economic growth, over and above the direct destruction of property and infrastructure. In a large panel of more than 200 countries and jurisdictions over 55 years, we document how the initial impact of major disasters gives way to subdued growth over several years, adding to the overall cost of disasters. This rich dynamic has gone largely unnoticed in existing studies. The overall macroeconomic cost exceeds the short-term impact by a factor of two or more. We estimate a growth impact of nearly 1 percentage points for a typical event (more for a mean disaster) and a cumulative output loss in the range of 2 to 4%. “Unmitigated disasters” thus belong to a class of macroeconomic shocks - alongside wars, political and financial crises - from which economies do not fully recover.

Our main novel finding is that risk transfer helps to mitigate the macroeconomic cost of disasters. Uninsured losses drive the macroeconomic cost of disasters, whereas insured losses leave no forgone output in the aggregate. The evidence for some physical types even suggests that insured losses boost growth over time as countries rebuild. The strongest growth-enhancing effects appear in the first three years after impact, in line with the average timing of insurance payouts. The mitigating role of risk transfer stands out across physical types of catastrophes, and can be helpful at any stage of development.

The case of natural disasters thus suggests that insurance has measurable macroeconomic value. Whether it is desirable to seek high coverage and international reinsurance depends on the frequency of catastrophes and on the cost of (re)insurance, which can be relatively high. The macroeconomic value we identify adds to the benefit side, but the cost of (re)insurance remains as relevant for choosing the optimal degree of coverage (Kunreuther and Michel-Kerjan 2009, Part II, and Borensztein et al, 2017). This is presumably why losses from disasters are shared internationally to a much lesser extent than the theory of international risk-sharing would suggest (Ito and McCauley, 2022).

The paper also adds to the literature on rare disasters by putting natural catastrophes on the map at a time when climate change underscores their growing importance. The finding that risk transfer plays a mitigating role suggests that financial instruments can alter the transmission of shocks to render the macroeconomic consequences transitory rather than permanent. By providing evidence on the macroeconomic value of insurance, the paper also contributes to the policy debate on the effectiveness of different forms of disaster-related spending. When assessing the balance between prevention ex ante and compensation ex post, the macroeconomic value identified in this paper should be part of a wider cost-benefit analysis.

Appendix

A.1. Data Appendix

Data Sources. All catastrophe-related data are from NatCatService of Munich Re, a global reinsurance group. Most macroeconomic data come from the World Bank's *World Development Indicators* (WDI), notably the real GDP growth series (dependent variable) described in the text, where we complement missing countries and jurisdictions with the United Nations' *National Accounts* data where available. Control variables include the World Bank's country income classification, aid flows and official development assistance from WDI, and variables measuring access to banking, credit and insurance from the World Bank's *Global Financial Development Database* (GFDD). Finally, man-made disasters, including financial crises, political crises and wars, are from Laeven and Valencia (2012) and other sources listed in Table A1.

[Table A1: Variables and Data Sources]

To prevent the inclusion of macroeconomic controls to decimate sample size, we run two fill-in operations on control variables. First, aid flows and official development assistance are set to zero for countries and periods with missing data. (Rich and most middle income and countries do not receive such flows anyway.) Similarly, missing data on man-made disasters were replaced by zeros, assuming that if there had been wars or crises they would be included in the respective sources (Table A1). Second, structural variables controlling for the stage of development, such as access and GDP/capita, were instead filled in by carry-operations, carrying forward the latest reported value, and carrying backward the first reported value. This operation only extends data for countries that reported the relevant series at some point; it does not fill in values for countries that lack the respective series altogether.

Aggregation. Two aggregation issues arise in matching disaster-related losses to the macroeconomic panel. First, natural catastrophes do not respect national borders - a case in point is the Indian Ocean Tsunami (26 December 2004) that affected many countries.[35] It was important to confirm that supranational events affecting entire regions come with country-level information needed for our approach. Testing the consistency between two datasets obtained from Munich Re (one event-based, one country-based) led to the conclusion that the reported country breakdowns consistently allocate the losses from supranational events to individual countries. Further tests also spoke to the quality of the NatCat statistics, e.g. the size of insured losses relative to total losses, and the completeness of earlier loss data (pre-1980) when compared to EM-DAT.

