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

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Abstract

This paper examines the patterns of macroeconomic recovery following natural disasters. In a panel with global coverage from 1960 to 2011, we make use of insurer-assessed losses to estimate growth responses conditional on risk transfer. We find that major disasters reduce growth by 1 to 2 percentage points on impact, and over time produce an output cost of 2% to 4% of GDP, on top of the initial damage to property and infrastructure. Akin to wars and financial crises, natural disasters have permanent effects, in the sense that output losses are not fully recovered over time. But it is the uninsured losses that drive the macroeconomic cost; insured losses are less consequential in the aggregate, and can even stimulate growth. By helping to finance the recovery, insurance mitigates the macroeconomic cost of disasters. Many countries lack the capacity to (re)insure themselves and would stand to benefit from international risk sharing.

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Introduction

Many results in macroeconomics depend on whether shocks have transitory or permanent effects. A growing literature documents that wars, political and financial crises 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 left many with the impression that losses have not been reversed over time. Yet, the endogenous nature of crises complicates this picture: poor economic performance increases the likelihood of crises in the first place, making their impact on output difficult to identify. This complication does not arise for natural disasters – they occur independently of economic conditions and present a clear case of cause and effect.

This paper shows that major natural disasters produce permanent output costs in the absence of risk transfer. They belong to a class of rare disasters from which countries do not fully recover. Fortunately, natural disasters can be insured, and insured losses have no adverse economic effects in the aggregate: risk transfer helps to mitigate the macroeconomic cost of disasters. However, only a share of disaster risk is insured, a fraction of which is reinsured internationally. Many countries could stand to gain from enhanced international risk sharing.

We examine the pattern of economic recovery after disasters in a large macroeconomic panel. Prior studies on the growth effects of disasters, surveyed in Cavallo and Noy (2011), Klomp and Valckx (2014) and Botzen et al (2019), differ widely in terms of methods, samples and the time horizon over which these effects are examined. While some focus on a specific physical type (e.g. cyclones), most rely on a public database covering all types of disasters. Apart from numerous case studies, most papers apply panel methods, while some use event studies (Borensztein et al 2017, Cavallo et al 2022) or synthetic control methods (Cavallo et al 2013). Some select disasters by their physical intensity (e.g. Strobl 2012, Felbermayr and Groeschl 2014, Bakkensen and Barrage, forthcoming), most others by the number or share of people killed. Moreover, limited data availability gives rise to different samples or time horizons over which economic effects are examined.[1] While each approach has its merits, there is little consensus on the shape of recovery; the short-term effect is negative, but the medium- to long-run effects remain elusive (Cavallo et al, 2022).

One contribution of our paper is to provide a unified analysis based on a dataset with global loss coverage. Our dynamic specification estimates the time profile of the growth response to disasters, encompassing impact and long-term effects. We rely on detailed statistics on disaster-related losses assessed by the insurance industry; they are more precise and complete than public data. With this, we identify major disasters by the immediate damage to property and infrastructure they cause. Direct losses are available for virtually all disasters, and may be more informative for economic growth than physical intensities or the number of lives lost in a

[1]For instance, Raddatz (2007), Noy (2009), Dermott et al (2014) and Felbermayr and Groeschl (2014) study the initial growth impact, others 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, Cavallo et al 2022). Some papers also estimate separate effects for different physical types (Fomby et al 2009, Loayza et al 2012).

natural disaster. The resulting dataset covers more than 200 countries and jurisdictions over a period of 52 years (1960-2011), merged with hundreds of disasters in four physical categories.

We find that major disasters are harmful to growth, leaving behind a permanent macroeconomic cost in terms of forgone output. This finding is not trivial, since the loss of physical capital is not part of measured GDP, whereas reconstruction investment is (supporting growth) – yet the negative effects dominate. On top of the immediate losses from damage to property and infrastructure, the initial hit to economic activity gives way to subdued growth in later years. The average response conceals substantial heterogeneity in individual growth paths following disasters; still, the distribution of growth outcomes looks worse after disasters than for periods without. In sum, the consequences of natural disasters are substantial and play out over years. Like wars and financial crises, "unmitigated disasters" are macroeconomic shocks with permanent effects.

Our second and most novel contribution is to show that the presence of risk transfer can turn these effects around. The negative growth response comes from *uninsured* disasters; *insured* losses can be inconsequential or even expansionary. Similar results hold for disasters of various physical types and at any stage of economic development. Some conflicting findings in the literature can be reconciled this way, since insurance cover differs across countries and physical types. Past research, for lack of data, had little to say about macroeconomic effects of insurance – even as policymakers have long emphasized the role of financial preparedness (Cummins and Mahul 2009, Kunreuther and Michel-Kerjan 2009, World Bank and United Nations 2010).

Risk transfer thus mitigates the macroeconomic cost of natural disasters. In the wake of a disaster, affected agents may be unable to mobilise funding for reconstruction, owing to the financial imperfections familiar from the literature on finance and growth (Levine and Zervos 1998). Risk transfer triggers insurance payouts that help fund economic recovery. For insured disasters, we typically observe a growth spurt in the year after, suggesting that insured losses help to finance reconstruction. Since policyholders selected the assets to insure ex ante, the payouts will automatically target the repair of important assets and infrastructure. Insurance also plays a mitigating role through better preparedness and disaster management, not least to limit insurers' own liability. The gains accruing through these channels add up to a measurable macroeconomic effect, which may be larger when the economy receives payouts from abroad.

The macroeconomic value of risk transfer can be greatest for those countries that lack the capacity to (re)insure themselves against major disasters, resonating with the model of Borensztein et al (2017). Their exogenous occurrence, coupled with their large real effects, should make natural disasters prime candidates for international risk sharing. And yet, surprisingly little disaster risk is shared internationally. Ito and McCauley (2022) find that only about 7.5% of direct losses associated with 93 major disasters had been reinsured internationally. When we include uninsured disasters in this estimate, the number falls to about 2%. The global reinsurance industry and the catastrophe bond market should be much larger under complete international risk sharing.

The finding that risk transfer plays a mitigating role at the macroeconomic level suggests that financial arrangements 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 ex ante and ex post measures, the macroeconomic value identified in this paper could be part of a wider cost-benefit analysis.

These issues will only grow in importance in the age of climate change. A small literature in macroeconomics takes into account rare disasters, referencing mainly wars and depressions.[2] Natural disasters have emerged as a growing threat, and they are not so rare. The frequency and severity of disasters may rise to an unknown extent (Stern 2007, Weitzman 2009). In its latest report, the IPCC states (with high confidence) that extreme events will become larger, and losses and damages will increase with global warming over the near term (IPCC 2023).

The paper proceeds as follows. Section 1 introduces direct loss statistics and presents our methodology for estimating the indirect output costs of disasters. Section 2 estimates the baseline response to disasters comparable to other studies, allowing for different physical types and other heterogeneity. Section 3 estimates growth responses conditional on risk transfer while controlling for various aspects of development. Section 4 draws implications from our findings, and discusses international risk sharing. Section 5 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. *Direct* losses are widely assessed and reported in the media. 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.

[2] Barro (2006) first incorporated rare disasters in macroeconomics; they raise the welfare cost of fluctuations and help explain asset-pricing puzzles (see also Gabaix 2012). The empirical results in Barro and Ursúa (2008) are mostly driven by the wars and depressions of the 20th century.

[3] We focus on GDP as the key measure of economic activity. This does not capture other important consequences that affect a nation's wellbeing (World Bank and United Nations 2010, IPCC 2023). The same method can be applied to other variables of interest, such as consumption or socio-economic measures.

1.1 Direct Losses from Natural Disasters

A critical input for our analysis is comprehensive and reliable statistics on the date, location and severity of natural disasters. Severity can be gauged by physical measures of intensity, by economic losses, or by the number/proportion of fatalities (Felbermayr and Groeschl 2014, Botzen et al 2019). Research to date mainly relied on the public Emergency Events Database (EM-DAT).[4] Toya and Skidmore (2002, 2007), Noy (2009), Schumacher and Strobl (2011), Cavallo 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 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). Other measures of severity are no close substitute for missing data for economic losses.[5]

Our starting point is a detailed quantitative database on damage to property and infrastructure. The loss data are based on the NatCat statistics of 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, Wirtz et al 2012, www.munichre.com/geo). Reinsurance companies are best placed to determine disaster-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.

The NatCat statistics have global coverage, 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 and repair costs (Wirtz et al 2012). Figures for *insured* losses are very reliable because they reflect claims actually paid by insurance companies; there is more uncertainty about *total* losses, which Munich RE estimates based on a wide range of sources (Appendix 1 provides more detail on the loss data). We received more than 22,000 event-level observations, covering direct losses to individual countries between 1950 and 2011 from disasters in four physical categories. During these six 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, matching our macroeconomic panel data.

Table 1 presents the disaster data by physical type, with summary statistics on frequency, severity and insurance cover. For 95% of all events, Munich Re reports positive economic losses. Overall, meteorological (storms) and hydrological events (flooding) are more common

[4] The EM-DAT is compiled by the Centre for Research on the Epidemiology of Disasters (www.emdat.be).

[5] 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 that killed more than 200,000 people. Their estimate of \$8.1 billion is very close to the insurance assessment (\$8.0). However, the R^2 of 40% in their regressions makes clear that fatalities and other public data cannot replace missing loss data.

than geophysical and climatological events (row 1). Smaller events are more frequent and less consequential; all other rows thus focus on disasters 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. Scaling economic losses by GDP also helps to offset the trend in losses induced by the rising value of infrastructure and productive assets over time. Frequencies are relatively high for earthquakes and flooding in Asia, storms in the 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 amounting to 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%).

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

For each disaster, we compute insurance cover 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 52 sample years had any insurance cover (30% in the latest 10 years). At over 90%, the share 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 empirical work. Figure 1 plots direct economic losses against insurance cover, with circles 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 (the circles to the left) at the expense of costlier disasters in large economies (the dots to the right). Second, severity and insurance cover 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 identification: 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 cover results from the aggregation of many individual contracts that commit insurance companies to pay for damages. The insurance industry 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 building 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

[6] A simple regression of coverage on the log of losses/GDP shows a weakly increasing relationship; it only explains 6% of variation for all events, and 3% for major disasters.

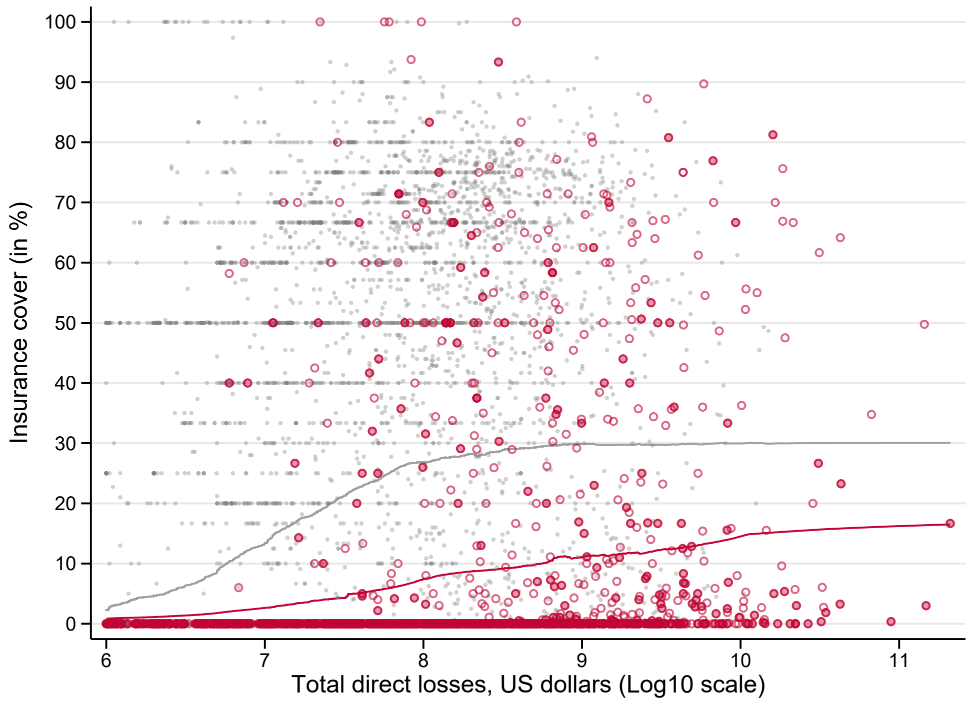

Figure 1: Direct Losses and Insurance Coverage, 1960-2011.
The scatter plot sets reported insurance cover against severity, measured by direct economic losses in constant 2011 US dollars, on a log10 scale (x=9 corresponds to $1 billion). The dots represent all natural disasters between 1960 and 2011 with reported losses of $1 million or more (9,876 events). The circles show major disasters where direct losses exceeded 0.1% (hollow), or 1.0% (filled), of the affected country's GDP. The lines trace out the smoothed coverage ratios for the respective groups, using locally weighted regressions.

retains the bulk of the underwritten risk, and transfers some peak risks through retrocession and securitization (e.g. catastrophe bonds).[7]

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,

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

and consider an autoregressive model of the form

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

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).

Estimating a time profile presents a fuller picture of growth dynamics than in earlier studies that focus on one segment of the growth response (see Introduction). This allows us to jointly estimate the impact on growth and long-term effects on the level of GDP, two key metrics that have commonly been measured separately (Cavallo et al 2022). The signs of the estimates of λ_n, if significant, capture whether natural disasters are harmful or conducive to growth. 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 captures extra growth in the year after a disaster. 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 response in equations (2) and (3). Second, the coefficients λ_n measure the *sensitivity* of growth rates, from impact to each lag, per unit of severity. Third, greater *persistence* in the growth process (β_n) compounds the long-term effect as deviations from trend growth are carried forward in time.

The novel aspect studied here is the role of *risk transfer*, which we incorporate in two ways. Both test whether insurance mitigates the macroeconomic cost of disasters. Specification A starts with the total indirect losses of the baseline, and examines whether the presence of insurance cover makes a measurable difference; if positive effects materialise, insurance mitigates a disaster in the sense of *reversing* part of the negative effects of the initial total loss. Specification B instead splits total losses into insured and uninsured parts, and examines whether the economy is more sensitive to the latter; if so, insurance mitigates the disaster in the sense of *reducing*

[8] The macroeconomic controls are centered in the empirical specification.

the size of the loss the economy suffers.[9]

Specification A thus augments equation (1) by incorporating the insurance cover associated with each disaster. Cover is observed only when disasters occur, and set to 0 in normal years. The level of cover may have a stand-alone effect; or it matters more for larger disasters; hence, we test whether the presence of insurance affects the growth response by interacting cover and severity,[10]

$$\begin{aligned} y_{it} \;=\;& \underbrace{\alpha_i + \sum\nolimits_{n=1}^{L_y} \beta_n \, y_{it-n}}_{\text{growth autoregression}} + \underbrace{\sum\nolimits_{n=0}^{L_x} \lambda_n \, x_{it-n}}_{\text{disaster effects}} + \underbrace{\sum\nolimits_{n=0}^{L_z} \theta_n' \, \mathbf{z}_{it-n}}_{\text{macro controls}} \\ & + \underbrace{\sum\nolimits_{n=0}^{L_x} \gamma_n \, cover_{it-n}}_{\text{insurance cover}} + \underbrace{\sum\nolimits_{n=0}^{L_x} \sigma_n \, cover_{it-n} \, x_{it-n}}_{\text{cover x loss interaction}} + \varepsilon_{it}, \end{aligned} \tag{4}$$

Finding positive growth effects ($\widehat{\sigma}_n > 0$) would indicate that risk transfer helps to reverse negative output effects after disasters. The cumulative effect of the cover-loss interaction over time would shift the long-term effect (3) by

$$\frac{\sum_{n=0}^{L_x} \sigma_n}{1 - \sum_{n=1}^{L_y} \beta_n} \, cover \; x. \tag{5}$$

Specification B instead treats insured and uninsured losses as distinct impulses, and allows for separate growth responses to each type. 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,

$$\begin{aligned} y_{it} \;=\;& \underbrace{\alpha_i + \sum\nolimits_{n=1}^{L_y} \beta_n y_{it-n}}_{\text{growth autoregression}} + \underbrace{\sum\nolimits_{n=0}^{L_z} \theta_n' \mathbf{z}_{it-n}}_{\text{macro controls}} \\ & + \underbrace{\sum\nolimits_{n=0}^{L_x} \mu_n \upsilon_{it-n}}_{\textbf{uninsured}\text{ catastrophe losses}} + \underbrace{\sum\nolimits_{n=0}^{L_x} \sigma_n \tau_{it-n}}_{\textbf{insured}\text{ losses}} + \varepsilon_{it}. \end{aligned} \tag{6}$$

The loss severities (τ or υ) and sensitivities (σ_n or μ_n) estimated in equation (6) yield separate impacts and long-term effects for insured and for uninsured losses when fed into equations (2) and (3). If the respective sensitivities to losses differ systematically from each other, then the presence of insurance alters the macroeconomic cost of disasters. The two specifications provide complementary information, and there is sufficient heterogeneity in observed coverage across disasters to implement both.

[9] A simple example helps illustrate the difference. Consider a disaster causing \$20 billion in direct damage of which \$5 billion were insured, leaving a \$15 billion uninsured loss. Specification A posits that the \$20 billion in damage hits the economy regardless of cover, and looks for positive growth effects from the insured \$5 billion. Specification B instead tests whether the \$15 billion loss hurts output more than the insured \$5 billion; if the latter are insignificant, it is as if the disaster had only been of size \$15 billion as far as output effects are concerned.

[10] We thank Eduardo Cavallo for proposing this specification. Note that the interaction *cover* x would simply equal the *insured* loss if one took the level of losses as the measure of severity x.

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.[11] 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.[12] The panel also includes macroeconomic variables and development controls (Appendix 1 lists definitions and sources).

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.[13] 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)-(6) 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 22,000 individual disaster events into 1,472 yearly panel observations with disasters. For each observation, we split total losses into their insured and uninsured parts. Appendix 1 describes this aggregation further, including the attribution of losses for disaster affecting several countries.

Scaling. 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 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. 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 (6).

Threshold. Including all recorded disasters would introduce noise: smaller events are more

[11] 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.

[12] These include 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).

[13] The real GDP growth series are based on constant local currency, "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.

frequent but inconsequential on a macroeconomic scale. We impose a minimum severity threshold of 1% of GDP for including disasters in the panel. This threshold leaves 460 disaster years, or 5% of the total number of country-year observations. Empirical results for some alternatives (a 0.5% threshold and other scaling options) are reported in the robustness Table A2.

Estimation. Our regression tables Tables 2-4 and A2 report the coefficients in equations (1) to (6), all estimated by linear panel data methods. 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.[14] After testing down the lag structure, we include four autoregressive lags on growth ($L_y = 4$). In addition to the contemporaneous impacts, we also use four lags on all disaster loss variables and on other controls ($L_x = L_z = 4$ in equations (1) to (6)). 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).

Sample. The final dataset is an unbalanced panel covering 214 countries and jurisdictions, with 8,921 observations spanning 1960-2011, containing 460 disaster-years with events causing direct losses of 1% of GDP or more. The time span is the intersection between the WDI growth series (starting in 1960) and the NatCat statistics (1950-2011), plus the four-year lag structure.

Tables. Our regression tables report scaled coefficients, to make results comparable across samples and disaster types. Instead of showing the estimated sensitivities $\widehat{\lambda}_n$, we report sensitivity times severity, since it is the product that shapes the macroeconomic response (e.g. $\lambda_n x$ in equations (1) to (3)). When scaling the coefficient by the *median* loss, we obtain the estimated growth effects of a typical disaster; scaling by the *mean* loss instead yields the effects of a disaster of average size. Due to the presence of large rare disasters, the average disaster (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.

2 The Output Cost of Natural Disasters

Our analysis starts with a baseline regression, estimating the full time profile of economic growth in response to disasters in a large panel dataset. The impact and longer-term effects can be compared to earlier research that ignores risk transfer. We provide results for poorer countries, and separate responses for different physical type of disasters. To capture more heterogeneity, we also characterise the distribution of individual growth outcomes in an event-study setting. The results in this section rely on a parsimonious specification (Table 2). This minimises the selection bias that can arise when missing data eliminate poorer or smaller countries more vulnerable to natural disasters. The next section introduces risk transfer while controlling for aid flows and the stage of development.

[14]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

The first specification maximises coverage by using only two autoregressive lags and country fixed effects (Table 2, column 1). The top rows show summary statistics for major disasters, where the typical (median) and average (mean) severities correspond to x in equations (1) to (3). The subsequent rows report our estimates of the associated growth effects, $\lambda_i x$, scaled by the median disaster (or by the mean disaster, in shaded rows).

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.[15] 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 disasters. That's not all: the lags identify further negative effects on growth two years after the event (row "Lag 2"). All 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%.