Second, the NatCat statistics must be matched with macroeconomic time series at the annual frequency. Where countries suffered several catastrophes within a single year, we aggregate all

[35] The event caused 220,363 fatalities and $12.055 billion in direct losses overall, which Munich Re 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 less affected countries.

disasters within a given year to obtain a unique observation for each country-year pair, $L_{it} = \Sigma_j\ loss_{jit}$ (see Table A1). This allows a series of smaller events to be as consequential as a single larger disaster. This step consolidates more than 22,000 individual disaster events into 1,954 observations at the country-year level, while retaining the number and type of disasters by folding this information into additional variables (Section 3.3 uses disaster losses by physical type). Total losses are split into their parts, where insured losses equal $T_{it} = \Sigma_j\ ins_{jit}$ and uninsured losses are the residual $U_{it} = L_{it} - T_{it}$. Finally, the severity of a disaster is defined by the natural log transform $x_{it} = \ln(L_{it}/GDP_{it} + 1)$, as shown in Table A1 and explained in Section 1.4.

A.2. Further Robustness Tests

Table A2 examines how changes in specification affect our main regression, departing from the "All controls" specification of Table 3 (reproduced here in column 0). Varying the number of lags or controls generally makes no material difference (not reported). Our long lag structure appears to captures the dynamics adequately.[36] A more substantive change is to alter the scaling and cutoffs used to define disasters (columns 1-3).

Column 1 considers the simplest definition of a disaster: an indicator valued 1 if disaster losses exceed 1% of a country's GDP in a year, and 0 otherwise. The estimated impact equals −1.15%, reducing growth more than in the main regression since the indicator pools all disasters, including those more severe than the median. The cumulative macroeconomic cost (1.75% of GDP) exactly equals that of uninsured median-sized disasters in column 0. As the indicator disregards the magnitude of losses, the cells for mean scaling and insured losses are empty. While not our preferred specification, it does have the virtue of true exogeneity: the *occurrence* of a natural disasters is independent of prevailing economic conditions; this is not necessarily the case for the *magnitude* of losses.

Column 2 reverts to disaster losses in percent of GDP, but allows for a more inclusive cutoff. Including all disasters causing 0.5% of GDP or more in damage (instead of 1% or more) raises the number of event-years from 355 to 556. As expected, this extension weakens the estimated responses while leaving significance and signs unchanged (comparing columns 0 and 2). Insured losses still support growth in the year after the disaster. Uninsured mean disasters now cost 2.7% (instead of 3.4%) of GDP; the 201 smaller disasters (below 1% in direct losses) have milder indirect macroeconomic effects. *Raising* the cutoff instead yields greater estimated growth effects (not reported). More severe natural catastrophes produce greater macroeconomic costs.

[36] This is the case even though some disasters occur relatively late in the year. In an earlier experiment, we altered the match between the event date and the impact year in the dataset (not reported). When events after month 9, 10 or 11 (e.g. the Indian Ocean Tsunami of December 26, 2004) are attributed to the *next* calendar year, estimates hardly change. Allocating events after month 6 to the next year, however, makes the negative impact weaker without strengthening subsequent lags - their impact is now confounded with next year's reconstruction activity. Conceptually, imposing earlier thresholds raises the risk of missing the early impact with no corresponding gain - hence we work with the original-year match, knowing that the lag structure takes care of any delay in growth effects over time.

Column 3 runs the main regression using the *level* of dollar losses as a measure of severity.[37] The mean level of losses, both insured and uninsured, exceeds median losses by a factor of more than 10 (italicized rows in column 3). The estimated growth responses come out stronger than in the main regression, at least for typical (median) losses. Insured losses tend to boost growth in year one *and* year two after the disaster, but the long-term effect remains insignificant (but significantly better than that of uninsured losses). These experiments make clear that quantitative information on damage to property and infrastructure is useful for identifying how disasters affect a country's growth path.

Next, we consider an alternative dependent variable, *GDP per capita,* a measure of the standard of living (column 4). Sample size falls by 465 observations; the estimated impact remains unchanged, but the long-term cost of uninsured losses falls to 2.6% for mean losses. For insured losses, the year after impact remains expansionary, partly offset by slower growth in year four. The findings remain qualitatively unchanged, if slightly weaker. Perhaps GDP per capita falls less for disasters with large death tolls (e.g. the 2010 earthquake killed 2-3% of Haiti's entire population). Yet disasters that decimate the population should not be associated with higher living standards. We thus prefer the real-growth specification, which captures the pattern of recovery of the economy as a whole.

The remaining columns test two specifications to address specific concerns. Column 5 runs the main regression replacing the time trend with time fixed effects to capture time-varying global factors. This weakens the estimated growth effects of uninsured losses without altering those of insured losses that still help boost growth in the year after a disaster. The yearly dummies identify global recession years (eg 1981-1983, 1991-1993 and 2009); however, various nearby years also witnessed disasters in at least twice as many countries as the average of 7 countries (1980, 1992, 1993 and 2007).

Finally, the NatCatService statistics became more comprehensive after Munich Re enhanced its data collection in 1980. Column 6 limits the main regression to the post-1980 sample. The growth responses to uninsured losses are more pronounced than in column 0 (while those for insured losses are similar). It is likely that major disasters (exceeding our cutoff of 1% of GDP) were well covered even before 1980. The result also suggests that the resilience to disasters shows little sign of having improved in more recent decades.

The results continue to point to uninsured losses as the key driver of the macroeconomic cost of disasters: they entail persistent costs, ranging from 1 to 4% of foregone GDP; insured losses, by contrast, tend to be expansionary in the year after a disaster or inconsequential overall. Insurance, even partial, thus helps mitigate the macroeconomic cost of disasters.

[37] We maintain the inclusion cutoff at 1% to keep the sample of disasters in line with that of the main regression.

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Table A1: Variable Definitions and Data Sources

Dep. variable: y_{it} = annual growth rate of real GDP, in %	World Bank (WDI), UN (SNA)
GDP in per capita, in constant US dollars	World Bank (WDI), and UN (SNA)
Country classification by income groups	World Bank (WDI)
Banking crisis = 1 in year crisis starts, 0 otherwise	Laeven-Valencia (2012), updated
Currency crisis = 1 in year crisis starts, 0 otherwise	Laeven-Valencia (2012), updated
Debt crisis = 1 in year crisis starts, 0 otherwise	Laeven-Valencia (2012), updated
Polit. crisis = 1 in year regime turns authoritative, 0 otherwise	Polity IV Dataset (executive constraint)
War = 1 in year war starts, 0 otherwise	Correlates of War Dataset, updated
Net official aid received, % of GDP	WDI
Net official development assistance, % of GNI	WDI
Access to banking: bank branches per 100,000 adults	Global Fin. Development Database (GFDD)
Access to insurance: nonlife insurance premia, % of GDP	GFDD
Access to credit: small firms with a bank loan or line, in %	GFDD
and domestic credit to the private sector, % of GDP	GFDD
$loss_{jit}$ = total loss (in \$ millions) for event j in country i, year t	NatCat Service, Munich Re
ins_{jit} = total insured loss (in \$ millions) for event j in (i, t)	NatCat Service, Munich Re
L_{it} = total losses from disasters in country-year pair (i, t)	$\Sigma_j \; loss_{jit}$ (by physical type)
T_{it} = insured part of total losses	$\Sigma_j \; ins_{jit}$ (by physical type)
U_{it} = uninsured part of total losses	$U_{it} = L_{it} - T_{it}$ (by physical type)
$N_{it} = 1$ if disaster losses exceeded 1% of GDP in year t	$N_{it} = 1$ if $L_{it}/GDP_{it} \geq 0.01$, else 0
Severity of disasters (total losses) x_{it}	$x_{it} = \ln(L_{it}/GDP_{it} + 1)$
Severity of disasters (insured losses) τ_{it}	$\tau_{it} = \ln(T_{it}/GDP_{it} + 1)$
Severity of disasters (uninsured losses) v_{it}	$v_{it} = \ln(U_{it}/GDP_{it} + 1)$.

Table 1 – Features of Natural Disasters (1960-2011)

	Properties	All types	Geophysical [A]	Meteorological [B]	Hydrological [C]	Climatological [D]
				Weather-related events		
Frequency	*# All events (types in %)*	21,768	*12%*	*42%*	*34%*	*12%*
	# Major events	1,566	158	525	475	408
	Africa	263	12	32	59	160
	Asia	463	60	137	200	66
	Europe	259	26	66	96	71
	Americas	425	46	200	97	82
	Pacific	156	14	90	23	29
Severity	*Maximum fatalities*	*300,000*	*242,769*	*300,000*	*26,000*	*300,000*
	Mean fatalities	*1,709*	*7,642*	*1,449*	*205*	*1,499*
	Maximum loss ($ billions)	210	210	144	43.0	28.6
	Mean loss ($ billions)	1.64	5.73	1.38	1.39	0.69
	Mean loss (% of GDP)	5.0	12.8	7.6	1.8	2.5
	Median loss (% of GDP)	0.5	0.7	0.5	0.3	0.6
Risk transfer	Insured events (% of all events)	24.8	43.0	36.4	21.7	6.4
	Mean coverage (if positive)	31.0	20.2	37.1	25.1	37.2
	Std deviation of coverage (if>0)	27.6	25.5	26.5	27.1	30.4
	Std deviation of coverage overall	19.2	19.4	24.0	16.3	11.8

Notes: The first row covers all events recorded from 1960 to 2011 in the NatCat statistics received from Munich Re, broken down by physical typ
The remaining rows summarize major events, defined as those with reported economic losses exceeding 0.1% of the affected country's GDP.
The table columns follow the standard categorization for physical types:

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: Authors' calculations based on data from Munich Reinsurance Company, Geo Risks Research, NatCatSERVICE.