Column 2 expands the specification by additional lags and basic controls. (We address the role of development more fully in Section 3.) The richer lag structure extends that of Noy (2009), Dermott et al (2014) or Felbermayr and Groeschl (2014), for instance, who focused on the growth impact during the disaster year, based on an AR(1) growth model. The basic controls now include a time trend and the log of GDP per capita to account for the stage of development (Toya and Skidmore 2007). We also include two count variables, on the view that the growth response may differ when a country faces multiple events within a year, or when it experienced major disasters in previous years.

The negative impact falls slightly short of 1.0%, but the output cost overall rises to 2.2% of GDP as the autoregressive lag 3 adds persistence. The time trend hints at a weak growth slowdown over time. GDP per capita is not significant in this simple specification. The number of events in the current disaster year is insignificant throughout: it is the magnitude of the aggregate loss that matters for aggregate outcomes. However, having a history of *prior* disasters helps support growth in a disaster year – presumably thanks to better preparedness. *Prior disasters*, the number of earlier years with major disasters, adds 0.2% to growth in the disaster year.

Column 3 runs the same regression on a subsample of poorer countries. The estimated impact is a little stronger, the second growth dip sooner, and the long-term cost larger than in the full sample. Disasters are more harmful to poorer countries, echoing Noy (2009) and Loayza et al (2012). Interestingly, this is not because poorer countries experience more severe disasters relative to the size of their economies: the typical (median) loss to GDP is no larger (3.11%) than for all countries combined (3.19%). Instead, poorer nations appear to be more *sensitive* to a given loss/GDP: the estimated $\widehat{\lambda}_0$ and $\widehat{\lambda}_1$ are more negative. More disasters are uninsured in poorer countries and other factors also limit their ability to cope. Section 3 thus controls for the stage of development when introducing risk transfer.

[15] The significance of coefficients is based on sensitivity; severity merely scales the estimated coefficients. From equation (2), the median impact is the product of estimated sensitivity, $\widehat{\lambda}_0 = -0.698$, and median severity $x = \ln(3.19 + 1)$.

Note that these results refer to the effects of a median (typical) disaster; scaling the sensitivities by the larger *mean* loss yields greater estimated costs.[16] Mean disasters reduce growth by nearly 2% on impact, and produce a long-term cost on the order of 4% in terms of GDP lost. The estimates can also be scaled by severities beyond the mean loss in order to predict the output 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 most earlier research (reviewed in Cavallo and Noy 2011, and Cavallo et al 2022). This is not a foregone conclusion: direct disaster losses do not enter measured GDP, while investment for reconstruction boosts output. And yet, the disruptive effects of disasters are sufficient to curb growth for years. This finding does not support the view that natural disasters promote growth – at least not in the short and medium term.[17] Our impact estimate lies between Noy's (2009) short-run response for developing countries (-1%) and Cavallo et al's (2022) estimate of -2.1% for the 50 worst disasters. Our lag structure also reveals a distinctive time profile, whereby growth dips again in year two after the event ($\widehat{\lambda}_2 < 0$), compounding the output cost. The estimated effects are so persistent that the cumulative cost is twice the size of the within-year impact. This output cost aligns with Hochrainer's (2009) estimated GDP drop of 2-4% by year 5 after the event. Long-term-effects have remained elusive in the literature, as many studies work with small samples of extreme disasters, selected on the number of deaths.[18] Our estimates are based on hundreds of disasters chosen on economic losses (in % of GDP) which may align more closely with subsequent economic performance.

2.2 Physical Types and Heterogeneity

Natural disasters differ in their physical characteristics: earthquakes bring instant destruction, whereas droughts build up over months or years – the growth responses will differ accordingly. To explore such heterogeneity, Table 2 column 4 allows for a separate sensitivity estimates for each of the main physical types (Table 1). To this end, we introduce four separate disaster terms with their respective lags in equation (1).

The results suggest that disasters affect output with long and variable lags across types. Geophysical disasters, comprising earthquakes and volcanic eruptions, produce the sharpest response. Output falls more than for other physical types – both in the year of, and the year

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

[17]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.

[18]Cavallo et al (2022) focus on the worst 20, 30 and 50 disasters by mortality (deaths per million inhabitants), and find strong impact but uncertain long-term costs. The R^2 between fatalities and economic losses is as low as 20% in our data; hence, a sample selection on the basis of fatalities misses many disasters that caused substantial economic losses.

after, the disaster – leaving a long-term cost of 5% on average. Storms and flooding also have sizeable impacts, and are associated with slower growth in years two or three after the disasters. For climatological events, the regression fails to identify significant output effects, perhaps because droughts are so variable in their duration.[19]

The average responses estimated so far conceal any heterogeneity in individual growth paths following disasters. The variety of disasters is one factor; there is an abundance of other influences on GDP. Regression analysis spends available degrees of freedom on estimating a coefficient of interest, which measures the average response in the sample. One can differentiate responses by disaster type or income groups, and estimate ever more coefficients with lower precision. Pushing this differentiation to the limit, we can treat every disaster as a unique event for which we measure "abnormal" growth and examine its distribution.

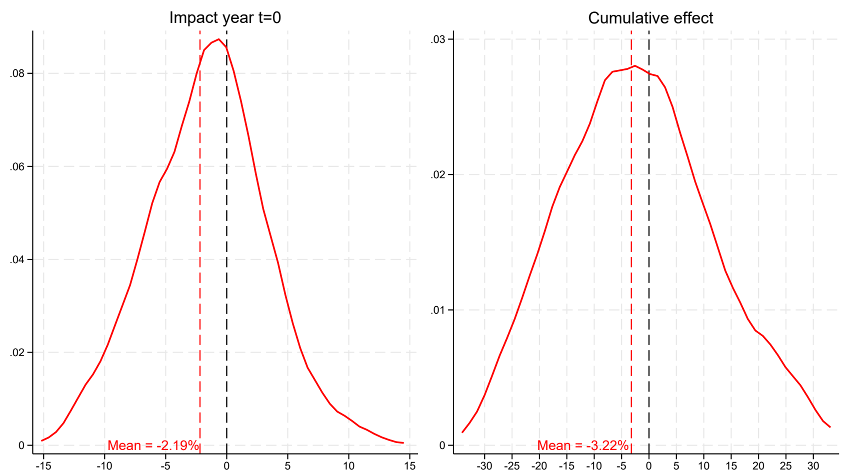

Figure 2: Distribution of "abnormal" growth following disasters.
The left panel shows the kernel density estimate of "abnormal" growth rates observed in the same year of a major disaster (t=0), defined as follows. We identify 178 growth episodes featuring a disaster at time t=0 with no other disasters occurring in the 3 years before and the 5 years after the disaster; another 5,158 series are entirely free from disasters. For each episode, we compute abnormal disaster growth rates by subtracting from observed growth rates the same country's average growth rate during normal episodes, separately every year in each episode. The left panel shows the kernel density over the 178 abnormal growth rates in the impact year (t=0). The right panel shows the cumulative effect, after compounding the abnormal growth rates from t=0 through t=5. Both panels use the default Epanechnikov kernel function. The dashed red lines mark the means of the respective distributions.

This exercise reveals considerable variation in growth outcomes (Figure 2). Event studies usually plot averages (e.g. Borensztein et al 2017, Cavallo et al 2022); here, these are shown

[19]The five-year intervals used by Loayza et al (2012) may be better suited for detecting any negative output effects of droughts. Cavallo et al (2022) set apart climatological events in their event study: summarising the properties of disaster types by frequency, duration and severity, they conclude that geophysical, meteorological and hydrological events are comparable shocks, whereas climatological events are distinct, slow-moving processes.

as dashed red lines, and are comparable in magnitude to the impacts and long-term effects estimated in the regressions so far. In addition, the density plot shows the full distribution of abnormal growth in disaster years (left panel). A broad range of growth rates are observed following disasters, even some instances of double-digit growth. But more realisations are below zero, as evidenced in the mass of the density to the left. The same holds for the distribution of cumulative effects (right panel). Disasters impart negative growth effects relative to normal times.

3 Risk Transfer and the Stage of Development

This section extends the analysis by introducing risk transfer while controlling for the stage of development. A case study of two similar earthquakes with starkly different consequences in Haiti and New Zealand illustrates why risk transfer and development should be analyzed jointly. We incorporate insurance cover in two alternative ways, with similar results. We also expand the specification to estimate separate growth responses for different physical types of disasters.

3.1 Insurance and Development

Haiti and New Zealand are island states exposed to recurring natural disasters. In 2010, both countries were 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.

In spite of these physical similarities, the macroeconomic consequences on the two islands were worlds apart. 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. New Zealand, by contrast, saw no fatalities in 2010 (and 185 in the 2011 earthquake) and experienced little impact on the aggregate economy (New Zealand Treasury 2010; Doyle and Noy 2015). 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.

The extent of risk transfer differed as much. Haiti was almost entirely uninsured and found itself dependent on foreign aid. New Zealand's earthquake, by contrast, was among the most insured disasters in history; as a result of a mandatory add-on to residential insurance, more than 95% of housing units in the area were covered by insurance, and most submitted claims (Nguyen and Noy 2020). In aggregate, 81% of disaster-related losses were covered and reimbursed. At 63%, an unusually high share of insured losses were covered by international reinsurance (Ito and McCauley 2022). The disaster thus triggered $5 billion in payments from primary insurance companies, backed by inflows of $3.5 billion from reinsurance companies abroad.

It would be implausible to attribute the stark difference in outcomes between Haiti and New Zealand to the presence of disaster insurance. The two countries are at different stages of development in many other respects that also affect the response to disasters. Hence, we need to control for the stage of development when trying to identify the role of risk transfer.

It is well documented that 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). That the number of fatalities falls with measures of development is also observed in our data. The same does not hold for direct economic losses, however: they do not decline as countries develop. 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). Richer countries also tend to be better insured against losses; in our data, the insurance cover observed for major disasters tends to rise with the stage of development, albeit slowly.[20]

We can therefore expect the indirect macroeconomic costs to depend on various aspects of development, alongside insurance. To disentangle the role of risk transfer from confounding factors, this section incorporates a host of regressors controlling for various aspects of financial development. We also estimate separate growth responses to four different physical types of disasters. These enhancements help corroborate the finding that risk transfer helps to mitigate the adverse growth effects of natural disasters.

3.2 The Role of Risk Transfer in Mitigating Disasters

We now test whether insurance cover helps to mitigate the macroeconomic cost of natural disasters. Tables 3A and 3B report the results of the two specifications set out in Section 1.2 side by side. They use the same sample, which now covers 6,812 observations and 355 country-year observations with disasters causing 1% of GDP or more in direct losses to property and infrastructure. The number of observation fell (from 8,921 in Table 2) due to data limitations when controlling for various aspects of development. We include access to banking, insurance, and credit, as well as aid flows and official development assistance; Table 3B further controls for five types of man-made crises that sometimes coincide with natural disasters, as discussed in Sections 3.3 and 3.4.