Table 2: The Macroeconomic Cost of Natural Disasters – Baseline Results

		Ignoring risk transfer				Distinguishing insured from uninsured losses					
	Explanatory variables	(1) Largest sample		(2) Basic controls		(3) All countries		(4) All but rich		(5) Poorer countries	
Uninsured disaster losses	*Median loss in % GDP*	*3.19*		*3.19*		*2.97*		*3.14*		*3.03*	
	Impact on growth	-1.00^{***}	(0.12)	-0.95^{***}	(0.12)	-0.83^{***}	(0.15)	-0.88^{***}	(0.15)	-0.95^{***}	(0.18)
	Lag 1	−0.13	(0.13)	−0.09	(0.13)	−0.09	(0.18)	−0.10	(0.18)	−0.14	(0.21)
	Lag 2	-0.49^{*}	(0.17)	-0.44^{*}	(0.17)	−0.39	(0.17)	-0.44^{*}	(0.18)	-0.54^{*}	(0.22)
	Lag 3	0.12	(0.10)	0.23	(0.11)	0.23	(0.12)	0.16	(0.12)	0.18	(0.14)
	Lag 4	0.02	(0.10)	0.00	(0.09)	0.17	(0.10)	0.14	(0.10)	0.16	(0.11)
	LT-effect in % of GDP	$\mathbf{-2.13^{***}}$	**[0.001]**	$\mathbf{-1.90^{***}}$	**[0.007]**	$\mathbf{-1.40^{**}}$	**[0.017]**	$\mathbf{-1.52^{***}}$	**[0.007]**	$\mathbf{-1.75^{***}}$	**[0.006]**
	Mean loss in % GDP	*15.4*		*15.4*		*13.9*		*15.1*		*15.9*	
	Impact on growth	-1.95^{***}	(0.12)	-1.85^{***}	(−5.61)	-1.63^{***}	(0.15)	-1.73^{***}	(0.15)	-1.92^{***}	(0.18)
	LT-effect in % of GDP	$\mathbf{-4.16^{***}}$	**[0.001]**	$\mathbf{-3.71^{***}}$	**[0.007]**	$\mathbf{-2.75^{**}}$	**[0.017]**	$\mathbf{-2.97^{***}}$	**[0.007]**	$\mathbf{-3.55^{***}}$	**[0.006]**
Insured disaster losses	*Median loss in % GDP*					*0.34*		*0.24*		*0.46*	
	Impact on growth					−0.15	(0.45)	-0.20^{*}	(0.50)	-0.45^{*}	(0.64)
	Lag 1					−0.01	(0.76)	−0.05	(1.02)	−0.46	(1.09)
	Lag 2					−0.03	(0.26)	−0.03	(0.35)	0.08	(0.41)
	Lag 3					−0.02	(0.37)	0.02	(0.45)	0.17	(0.53)
	Lag 4					-0.21^{***}	(0.24)	-0.14^{**}	(0.31)	−0.28	(0.49)
	LT-effect in % of GDP					**−0.63**	**[0.32]**	**−0.54**	**[0.36]**	**−1.27**	**[0.34]**
	Mean loss in % GDP					*5.28*		*5.34*		*9.83*	
	Impact on growth					−0.95	(0.45)	-1.71^{*}	(0.50)	-2.85^{*}	(0.64)
	LT-effect in % of GDP					**−3.98**	**[0.32]**	**−4.63**	**[0.36]**	**−7.98**	**[0.34]**
Basic controls	Growth Lag 1	0.22^{***}	(0.04)	0.20^{***}	(0.05)	0.20^{***}	(0.05)	0.17^{***}	(0.06)	0.19^{**}	(0.07)
	Lag 2	0.09^{***}	(0.02)	0.09^{***}	(0.03)	0.09^{***}	(0.03)	0.07^{***}	(0.02)	0.07^{**}	(0.03)
	Lag 3			0.08^{***}	(0.03)	0.08^{***}	(0.03)	0.05^{***}	(0.02)	0.07^{***}	(0.02)
	Lag 4			−0.02	(0.03)	−0.02	(0.03)	−0.03	(0.02)	-0.05^{*}	(0.03)
	Log GDP/capita			−0.67	(0.53)	−0.66	(0.54)	0.46	(0.49)	0.76	(0.61)
	Time trend			−0.01	(0.01)	−0.01	(0.01)	−0.01	(0.01)	−0.01	(0.01)
	Fixed effects	included		included		included		included		included	
Sample	# Observations	8,921		8,459		8,459		5,814		3,705	
	# Countries	214		212		212		148		93	
	# Event-years	460		445		445		392		277	
	R^2	0.115		0.104		0.105		0.076		0.086	

Notes. Table 2 reports fixed-effects regressions on an unbalanced panel (1960-2015), of real GDP growth on disaster-related losses: columns (1)-(2) are based on equation (1) in the main text, columns (3)-(5) on equation (4) that distinguishes between insured and uninsured losses. Column (1) runs a parsimonious specification to maximize sample size; the remaining columns use four growth lags and basic controls (a time trend and GDP per capita to proxy for development).

The regressions distinguishing insured losses start with the all-countries baseline (Column 3), followed by subsamples based on the World Bank income classification (4 groups): Column (4) excludes high-income countries (retaining 3 groups), while Column (5) retains only 2 groups, low-income and lower-middle-income economies. All columns show robust standard errors (in parentheses), and report the significance of long-term effects based on a non-linear Wald test evaluating equation (3) [p-values in square brackets]. Stars represent standard significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Disaster losses are expressed in (the logarithm of) percent of GDP and include event-years with disasters causing direct losses of 1% of GDP or more in a given year. For reference, the *rows in italics* report the severity of events in the (sub)samples, i.e. the median direct losses from disasters in percent of GDP. All disaster coefficients are scaled by the log severity of disasters in the respective subsample, as defined in equation (2) for the impact, and in equation (3) for the long-term effect (LT-effect, bold font). The blue shaded rows present the same coefficient estimates, scaled instead by the log severity of *mean* losses, which far exceed median losses (comparing italicized rows). To save space, the shaded rows only report the scaled impact and the long-term effects.

Table 3: Controlling for the Stage of Development

	Explanatory variables	(1) Access and Aid						(2) All Controls					
		Impact	Lag 1	Lag 2	Lag 3	Lag 4	LT-effect	Impact	Lag 1	Lag 2	Lag 3	Lag 4	LT-effect
Uninsured losses	*Median: 2.97% of GDP*												
	Effects on growth	-1.00***	-0.30	-0.54***	0.40**	0.17	**-1.95****	-0.89***	-0.29	-0.48**	0.38**	0.12	**-1.75****
	Mean: 13.9% of GDP												
	Effects on growth	-1.96***	-0.59	-1.06***	0.77**	0.33	**-3.81****	-1.75***	-0.57	-0.95**	0.74**	0.24	**-3.43****
Insured losses	*Median: 0.34% of GDP*												
	Effects on growth	0.04	0.58***	0.19	-0.12	-0.22	**0.70**	0.07	0.57***	0.15	-0.11	-0.21	**0.71**
	Mean: 5.28% of GDP												
	Effects on growth	0.27	3.67***	1.17	-0.77	-1.42	**4.43**	0.43	3.57***	0.96	-0.67	-1.30	**4.46**
Basic controls	Growth Lags		0.19***	0.08**	0.08**	-0.01			0.18***	0.07**	0.08**	-0.01	
	Time trend	0.01						0.00					
	Fixed effects	included						included					
	Log GDP/capita	-0.58						-0.72					
	* interactions	-0.36	-0.71**	-0.56*				-0.29	-0.73**	-0.47			
Access to finance	Access to banking	-0.00						-0.01					
	* interactions	0.04*	0.04**	0.04*				0.04*	0.05***	0.03			
	Access to insurance	-0.20**						-0.12					
	* interactions	0.31	0.26	-0.07				0.09	0.19	-0.04			
	Credit-to-GDP %	-0.02***						-0.02***					
	* interactions	0.00	0.01	0.02*				0.00	0.01	0.02**			
Aid flows	Net Aid flows	0.13						0.39					
	* interactions	-6.59***	2.01***	-0.17				-7.22***	1.41*	-0.53			
	Net Off.Dev.Assist	-0.02						-0.02					
	* interactions	0.01	0.10**	0.04				-0.00	0.09*	0.03			
Man-made crises	Banking crises							-1.69***	-2.35***	0.50	0.14	0.03	**-5.02*****
	Currency crises							-1.87***	0.11	0.65	0.65	0.94*	**0.72**
	Debt crises							-4.05***	-1.92*	-0.50	1.10	-0.99	**-9.50*****
	Political crises							-2.28**	1.27	-0.67	0.45	-0.68	**-2.88**
	Wars							-3.44***	-1.85	-0.49	0.36	0.01	**-8.07*****
Sample	# Observations	6,812						6,812					
	# Countries	162						162					
	# Event-years	355						355					
	R^2	0.098						0.122					