Specification A takes the growth response to total indirect losses as the baseline, and tests whether insurance cover helps reverse part of its negative effects (see equation (4)). Accordingly, the estimates for total losses (top rows of Table 3A) correspond to the baseline results (Table 2, column 2). They again imply about 1.0% in foregone growth in the impact year, and an overall cost of 2.2% of GDP for a median disaster, and about twice that for mean losses. The new cover-loss interaction term shows a significant lag: the observed insurance cover for median (or

[20] The predicted cover increases from 16% to 19% when GDP per capita doubles from $10,000, with substantial variation around the fitted curve. A simple regression of observed insurance cover on the log of GDP per capita, a common proxy for the stage of development, explains 23% of variation in cover, or 33% when a squared cover term is added.

mean) losses adds 0.4% (or 1.9%) percentage points to growth in the year after a disaster. The estimated growth spurt increases to 0.56% (or 2.8%) percentage points when cover is added as a stand-alone variable (column 2).

This is a first hint that insurance cover helps countries recover. Cover has no clear sign when standing alone, but the interaction with severity suggests that covering larger losses helps to reverse some of the initial impact on growth. The signs of recovery appear mostly in the year (or two years) after a disaster (columns 1 and 2, respectively). The longer-term effect is measured with lower precision, since it compounds all lagged terms – it can be statistically significant (column 2) or not (column 1).[21]

The alternative specification B splits total losses into insured and uninsured parts, and tests whether the economy suffers mainly as a result of uninsured losses. Table 3B contrasts the respective estimates from equation (6) in the first two sets of rows. The sensitivities to insured and uninsured losses differ substantially. *Uninsured* losses continue to have a negative effect on growth: the median uninsured disaster again reduces growth by 1.0% on impact ($\widehat{\mu}_0 \upsilon$ in equation (6)), and by a cumulative 2.35% over time (Table 3B, column 1). By contrast, *insured* losses turn out to be mostly insignificant on impact; in the year after a disaster, they even stimulate growth. This growth spurt is significant in statistical and economic terms: +0.6% following a median loss, or +3.77% for a mean loss.[22] This boost dissipates in years 3 and 4, leaving the long-term response to insured losses marginally insignificant overall, with p-values just above 0.1 in both columns.

[Tables 3A and 3B: Risk Transfer]

The results in Tables 3A and B have much in common. Uninsured losses, which account for the bulk of total losses in most disasters, have unambiguous negative effects on growth, on impact and in the longer term. Insurance helps reduce or reverse some of these effects, as evidenced by the growth spurts observed in year after a disaster. These results hold across both specifications, while controlling for development. An advantage of specification B is that it allows us to identify separate impacts and long-term effects for insured and for uninsured losses. Even an insignificant response to insured losses stands in sharp contrast with the large negative response to uninsured losses. This discrepancy suggests that uninsured losses cause substantial macroeconomic costs, whereas insured losses appear inconsequential, sometimes even positive, for growth. Risk transfer thus helps to mitigate the adverse macroeconomic effects of disasters.

[21] The p-value for insurance cover in Table 3A evaluates equation (5) using the same non-linear Wald test as that used for the coefficients on total losses in equation (3).

[22] This number corresponds to $\widehat{\sigma}_1 \tau$ from equation (6), the product of the estimated sensitivity (2.05) and severity $\tau = \ln(Loss/GDP + 1)$ with a mean insured loss of 5.28%.

3.3 Controlling for Development and Crises

have incorporated various aspects of development in Tables 2 and 3. The disaster variables express losses as a ratio to GDP, which ensures that this measure of severity covers the costliest disasters at any stage of development – including many disasters that affected small or poor countries (Figure 1). 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. Countries also differ in institutional characteristics that shape their ability to recover from disasters, such as differential access to resources that help countries finance the recovery (Cummins and Mahul 2009).

Tables 3A and B therefore contains a battery of controls. We include measures of financial development, and control for factors that might substitute for (re)insurance transfers, notably foreign aid and development assistance. These external sources may help finance the recovery and mitigate the macroeconomic cost of disasters over time. For financial development, we include access to banking (the number of bank branches per 100,000 adults), non-life insurance penetration, and access to credit proxied by the credit-to-GDP ratio (definitions and sources are in Table A1). 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. (Well-insured countries would not attract major aid flows – the two forms of relief rarely coincide.) We also control for five types of man-made crises, to avoid confounding their output effects with those of natural disasters when they coincide.

We do not control for fiscal and monetary policies, which are part of the response of an economy to shocks – like other endogenous macroeconomic variables. If an economy has the means to offset the effect of disaster through fiscal or monetary stimulus, for instance, then this will be part of our measured response to disasters. That said, fiscal support in most economies tends to small compared to the scale of disasters. Middle and low-income countries even exhibit procyclical dynamics, where lower spending and higher revenues exacerbate disaster effects (Noy and Nualsri 2011). Most countries simply lack the fiscal space for providing support at scale in the wake of a disaster. In a large panel, Kose et al (2022) found that natural disasters were not associated with significant change in fiscal variables, in contrast to banking crises and recessions. Deficits, government debt and external debt show no systematic fiscal support after disasters. The ability to tap markets for financing recovery may be limited to a few highly rated sovereigns, such as Japan and the United States.

All development variables in Tables 3A and B enter on a stand-alone basis and as interactions, to test whether they matter specifically in years when natural disasters strike. 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 allow for a fuller dynamic profile. The interactions with the disaster indicator identify separate effects in the year of, and the two years after, major disasters.

The results suggest that the stage of development matters most in the year after disasters strike. Access to banking and aid flows appear to help the most at that time. Access to banking is mostly significant in the interaction terms across columns. With a two-year lag, credit-to-GDP also goes with higher growth. So do foreign aid and official development assistance, but only in the year after. In the disaster year, aid flows are associated with negative growth; this may reflect cases where aid has been mobilised in response to major disasters to meet humanitarian needs (eg Haiti 2010).[23] GDP per capita, a common proxy for development, comes out with a counter-intuitive sign. Richer countries grow more slowly in normal years, but higher GDP per capita should help in a disaster if it reflects better institutions or preparedness. The number of prior disasters provides somewhat more support to the idea that better preparedness helps limit the downturn.[24] However, development variables are used here as controls, to obtain reliable estimates for un/insured disaster losses.

Another aspect of development is institutional quality and stability, or its absence in the form of crises. In Tables 3B and 4, we control for five types of crises: wars, political crises, as well as banking, currency, and debt crises.[25] 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. Excluding those controls may lead to overestimating the negative effects of natural disasters. On the other hand, when 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.[26]

Man-made crises are associated with substantial macroeconomic costs (Table 3B, column 2). All five types reduce growth by between 1.7 and 4.0 percentage points at the onset of the crisis. The impact is highly significant for every type of crisis, and some 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 9.4% in terms of foregone output. The long-term effects of currency and political crises is uncertain in this specification, but significantly negative in Table 4 below.

[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.

[24]The positive effect of this variable is weaker than in Table 2. Countries with prior disasters may also find it more costly to insure themselves as repeat events drive insurance premiums up.

[25]The five types of crises are 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).

[26]Rahman et al (2022) document that major storms in island economies erode political institutions and often lead to a more 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.

3.4 Refinement: Physical Types of Disasters

Growth responses were seen to vary according to the physical type of disasters (Table 2). Some physical types also tend to be better insured than others (e.g. storms vs droughts, Table 1). To nuance the role of risk transfer in the light of such heterogeneity, Table 4 estimates equation (6) by physical type. We maintain the un/insured distinction, fixed effects, and include all development controls with interactions, as in Table 3B, "All controls". That specification already involved 66 parameters (not counting fixed effects), and a regression by type multiplies the number of disaster coefficients by four. To preserve degrees of freedom, we reduce the number of lags; in Tables 2-3, most lags in years 3 and 4 were small or insignificant.

Geophysical events cause the largest growth effects (Table 4, full sample). A typical earthquake or volcanic eruption in the sample (causing 4.4% in direct losses) entails a macroeconomic cost of 6.6% of GDP, curbing growth by 2.1% in the first year alone. By contrast, insurance turns negative into positive growth effects, yielding a cumulative expansion of 2.1% of GDP. The growth response to mean disasters is much larger still (shaded results).[27] The analysis by type comprises only 48 major geophysical events, and includes devastating earthquakes and volcanic eruptions.

The other three physical types feature more than 100 disaster-years each. For meteorological events, we observe a negative impact for uninsured losses, but with insurance there is a positive growth spurt in the year after a storm. The estimated long-term effects differ sharply, depending on whether a mean-sized storm was insured (+4.6%) or uninsured (−5.1%). With intermediate insurance cover, the expected output cost will be in-between those extremes. The results for hydrological disasters come out insignificant, in contrast to Table 2 where flooding had clear negative effects. Climatological disasters again follow the pattern we found, whereby insured losses help and uninsured losses harm growth. The growth slowdown we identified in year two after a disaster (Table 3) apparently stems from these events, which include long-lasting droughts.

The timing of the growth responses largely reflects the different physical types of disasters. We observe positive growth effects in the year of a disaster only for geophysical events, perhaps because the damage is immediate and can be assessed promptly (Table 4, row "Impact"). For other physical types, the growth-enhancing effects of insurance materialise later, in the year after the disaster ("Lag 1").

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

These findings are not limited to rich countries, which tend to be better insured. The growth effects, both positive and negative, remain similar when excluding the countries in the top income group (Table 4, column 2). As before, uninsured losses cause significant macroeconomic costs, whereas insured losses tend to fuel growth over time as countries rebuild.

[27] 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. The 20% expansion estimated for a fully insured disasters, however, appears implausibly large.

Our analysis by type helps disentangle conflicting findings in the literature. Prior research on the effects of disasters has not estimated growth responses conditional on risk transfer. Loayza et al (2012), for example, 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 cost of 0.83%. When conditioning on risk transfer, our results suggest that storms are typically harmful when uninsured but growth-enhancing when insured, with responses as large as ±5% for mean storms (Table 4, meteorological). Ignoring insurance confounds the positive and negative effects and produces an estimate near zero, since more than a third of storms have substantial insurance coverage (Table 1).