Notes. Table 3 extends the baseline regression distinguishing between insured and uninsured losses (Table 2, column 3) by adding three groups of controls: Access to finance (the 3 variables shaded green), Aid flows (2 variables, yellow) and Man-made crises (5 types of crises, red). Appendix 1 lists definitions and data sources. The controls for access, aid and development enter both alone and interacted with a disaster dummy to test whether they matter (more) in years when natural disasters strike and in the following two years. The long-term effects (LT-effect, in bold) of natural disasters and man-made crises are based on estimated impacts and four lags of the respective variables, computed as in equation (3).

All other aspects remain as in Table 2, including the scaling of disaster losses and loss-related coefficients. The blue shaded rows scale disaster coefficients by *mean* severity. All regressions include four autoregressive lags, country fixed effects and basic controls. Insured and uninsured losses enter contemporaneously and with four lags each. To save space, Table 3 reports all lags (including lags of interactions) in columns and omits robust standard errors and p-values from testing long-term effects, showing significance levels as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The Cost of Disasters of Different Physical Types

		(1) Full sample				(2) All but rich countries			
	Explanatory variables	Geophys.	Meterol.	Hydrol.	Climatl.	Geophys.	Meterol.	Hydrol.	Climatl.
Uninsured losses	*# Event-years*	*48*	*114*	*101*	*109*	*38*	*101*	*94*	*101*
	Median loss in % GDP	*4.43*	*2.85*	*2.38*	*2.45*	*4.88*	*3.03*	*2.47*	*2.79*
	Impact on growth	-2.07^{**}	-1.00^{**}	-0.42	-1.03^{**}	-2.68^{**}	-0.99^{**}	-0.53	-1.12^{**}
	Lag 1	-1.40	-0.31	0.35	-0.38	-2.24	-0.30	0.37	-0.36
	Lag 2	-1.16	-0.27	-0.39	-0.78^{*}	-1.94	-0.36	-0.41	-0.86^{*}
	LT-effect in % GDP	$\mathbf{-6.36^{*}}$	$\mathbf{-2.17^{**}}$	$\mathbf{-0.64}$	$\mathbf{-3.00^{***}}$	$\mathbf{-8.81^{*}}$	$\mathbf{-2.11^{**}}$	$\mathbf{-0.74}$	$\mathbf{-2.99^{***}}$
	LT-effect p-value	0.093	0.018	0.510	0.003	0.075	0.021	0.431	0.004
	Mean loss in % GDP	*27.6*	*17.5*	*6.77*	*6.76*	*32.1*	*19.6*	*7.15*	*7.11*
	Impact on growth	-4.09^{**}	-2.17^{**}	-0.71	-1.70^{**}	-5.31^{**}	-2.15^{**}	-0.90	-1.75^{**}
	LT-effect in % GDP	$\mathbf{-12.6^{*}}$	$\mathbf{-4.69^{**}}$	$\mathbf{-1.07}$	$\mathbf{-4.96^{***}}$	$\mathbf{-17.4^{*}}$	$\mathbf{-4.59^{**}}$	$\mathbf{-1.24}$	$\mathbf{-4.70^{***}}$
Insured losses	*Median loss in % GDP*	*0.25*	*1.37*	*0.10*	*0.43*	*0.27*	*0.97*	*0.05*	*2.21*
	Impact on growth	0.42^{**}	0.04	-0.23^{*}	-0.37^{*}	0.69^{**}	0.01	-0.24^{*}	-1.41^{**}
	Lag 1	0.49	1.64^{***}	0.16	1.44^{***}	0.92	1.34^{***}	0.16^{*}	5.83^{***}
	Lag 2	0.60^{*}	-0.25	0.08	-0.24	1.12^{**}	-0.19	-0.03	-1.96^{***}
	LT-effect in % GDP	$\mathbf{2.08^{**}}$	$\mathbf{1.97^{*}}$	$\mathbf{0.005}$	$\mathbf{1.14^{**}}$	$\mathbf{3.50^{**}}$	$\mathbf{1.49^{**}}$	$\mathbf{-0.14}$	$\mathbf{3.16^{**}}$
	LT-effect p-value	0.036	0.057	0.983	0.011	0.022	0.049	0.262	0.012
	Mean loss in % GDP	*7.49*	*6.85*	*0.29*	*0.77*	*9.72*	*6.29*	*0.23*	*2.21*
	Impact on growth	4.01^{**}	0.09	-0.63^{*}	-0.59^{*}	6.92^{**}	0.04	-0.93^{*}	-1.41^{**}
	LT-effect in % GDP	$\mathbf{19.9^{**}}$	$\mathbf{4.68^{*}}$	$\mathbf{0.01}$	$\mathbf{1.80^{**}}$	$\mathbf{35.0^{**}}$	$\mathbf{4.38^{**}}$	$\mathbf{-0.57}$	$\mathbf{3.16^{**}}$
Extended controls	Growth Lag 1	0.20^{***}				0.18^{***}			
	Lag 2	0.08^{**}				0.04^{*}			
	Time trend	-0.004				-0.004			
	Log GDP/cap + interacted	Included				Included			
	Access to banking	Included				Included			
	Access to insurance	Included				Included			
	Credit-to-GDP %	Included				Included			
	Net Aid flows	Included				Included			
	Net Off.Dev.Assist.	Included				Included			
Man-made crises	Banking crises: Impact	-1.67^{***}				-1.56^{**}			
	LT-effect	$\mathbf{-4.41^{***}}$				$\mathbf{-3.32^{**}}$			
	Currency crises: Impact	-2.16^{***}				-2.20^{***}			
	LT-effect	$\mathbf{-2.40^{*}}$				$\mathbf{-2.57^{**}}$			
	Debt crises: Impact	-3.93^{***}				-3.98^{***}			
	LT-effect	$\mathbf{-8.86^{***}}$				$\mathbf{-8.79^{***}}$			
	Political crises: Impact	-2.34^{***}				-2.65^{***}			
	LT-effect	$\mathbf{-2.45}$				$\mathbf{-3.19^{***}}$			
	Wars: Impact	-3.52^{***}				-4.01^{***}			
	LT-effect	$\mathbf{-7.44^{***}}$				$\mathbf{-8.34^{***}}$			
Sample	# Observations	7,109				4,950			
	# Countries	162				114			
	R^2	0.137				0.089			