Loayza et al (2012) also find **droughts** to be costlier than any other type of disaster. This may reflect the fact that the vast majority of climatological events – including droughts in Africa – are entirely uninsured (Table 1). The macroeconomic cost could have been mitigated with more risk transfer, judging by the results for insured climatological losses. For **flooding**, the positive effects found in Loayza et al (2012) and Fomby et al (2009) are not inconsistent with our (insignificant) estimates, since floods disrupt activity but also deposit nutrient-rich silt and increase hydroelectric power boosting industrial growth (World Bank and United Nations 2010).[28] 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 not as robust to variation as those for all types combined (Tables 2-3), as we estimate more coefficients on fewer disasters per physical type. Appendix 2 reports specific tests to examine whether our main 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 alternative dependent variables (GDP, GNI, and GDP per capita). These experiments alter the point estimates of impact and long-term costs, but do not change our main findings.

4 Partial Recovery and International Risk Sharing

This section discusses explanations and implications of our findings. The empirical results show that natural disasters entail sizeable macroeconomic costs in the absence of risk transfer. The mitigating effects of insurance are not merely a by-product of other aspects of development: the positive growth effects conditional on insurance are well-identified even in the presence of multiple controls for development. In all tables, natural disasters continue to have substantial output effects: negative when uninsured and weakly positive when insured. Risk transfer can help mitigate disasters at any stage of development.

[28] That said, detailed microeconomic evidence in Fatica et al (2022) points to the disruptive and persistent negative effects of water damages on the performance of European manufacturing firms.

The growth effects of natural disasters are comparable to those of man-made crises, except that natural disasters can be insured. Wars, political and financial crisis are associated with large negative output effects, both on impact and over the longer term (Tables 3B and 4). Both the full sample (162 countries) and that excluding rich nations (114 countries) exhibit consistently negative effects. 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, the results show that major natural disasters spell long-term costs not far off those following wars, political and financial crises.[29]

4.1 The Myth of Economic Recovery Revisited

Our work extends a line of research on the nature of economic recovery after major shocks, which tends to be slow and partial. Cerra and Saxena (2008) first documented that financial and political crises have permanent effects, in the sense that output losses are not reversed over time. Reinhart and Rogoff (2014) found that it takes about eight years on average to reach the pre-crisis level of income following financial crises, not to mention the previous trend.

The findings of this literature have far-reaching implications. The persistence of shocks, for instance, calls into question the practice of treating growth and business cycles independently (Cerra et al 2023). For man-made crises, however, the endogenous forces at work can blur identification: economic slowdowns make crises more likely in the first place. For natural disasters, the direction of causality is clear: the occurrence of disasters is exogenous, and therefore a probable cause of abnormal growth.

Against this background, we draw four implications from our findings, illustrated by a visual representation of our estimates. Figure 3 traces out the simulated growth response to mean-sized natural disasters, contrasting uninsured losses (top row) with insured losses (bottom row). The left panels show growth paths as deviations from zero which represents the absence of disasters. The right panels cumulate the growth responses over time, to obtain the permanent macroeconomic effect.

The first implication is that major natural disasters can spell substantial macroeconomic costs, over and above the direct losses from the destruction of property and infrastructure. The top left panel shows that (uninsured) natural disasters can harm growth for years. In response to mean uninsured losses, real growth drops nearly 2% on impact and continues to underperform in year 1 and 2 after the disaster (Figure 3, top left panel).[30]

Second, the macroeconomic cost in terms of foregone GDP has a permanent component. The impulse response in the top left panel bears the signs of a partial recovery. Even if the growth

[29] 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. The estimated cost of disasters remains close to our previous results (Appendix Table A2, column 1).

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

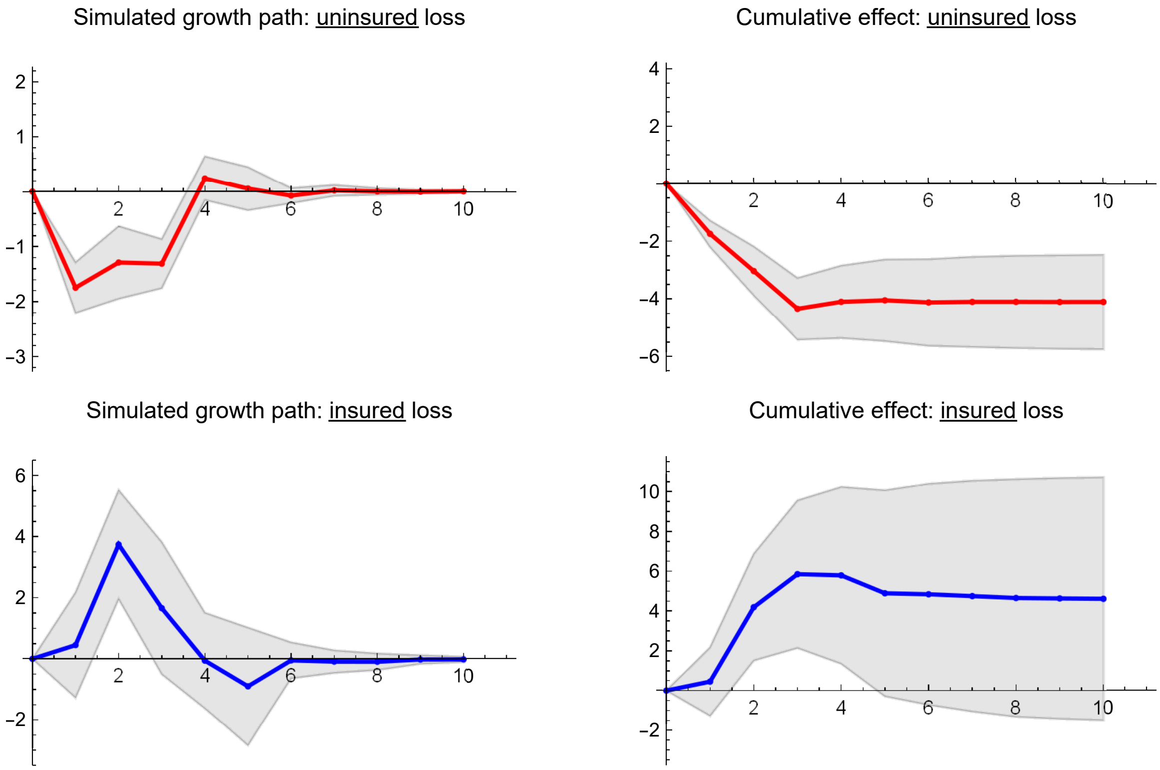

Figure 3: The growth response to insured vs uninsured losses.
The figure contrasts the effects of mean-sized uninsured losses (top row) and mean-sized insured losses (bottom row), by simulating equation (6) using the estimated coefficients from Table 3B (column 2). The left panels trace out the path 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 ($\widehat{\mu}'_r = \widehat{\mu} + s * e_r$) to produce as many paths from equation (6), and identify point-wise for every period the realization that lies ± 2 standard deviations from the central path (see also Sims and Zha 1999).

rate eventually recovers, the disaster leaves behind a measure of forgone output: the economy does not recover to its previous growth path. Countries never fully recoup the output lost in the wake of a major disaster.[31] This is evident in the top right panel, which cumulates the top left panel over a ten-year period, converging to the cumulative effect defined in equation (3). It represents a permanent macroeconomic cost of some 4% of GDP, about twice the initial impact on growth.[32] The effects of major disasters play out over several years; attention to affected

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

[32] Using the previous trend as a reference is consistent with Cavallo et al's (2022) event-study finding that the pre- and post-disaster trends of GDP are not statistically different, even as the early impact on growth is not reversed over time.

areas or populations should not be limited to the immediate aftermath of a natural disaster.[33]

Third, "unmitigated disasters" (top panels) stand in sharp contrast with the response to fully insured losses (bottom panels). Insured losses turn out to be inconsequential, if not expansionary, at the country level. The bottom left panel highlights the growth spurt in the year after an insured disaster. If a country receives the average insured loss 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. Over time, the positive growth effects dissipate and the confidence interval widens, leaving the cumulative growth response statistically indistinguishable from zero (bottom right panel).

The differential responses in Figure 3 illustrate the *mitigating* effect of insurance. This effect would support economic activity even if insured losses did not deliver a positive growth spurt. As long as insured losses are *less* damaging to the economy than uninsured losses, risk transfer helps mitigate the adverse macroeconomic effects. Shifting the balance toward insured losses reduces the size of the remaining (uninsured) loss the economy suffers.

Fourth, the mitigating effect reflects the role of insurance in supporting economic recovery. Insurance payouts help finance reconstruction investment, which contributes to measured GDP. Property insurance automatically targets those assets and 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 to rebuilding the economy ex post. Insurance payouts are more geared toward repair and replacement of physical assets than other forms of relief. Aid disbursements or emergency spending primarily respond to the humanitarian exigencies of saving lives and reducing human suffering.[34]

In line with this interpretation, the growth-enhancing effects accrue mostly around the year after the disaster (Figure 3, bottom row). This is the horizon over which investment and reconstruction takes 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 4). To the extent that insurance payouts help finance reconstruction, it is plausible that economic activity shares similar dynamics (comparing Figures 3 and 4). The estimated growth effects match the time profile not only as funds come in; they also subside once insurance payments peter out.

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

[33]Important social consequences also include adverse effects on health, nutrition and education (World Bank and United Nations 2010, IPCC 2023). United Nations ESCAP (2021) documents the negative impacts of natural disasters on poverty and inequality for developing Asia-Pacific countries.

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

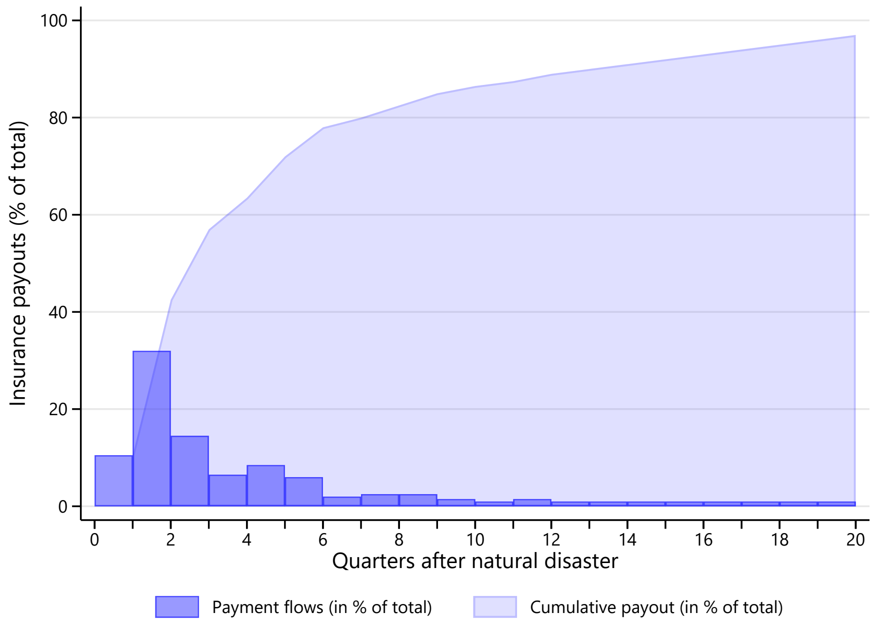

Figure 4: The Profile of Insurance Payments.
The figure shows the average flow of insurance payments (bars) and the cumulative payout (shaded area), as shares of the total ultimate payout on "catastrophe excess of loss" contracts, based on worldwide historical paid loss development comprising mature loss events until 2010. Point "0" represents the date of the natural disaster. Factors contributing to payout profile include different reporting timelines of the insured, damage analysis undertaken by the insurer and the additional payments after the full damage has been assessed, as well as specific timing provisions in contracts, such as business interruption insurance. Source: Proprietary data from Reinsurance Association of America (RAA, 2011).

destroyed assets whereas those without insurance did not. In the context of the December 2004 Asian tsunami, De Mel et al (2011) used random allocations of cash grants to firms and find that providing additional capital accelerated the recovery. After the New Zealand earthquakes in 2010-11 – among the largest insured events on record – insurance payouts contributed significantly to local residential recovery in the years following the earthquakes (Nguyen and Noy 2020). Whether a country can grow its way out of a disaster by repairing infrastructure and productive assets often depends on available financing (Cummins and Mahul 2009, World Bank and United Nations 2010).

More surprising is the finding that the *contemporaneous* impact of insured losses was often insignificant (Tables 3 and 4, "Impact"). One would expect a disaster to cause a certain amount of destruction, with insurance at best speeding up the recovery as payouts finance reconstruction. Yet, even the initial impact of a disaster is mitigated when losses are insured. Two distinct reasons account for this. Owners of insured assets can rebuild or borrow sooner when they (and their banks) know that payouts are forthcoming.[35] Insurance arrangements also contribute to prevention and preparedness ex ante. Insurance companies may insist on solid

[35]This is why we treated insured losses as a different type of loss, with a separate sensitivity in our preferred specification B (Tables 3B and 4).

building codes when providing coverage, and promote best practices in disaster management – not least to limit their own liability. There is broad consensus on the usefulness of prevention and preparedness, yet too little is done in practice (World Bank and United Nations 2010).

4.2 International Risk Sharing

Risk transfer to the insurance industry supports economic recovery in the wake of disasters. Natural disasters would seem to be prime candidates for international risk sharing. Small countries, in particular, lack the capacity to insure themselves: a disaster of a given scope may well affect the entire nation. At the same time, the occurrence of disasters – unlike man-made crises – is largely exogenous and normally afflicts one country at a time, which should make it attractive for insurers and investors seeking diversification. Moreover, the physical properties of disasters are observable and quantifiable in principle, a feature used for triggering parametric catastrophe bonds.

It stands to reason that international sharing of disaster risk improves welfare. Borensztein et al (2017) quantify the welfare gains from insurance against natural disasters in a small open economy model. When large disasters have a permanent output effects, they entail a loss of intertemporal income. In this context, catastrophe bonds, as one form of risk transfer, can provide two types of welfare gains: they help smooth domestic income and consumption, and allow the country to issue more default-free debt. But the actual cost of issuing catastrophe bonds is an impediment to their use, even as the welfare gains can be several percentage points of annual consumption. Those gains would be larger still if the model also incorporated other benefits of risk transfer that our paper highlighted, such as payouts relaxing liquidity constraints, and insurance expertise improving preparedness and disaster management.

In spite of the sizeable potential benefits of risk transfer, only a small fraction of disaster-related losses is in fact insured *and* shared internationally. Ito and McCauley (2022) combed the balance of payments for evidence of international insurance payouts, and identified corresponding transfers for 93 major disasters. Their findings reveal that merely 21% of insured losses had been reinsured internationally. But primary insurers had covered only 36% of total losses in the first place.[36] Hence only 7.5% of total losses were insured *and* reinsured internationally (0.36*0.21=0.075). And this is for their sample of 93 disasters with primary insurance. Including uninsured disasters (Table 1) in this calculation puts the estimate of internationally reinsured losses closer to 2%.

This degree of under-insurance is remarkable. Even the best insured disaster on record had only 47% of losses reinsured internationally: this was the 2010 earthquake in New Zealand described in Section 3.1. The New Zealand quakes are outliers in terms of international risk sharing (Ito and McCauley 2022). This form of international risk sharing is primarily conducted by the global reinsurance industry. The catastrophe bond market remains relatively small with $45 billion in bonds outstanding (Artemis 2023).

[36] Their 36% figure is close to the 31% mean cover in our dataset computed on insured events, but another 75% of disasters were entirely uninsured (Table 1).

Several reasons account for the low degree of international risk sharing. To reinsure disaster risk, the risks have to be covered by a primary insurer to begin with (recall Section 1.1). That requires institutional factors that many countries lack, such as a reliable legal environment that enforces contractual agreements and facilitates the just resolution of disputes. Hence, it is not only the cost of insurance that can deter adoption.[37] Insurers, in turn, may not reinsure their exposures. In some countries, the regulatory environment discourages the dependence of insurers on external reinsurers. Where primary insurers are free to reinsure abroad, they set the cost of buying reinsurance against the benefit of reducing exposure of their portfolio. When reinsurers take on peak risk, they incur large potential exposures and charge premiums accordingly. Whether it is optimal to insure disasters and transfer peak risk abroad depends on their frequency and on the cost of (re)insurance (Kunreuther and Michel-Kerjan 2009, Borensztein et al 2017). Many countries lack the financial means or the political will to commit annual premium payments for improbable future events.

International cooperation can play a catalytic role in this respect. International agencies can harness expertise and resources across the public and private sectors.[38] Dismantling regulatory barriers to international reinsurance would also foster more risk sharing; so would a reduction in various costs imposed on reinsurers operating across countries.[39] The issue of cooperation should also remain on the international policy agenda. Developing countries vulnerable to floods, storms or droughts suffer the consequences of climate change. The COP27 agreement to establish a Loss and Damage Fund recognizes this issue along with the need for financial assistance to help vulnerable countries respond to the catastrophic effects of climate change. Compensation for loss and damage can also contribute to efficient risk sharing with the kind of macroeconomic gains measured this paper.

5 Concluding Remarks

This paper documents that major natural disasters harm economic growth in the absence of risk transfer. In a large panel covering more than 200 countries and jurisdictions over 52 years, we examine the pattern of macroeconomic recovery and capture rich dynamics in post-disaster growth. The negative impact of disasters is compounded by subdued growth over several years (variable across physical types), leading to a cumulative output cost in the range of 2 to 4% of GDP. "Unmitigated disasters" thus belong to a class of macroeconomic shocks – alongside wars, political and financial crises – from which economies do not fully recover.

[37] A literature documents that weak demand for insurance is rooted in concerns over price and quality, as well as limited trust in insurers and a general lack of understanding of insurance (Platteau et al 2017). For instance, the take-up of crop-insurance, even at actuarially-favorable prices, has been very low in the absence of other incentives (Vargas Hill et al 2019).

[38] IAIS (2023) and OECD (2023) underline from a policy perspective the need for worldwide risk mitigation approaches. Examples of international cooperation include the Caribbean Catastrophe Risk Insurance Facility, the Pacific Catastrophe Risk Assessment and Financing Initiative, or the African Risk Capacity.

[39] OECD (2018) notes the impediments to cross-border risk transfer to reinsurance markets arising from the regulatory and supervisory requirements that regulators and supervisors in most jurisdictions impose.

Our main novel result is that risk transfer helps to mitigate the macroeconomic cost of disasters. It is the uninsured losses that drive the macroeconomic cost of disasters; insured losses are inconsequential, if not expansionary, in the aggregate. The strongest growth-enhancing effects appear in the year after impact, in line with the timing of insurance payouts. The mitigating role of insurance stands out across physical types of disasters, and can be helpful at any stage of development. Whether shocks have transitory or permanent effects depends on risk transfer.

The results imply that insurance has measurable macroeconomic value, beyond the compensation for direct losses. In view of this finding, the lack of insurance cover for so many disasters around the world appears suboptimal. Whether it is desirable for countries to seek higher cover and international reinsurance depends on premiums and the frequency and severity of disasters – a cost-benefit analysis is beyond the scope of this paper. But if the observed insurance cover in the market was determined on the basis of direct losses alone, then the macroeconomic value we identified should tip the scales in favor of more insurance.

Appendix

A.1. Data Appendix

Macroeconomic data. 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 generally do not receive such flows.) 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. 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 series altogether.

Natural disasters. All catastrophe-related data are from NatCatService of Munich Re, a global reinsurance group. Total losses and insured losses refer to damage to or destruction of real physical assets and infrastructure as well as business continuity, excluding life. According to Wirtz et al (2012), this includes: buildings (e.g. homes, schools, hospitals); vehicles and vessels; infrastructure (e.g. bridges, roads); arable farming, livestock, aquaculture; transport and marine (e.g. shipping, oil platforms); industrial losses; and ecological damage (e.g. oil spills). Insurers face challenges when classifying losses by physical type. Multi-type catastrophes are generally coded by the triggering event (Wirtz et al 2012). For example, Japan in March 2011 first suffered an earthquake, even as the flooding (tsunami) and the nuclear incident added to recorded losses.

Note that figures for *insured* losses are very reliable as they are based on claims actually paid by insurance companies; there is more uncertainty about *total* losses, which are derived from a wide range of sources. Wirtz et al (2012) report that Munich Re estimates total losses on the basis of insurance claims, information on insurance penetration for the different perils and different countries, and a range of available loss indicators collected from internal company reports, expert appraisals, insurance, associations, scientific sources, governmental and non-governmental organisations. Losses reported in the media are often unreliable, as some may exaggerate losses, or fail to track growing losses over time.

Aggregation. Two aggregation issues arise in matching disaster-related losses to the macroeconomic panel. First, natural disasters do not respect national borders – a case in point is the Indian Ocean Tsunami (26 December 2004) that affected many countries. It was important to confirm that supranational events affecting entire regions come with full country-level information. 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 were matched with macroeconomic time series at the annual frequency. Where countries suffered several catastrophes within a single year, we aggregate all events (indexed by j) 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 1,472 observations at the country-year level, while retaining the number and type of disasters by folding this information into additional variables (Table 1). Total losses are split into parts, where insured losses equal $T_{it} = \Sigma_j \; ins_{jit}$ and uninsured losses are the residual $U_{it} = L_{it} - T_{it}$. The severity of a disaster is defined by the natural log transform $x_{it} = \ln(L_{it}/GDP_{it} + 1)$, as explained in Section 1.3.