Notes. Table 4 reports two regressions (1960-2015) based on equation (4) in the text, which allows for distinct estimates specific to each physical type: geophysical, meteorological, hydrological, or climatological disasters (see also Table 1). For reference, the *rows in italics* report the number of events and their *median* severity, based on disasters of this physical type causing direct losses of 1% of GDP or more in a given year. The blue shaded rows represent *mean* severities instead.

Column (1) reports full-sample results (as in Table 3, column 2), and column (2) excludes high-income countries (as in Table 2, column 2). As before, all long-term effects (LT-effect, in bold) are based on the estimated impacts and four lags (equation (3)). Both specifications use all the controls from Table 3. Only selected results are reported to save space; controls marked "included" enter contemporaneously in levels and interacted with a disaster dummy, and with two lags of the interaction term (as shown in Table 3, column 2). The notes to Tables 2-3 explain all other aspects. Similarly, the table omits robust standard errors and p-values from testing long-term effects, showing significance levels as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Further Robustness Experiments

		(0)	(1)	(2)	(3)	(3)	(5)	(6)
	Explanatory variables	Table 3	Indicator	Cutoff	Log-levels	Post-1980	GDP/capita	Yearly FEs
Uninsured disaster losses	*Median loss*	*2.97*	*2.97*	*1.66*	*$204mn*	*2.92*	*2.97*	*2.97*
	Impact on growth	-0.89^{***}	-1.15^{***}	-0.59^{***}	-1.02^{***}	-0.99^{***}	-0.87^{***}	-0.78^{***}
	Lag 1	-0.29	0.15	-0.20	-0.25	-0.32	-0.27	-0.15
	Lag 2	-0.48^{**}	-0.51^{*}	-0.33^{**}	-0.68^{**}	-0.34	-0.42^{**}	-0.41^{**}
	Lag 3	0.38^{**}	0.36	0.26^{**}	0.41	0.28	0.39^{**}	0.28
	Lag 4	0.12	-0.03	0.11	0.04	0.10	0.25	0.07
	LT-effect in % of GDP	**-1.75^{**}**	**-1.75^{**}**	**-1.11^{**}**	**-2.24^{**}**	**-1.96^{**}**	**-1.32^{*}**	**-1.47^{*}**
	Mean loss	*13.9*		*9.64*	*$2745mn*	*13.4*	*13.9*	*13.9*
	Impact on growth	-1.75^{***}		-1.42^{***}	-1.52^{***}	-1.94^{***}	-1.71^{***}	-1.53^{***}
	LT-effect in % of GDP	**-3.43^{**}**		**-2.68^{**}**	**-3.33^{**}**	**-3.82^{**}**	**-2.58^{*}**	**-2.89^{*}**
Insured disaster losses	*Median loss*	*0.34*		*0.23*	*$110mn*	*0.34*	*0.34*	*0.34*
	Impact on growth	0.07		0.01	0.34	0.10	0.03	-0.05
	Lag 1	0.57^{***}		0.38^{***}	1.39^{**}	0.57^{***}	0.56^{***}	0.51^{***}
	Lag 2	0.15		0.06	1.02^{**}	-0.10	0.10	0.16
	Lag 3	-0.11		-0.07	-0.69^{*}	-0.03	-0.16	-0.08
	Lag 4	-0.21		-0.16	-0.70	-0.25^{*}	-0.25^{*}	-0.18
	LT-effect in % of GDP	**0.71**		**0.34**	**2.03**	**0.44**	**0.38**	**0.54**
	Mean loss	*5.28*		*3.49*	*$1626mn*	*5.60*	*5.28*	*5.28*
	Impact on growth	0.43		0.07	0.53	0.66	0.16	-0.34
	LT-effect in % of GDP	**-4.46**		**2.48**	**3.18**	**2.89**	**2.41**	**3.39**