A.2. Further Robustness Tests

Table A2 examines whether our main results are sensitive to the definition of disaster variables, or to changes in the dependent variable. The point of comparison is the "All controls" specification of Table 3B (reproduced 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. This is the case even though some disasters occur relatively late in the year. [40] 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. This puts natural disasters on the same footing as man-made crises coded as dummy variables equal to one in the year a crisis begins. While not our preferred specification, it also addresses potential endogeneity. 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. The estimated impact now equals -1.14%, reducing growth more than in the main table since the indicator pools all disasters, including those more severe than the median. The cumulative macroeconomic cost (2.1% of GDP) equals that of uninsured median-sized disasters in column 0.

Column 2 reverts to losses in percent of GDP, but applies a more inclusive cutoff. Including all disasters causing 0.5% of GDP or more in damage (instead of our regular threshold of 1%) substantially raises the number of event-years, from 355 to 556. Unsurprisingly, this weakens the estimated responses and significance levels, but does not qualitatively alter the results (comparing columns 0 and 2). The additional 201 smaller disasters (between 0.5% and 1% in direct losses) have milder indirect macroeconomic effects. Raising the cutoff instead yields greater estimated growth effects (not reported), as in other studies (Cavallo et al 2023).

Column 3 runs the main regression using the *level* of dollar losses as a measure of severity. We maintain the inclusion criterion at 1% of GDP to keep the sample of disasters aligned with that used in other regressions. 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). The mean level of losses, both insured and uninsured, exceeds median losses by a factor of more than 10 (italicized rows in column 3).

Column 4 limits the main regression to the post-1980 sample to avert a possible break in the reported loss data. The NatCatService statistics attained full global coverage after Munich

[40] 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.

Re enhanced its data collection in 1980. The growth responses to uninsured losses are more pronounced than in column 0, while those for insured losses are somewhat weaker. The result also suggests that the resilience to disasters shows little sign of having improved in more recent decades.

Taken together, 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. The remaining columns consider alternative dependent variables.

In column 5, we use *GDP per capita,* a measure of the standard of living. The estimates reflect a similar impact, but the long-term cost of uninsured losses are somewhat smaller in magnitude. Perhaps GDP per capita falls less for disasters with large death tolls; e.g. the 2010 earthquake killed more than 2% of Haiti's entire population. It would be cynical to associate disasters that decimate a population with higher living standards for the survivors. We prefer the real-growth specification to capture the evolution of economic activity overall.

Finally, column 6 replaces GDP growth by growth in Gross National Income where available (using only GNI cuts the sample by half). GNI includes net income from abroad that might help mitigate the economic effects. In response to uninsured losses, GNI growth drops more than GDP growth in the first years, but also rebounds more strongly in year 3 after the disaster, leaving less of an overall loss in GNI than in GDP. For insured losses, GNI and GDP exhibit very similar dynamics. The responses of GNI and GDP are similar because GNI includes only *primary* net income from abroad – it does not include those flows likely to move the most after disasters, such as remittances, insurance payouts and unilateral transfers (which are recorded either as *secondary* net income or in the capital account).

The results of these robustness tests continue to point to uninsured losses as the key driver of the macroeconomic cost of disasters: they entail permanent costs, whereas insured losses tend to be inconsequential, if not expansionary, in the year after a disaster. Insurance, even partial, thus helps mitigate the macroeconomic cost of disasters.

References

Bakkensen, Laura, and Lint Barrage (forthcoming), "Climate Shocks, Cyclones, and Economic Growth: Bridging the Micro-Macro Gap", *Economic Journal*, forthcoming.

Barro, Robert (2006), "Rare Disasters and Asset Markets in the Twentieth Century", *Quarterly Journal of Economics 121(3)*, 823-866.

Barro, Robert, and José Ursúa (2008), "Macroeconomic Crises since 1870", *Brookings Papers on Economic Activity 39(1)*, 255-350.

Becerra, Oscar, Eduardo Cavallo and Ilan Noy (2014), "In the Aftermath of Large Natural Disasters, what Happens to Foreign Aid?", *Review of Development Economics 18(3).*

Borensztein, Eduardo, Eduardo Cavallo and Olivier Jeanne (2017), "The welfare gains from macro-insurance against natural disasters", *Journal of Development Economics 124*, 142-156.

Botzen, Wouter, Olivier Deschenes and Mark Sanders (2019), "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies", *Review of Environmental Economics and Policy 13(2).*

Burke, Marshall, Solomon Hsiang, and Edward Miguel (2015), "Climate and Conflict", *Annual Review of Economics 7*, 577-617.

Cavallo, Eduardo, Andrew Powell and Oscar Becerra (2010), "Estimating the Direct Economic Damage of the Earthquake in Haiti", *The Economic Journal 120(546)*, F298-F312.

Cavallo, Eduardo, and Ilan Noy (2011), "Natural Disasters and the Economy A Survey", *International Review of Environmental and Resource Economics 5(1), 63-102.*

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano (2013), "Catastrophic Natural Disasters and Economic Growth", *Review of Economics and Statistics 95(5),* 1549-1561.

Cavallo, Eduardo, Oscar Becerra and Laura Acevedo (2022), "The impact of natural disasters on economic growth", Chapter 9 in Mark Skidmore (ed) Handbook on the Economics of Disasters, Edward Elgar Publishing.

Cerra, Valerie, Antonio Fatás, and Sweta Saxena (2023), "Hysteresis and Business Cycles", *Journal of Economic Literature 61(1)*, 181-225.

Cerra, Valerie, and Sweta Saxena (2008), "Growth Dynamics: the Myth of Economic Recovery", *American Economic Review 98(1)*, 439-457.

Clauset, Aaron, Cosma Shalizi and Mark Newman (2009), "Power-Law Distributions in Empirical Data", *SIAM Review 51(4),* 661-703.

CRED (2021), "Missing Data on Economic Losses Variables from EM-DAT", *Cred Crunch, Issue 63, Centre for Research on the Epidemiology of Disasters, July 2021.*

Cummins, David, and Olivier Mahul (2009), *Catastrophe Risk Financing in Developing Countries –*

Principles for Public Intervention, The World Bank, Washington DC.

De Mel, Suresh, David McKenzie, and Christopher Woodruff (2011), "Enterprise Recovery following Natural Disasters", *The Economic Journal 122*, 64-91.

Dermott, Thomas, Frank Barry, and Richard Tol (2014), "Disasters and Development: Natural Disasters, Credit Constraints and Economic Growth", *Oxford Economic Papers 66*, 750-773.

Doyle, Lisa, and Ilan Noy (2015), "The short-run nationwide macroeconomic effects of the Canterbury earthquakes", *New Zealand Economic Papers 49(2)*, 64-91.

Eisensee, Thomas, and David Strömberg (2007), "News Droughts, News Floods and U.S. Disaster Relief", *Quarterly Journal of Economics 122(2)*, 693-728.

Fatica, Serena, Gabor Katay and Michela Rancan (2022), "Floods and Firms: Vulnerabilities and Resilience to Natural Disasters in Europe", *Joint Research Centre Working Papers in Economics and Finance 13,* , European Commission.

Felbermayr, Gabriel, and Jasmin Groeschl (2014), "Naturally negative: The Growth Effects of Natural Disasters", *Journal of Development Economics 111*, 92-106.

Froot, Kenneth (2001), "The Intermediation of Financial Risk: Evolution of the Catastrophe Reinsurance Market", *Journal of Financial Economics 60*, 529-571.

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

Gabaix, Xavier (2012), "Variable Rare Disasters: an Exactly Solved Framework for Ten Puzzles in Macro-Finance", *Quarterly Journal of Economics 127*, 645-700.

Gourio, François (2008), "Disasters and Recovery", *American Economic Review 98(2)*, 68-73.

Gourio, François (2012), "Disaster Risk and Business Cycles", *American Economic Review 102(6)*, 2734-2766.

Hochrainer, Stefan (2009), "Assessing the Macroeconomic Impacts of Natural Disasters – Are there any?", *World Bank Policy Research Working Paper 4968*.

Ito, Hiro, and Robert McCauley (2022), "A Disaster Under(Re)Insurance Puzzle: Home Bias in Disaster RiskBearing", *IMF Economic Review* 70, 735772.

International Association of Insurance Supervisors (2023), "A Call to Action: The Role of Insurance Supervisors in Addressing Natural Catastrophe Protection Gaps", IAIS Report, November 2023.

Jones, Rebecca, Debarati Guha-Sapir, and Sandy Tubeuf (2022), "Human and economic impacts of natural disasters: can we trust the global data?", *Scientific Data volume 9, No. 572*

Johnson, Simon, William Larson, Chris Papageorgiou, and Arvind Subramanian (2013), "Is newer better? Penn World Table Revisions and their Impact on Growth Estimates", *Journal of Monetary Economics 60*, 255-274.

Klomp, Jeroen, and Kay Valckx (2014), "Natural Disasters and Economic Growth: A Meta-Analysis", *Global Environmental Change 26*, 183-195.

Kunreuther, Howard and Erwann Michel-Kerjan (2009), *At War with the Weather: Managing Large-Scale Risks in a New Era of Catastrophes*, Cambridge, MA, The MIT Press.

Laeven, Luc and Fabian Valencia (2012), "Systemic Banking Crises Database: An Update", *IMF Working Paper 12/163*.

Levine, Ross and Sara Zervos (1998), "Stock Markets, Banks, and Economic Growth", *American Economic Review 88(3)*, 537-558.

Loayza, Norman, Eduardo Olaberria, Jamele Rigolini and Luc Christiaensen (2012), "Natural Disasters and Growth: Going Beyond the Averages", *World Development 40(7)*, 1317-1336.

Munich Re (2011), "NatCatService: Natural Catastrophe Know-How for Risk Management and Research", online resources available at www.munichre.com/geo.

Nelson, Charles, and Charles Plosser (1982), "Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications", *Journal of Monetary Economics 10(2)*, 139-62.

New Zealand Treasury (2010), "Economic Impact of Canterbury Earthquake", *Economic Brief*, 10 September 2010.

Nguyen, Cuong Nhu and Ilan Noy (2020), "Measuring the impact of insurance on urban earthquake recovery using nightlights", *Journal of Economic Geography 20, 857-877.*

Nickell, Steven (1981), "Biases in Dynamic Models with Fixed Effects", *Econometrica 49(6)*, 1417-26.

Noy, Ilan (2009), "The Macroeconomic Consequences of Disasters", *Journal of Development Economics 88*, 221-231.

Noy, Ilan, and Aekkanush Nualsri (2011), "Fiscal Storms: Public Spending and Revenues in the Aftermath of Natural Disasters", *Environment and Development Economics 16*, 113-128.