Man-made crises and development controls	Growth Lag 1	0.18^{***}	0.18^{***}	0.18^{***}	0.18^{***}	0.21^{**}	0.22^{***}	0.17^{***}
	Lag 2	0.07^{**}	0.07^{**}	0.08^{**}	0.07^{**}	0.06^{***}	0.05	0.07^{**}
	Lag 3	0.08^{**}	0.08^{**}	0.09^{**}	0.08^{**}	0.05^{***}	0.02	0.09^{**}
	Lag 4	-0.01	-0.01	-0.01	-0.01	0.03	0.02	-0.01
	Log GDP/cap + interacted	included	included	included	included	included	included	included
	Country fixed effects	included	included	included	included	included	included	included
	Time trend	0.00	0.01	0.01	0.00	0.05^{***}	0.02^{**}	Yearly FEs
	Access to banking	included	included	included	included	included	included	included
	Banking*event lag 0	0.04^{*}	0.03^{*}	0.02	0.04^{*}	0.03	0.04^{**}	0.03
	Banking*event lag 1	0.05^{***}	0.04^{**}	0.03^{**}	0.05^{***}	0.05^{**}	0.04^{**}	0.04^{**}
	Access to insurance	included	included	included	included	included	included	included
	Credit-to-GDP %	included	included	included	included	included	included	included
	Credit*event lag 2	0.02^{**}	0.02^{**}	0.02^{**}	0.02^{*}	0.007	0.02^{**}	0.01^{*}
	Net Aid flows	included	included	included	included	included	included	included
	Net Off.Dev.Assist.	included	included	included	included	included	included	included
	Man-made crises 5 types	included	included	included	included	included	included	included
Sample	# Observations	6,812	6,812	6,812	6,812	4,662	6,347	6,812
	# Countries	162	162	162	162	162	162	162
	# Event-years	355	355	556	355	294	347	355
	R^2	0.122	0.120	0.120	0.122	0.140	0.137	0.159

Notes. The table reports robustness experiments based on the more final development specification (Table 3 column 2) reproduced in column (0), using the same sample (1960-2015) and groups of controls with interactions and lags, except that column:

(1) uses a disaster **indicator** (ignoring severity): 1 for years where disasters cost 1% GDP or more, and 0 otherwise
(2) returns to the log of dollar losses as % of GDP, but with more inclusive **cutoff** (0.5% instead of 1% of GDP)
(3) replaces severity by the **level of losses,** expressed in constant 2011 US dollars (not scaled by GDP), in logs
(4) starts the sample in **1981** (instead of 1960), after Munich Re improved its data collection of disasters in 1980
(5) employs real growth in **GDP per capita** as the dependent variable (instead of real GDP growth)
(6) replaces the time trend by **time fixed effects**, with one separate estimate for each year from 1960 to 2015.

Only selected results are reported to save space; controls marked "included" enter contemporaneously in levels and interacted with a disaster dummy, and with two lags of the interaction term (as shown in Table 3, column 2). The notes to Tables 2-3 explain all other aspects. Standard errors and p-values from testing long-term effects (LT-effect) are omitted; significance levels and p-values are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.