OECD (2018), "The Contribution of Reinsurance Markets to Managing Catastrophe Risk", OECD Report, December 2018.

OECD (2023), "Recommendation on Building Financial Resilience to Disaster Risks", OECD Legal Instruments, November 2023.

IPCC (2023), "Synthesis Report of the IPCC Sixth Assessment Report (AR6)", Intergovernmental Panel on Climate Change; Longer Report.

Platteau, Jean-Philippe, Ombeline De Bock, Wouter Gelade (2017), "The Demand for Microinsurance: A Literature Review", *World Development 94*, 139-156.

Raddatz, Claudio (2007), "Are External Shocks Responsible for the Instability of Output in Low-Income Countries?", *Journal of Development Economics 84(1)*, 155-187.

Rahman, Muhammad, Nejat Anbarci and Mehmet Ulubasoglu (2022), "Storm autocracies: Islands as Natural Experiments", *Journal of Development Economics 159*, 102982.

Reinhart, Carmen, and Kenneth Rogoff (2014), "Recovery from Financial Crises: Evidence from 100 Episodes.", *American Economic Review, 104 (5)*, 50-55.

Reinsurance Association of America (2011), *Historical Loss Development Study.* Washington DC.

Runyan, Rodney (2006), "Small Business in the Face of the Crisis: Identifying Barriers to Recovery from a Natural Disaster", *Journal of Contingencies and Crisis Management 14(1)*, 12-26.

Schumacher, Ingmar, and Eric Strobl (2011), "Economic Development and Losses due to Natural Disasters: the Role of Hazard Exposure", *Ecological Economics 72*, 97-105.

Sims, Christopher, and Tao Zha (1999), "Error Bands for Impulse Responses", *Econometrica 67(5)*, 1113-55.

Skidmore, Mark, and Hideki Toya (2002), "Do Natural Disasters Promote Long-Run Growth?", *Economic Inquiry 40(4)*, 664-687.

Stern, Nicholas (2007), The Economics of Climate Change. New York: Cambridge University Press.

Strobl, Eric (2012), "The Economic Growth Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in the Central American and Caribbean Regions ", *Journal of Development Economics 97*, 130-141.

Toya, Hideki, and Mark Skidmore (2007), "Economic Development and the Impacts of Natural Disasters", *Economics Letters 94*, 20-25.

United Nations ESCAP (2021), "Towards Post-COVID-19 Resilient Economies", Report, Economic and Social Survey of Asia and the Pacific 2021 March 2021.

Vargas Hill, Ruth, Neha Kumar, Nicholas Magnan, Simrin Makhija, Francesca de Nicola, David Spielman, Patrick Ward (2019), "Ex Ante and Ex Post Effects of Hybrid Index Insurance in Bangladesh", *Journal of Development Economics 136*, 1-17.

von Dahlen, Sebastian, and Goetz von Peter (2012), "Natural Catastrophes and Global Reinsurance – Exploring the Linkages", *BIS Quarterly Review*, December.

Weitzman, Martin (2009), "On Modeling and Interpreting the Economics of Catastrophic Climate Change", *Review of Economics and Statistics 91(1)*, 1-19.

Wirtz, Angelika, Wolfgang Kron, Petra Löw and Markus Steuer (2012), "The Need for Data: Natural Disasters and the Challenges of Database Management", *Natural Hazards 70*,135-157.

World Bank and United Nations (2010), *Natural Hazards, Unnatural Disasters – the Economics of Effective Prevention.* The World Bank: Washington DC.

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

	Properties	All types	Geophysical[A]	Climate-related disasters: Meteorological[B]	Hydrological[C]	Climatological[D]
Frequency	*# All events (types in %)*	*21,768*	*12%*	*42%*	*34%*	*12%*
	# Major disasters	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 disasters (in %)	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 type. The remaining rows summarize major disasters, 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

		(1)	(2)	(3)	(4)			
	Regressors	Largest	Baseline	Poorer	Geophys	Meteorol	Hydrol	Climatol
Disasters	*Disaster years (#)*	*460*	*445*	*277*	*56*	*171*	*103*	*125*
	Median loss in % of GDP	*3.19*	*3.19*	*3.11*	*4.84*	*3.57*	*2.55*	*2.54*
	Mean loss in % of GDP	*15.4*	*15.4*	*17.1*	*31.5*	*20.0*	*6.83*	*6.79*
Growth response to total losses	Impact (median disast)	**−1.00*****	**−0.95*****	**−1.03*****	**−1.58*****	**−0.96*****	**−1.41*****	**−0.54**
		(0.12)	(0.12)	(0.16)	(0.34)	(0.14)	(0.34)	(0.33)
	Lag 1	**−0.13**	**−0.30**	**−0.56****	**−1.34***	**−0.03**	**−0.15**	**−0.35**
		(0.13)	(0.16)	(0.20)	(0.46)	(0.17)	(0.28)	(0.25)
	Lag 2	**−0.49***	**−0.44***	**−0.54**	**−0.40**	**−0.64**	**−0.61****	**−0.18**
		(0.17)	(0.17)	(0.25)	(0.40)	(0.26)	(0.20)	(0.29)
	Lag 3	**0.12**	**0.23**	**0.26**	**−0.25**	**0.16**	**0.48**	**0.50***
		(0.10)	(0.11)	(0.15)	(0.23)	(0.15)	(0.24)	(0.24)
	Lag 4	**0.02**	**−0.01**	**0.05**	**0.23**	**−0.37****	**−0.22**	**0.43**
		(0.10)	(0.09)	(0.11)	(0.27)	(0.11)	(0.24)	(0.21)
	LT-effect in % of GDP	**−2.13*****	**−2.20*****	**−2.51*****	**−4.99***	**−2.76*****	**−2.86****	**−0.22**
		[0.001]	[0.003]	[0.007]	[0.098]	[0.0003]	[0.012]	[0.880]
	Impact (mean disaster)	−1.95***	−1.85***	−2.12***	−3.12***	−1.92***	−2.29***	−0.88
	LT-effect in % of GDP	−4.16***	−4.30***	−5.16***	−9.85*	−5.52***	−4.64**	−0.36
Basic controls	Growth Lag 1	0.22***	0.20***	0.19***	0.19***			
		(0.04)	(0.05)	(0.07)	(0.05)			
	Lag 2	0.09***	0.08***	0.07**	0.08***			
		(0.02)	(0.02)	(0.03)	(0.02)			
	Lag 3		0.08***	0.07***	0.08***			
			(0.03)	(0.02)	(0.03)			
	Lag 4		−0.02	−0.05*	−0.02			
			(0.03)	(0.03)	(0.03)			
	Events in same year (#)		0.01	−0.03	0.02			
			(0.02)	(0.06)	(0.02)			
	Prior disasters(#)		0.19**	0.22**	0.19**			
			(0.08)	(0.11)	(0.08)			
	Log GDP/capita		0.03	0.19*	0.03			
			(0.15)	(0.11)	(0.15)			
	Time trend		−0.02***	0.01*	−0.02***			
			(0.01)	(0.01)	(0.01)			
	Fixed effects	country	country	country	country			
Sample	# Observations	8921	8459	3705	8459			
	# Countries	214	212	93	212			
	R^2	0.115	0.123	0.077	0.12			

Notes. Table 2 reports fixed-effects panel regressions (1960-2011) of real GDP growth on total indirect disaster losses (aggregated at the country-year level), estimating equation (1). Disaster losses are expressed in percent of GDP (in natural logarithms) and include disaster-years with events causing direct losses of 1% of GDP or more in a given year. For reference, the *rows in italics* report the severity of events. All disaster coefficients are scaled by the log of the *median* severity of disasters, as defined in equation (2) for the impact, and in equation (3) for the long-term effect (LT-effect). The shaded rows present the same sensitivity estimates scaled by the log severity of *mean* losses (showing impact and long-term effects).

Column (1) runs a parsimonious specification to maximize sample size; the remaining columns use four growth lags and basic controls, including: a time trend; GDP per capita (a proxy for the stage of development); and two counters (by country, for disaster years): the number of events that contributed to the current disaster year, and the number of disaster-years a country suffered prior to the current one. Column (3) retains low-income and lower-middle-income countries, based on the World Bank income classification (4 groups). Column (4) reports a regression that allows for distinct estimates specific to each physical type: geophysical, meteorological, hydrological, and climatological disasters (listed in Table 1).

All columns quote robust standard errors (in parentheses), and report p-values for the long-term effects based on a non-linear Wald test of equation (3) [p-values in square brackets]. Stars denote significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3A Risk Transfer: Cover-loss interaction (Specification A)

		(1) Risk Transfer & Access and Aid						(2) Adding stand-alone Cover					
		Impact	Lag 1	Lag 2	Lag 3	Lag 4	LT-effect	Impact	Lag 1	Lag 2	Lag 3	Lag 4	LT-effect
Total losses	Response to median[1]	−1.05***	−0.40	−0.48**	0.37*	0.11	−2.19**	−1.04***	−0.43	−0.50**	0.35*	0.11	−2.27**
	Response to mean[2]	−2.05***	−0.77	−0.94**	0.72*	0.21	−4.28**	−2.03***	−0.83	−0.97**	0.69**	0.21	−4.45**
	p-value of LT-effect						0.011						0.009
Insurance cover	Cover alone							0.002	−0.03	−0.05	−0.03	0.005	−0.167
	Cover-loss interact:												
	Response to median[1]	0.08	0.38***	0.04	−0.09	−0.15	0.40	0.06	0.56***	0.33*	0.11	−0.18	1.34**
	Response to mean[2]	0.40	1.89***	0.20	−0.44	−0.73	1.99	0.30	2.78***	1.61*	0.56	−0.91	6.58**
	p-value of LT-effect						0.200						0.087
Basic controls	Growth Lags		0.19***	0.08**	0.08**	−0.01			0.19***	0.07**	0.08**	−0.01	
	Prior disasters(#)	0.14						0.16*					
	Log GDP/capita	−0.57						−0.58					
	x interactions	−0.35	−0.68**	−0.50*				−0.35	−0.65**	−0.43			
	Time trend	0.01						0.01					
	Fixed effects	country						country					
Access to finance	Access to banking	−0.004						−0.004					
	x interactions	0.04**	0.05**	0.04				0.04**	0.05**	0.04*			
	Access to insurance	−0.20**						−0.19**					
	x interactions	0.27	0.29	−0.05				0.26	0.26	−0.10			
	Credit-to-GDP %	−0.02***						−0.02***					
	x interactions	0.004	0.005	0.02*				0.004	0.005	0.02*			
Aid flows	Net Aid flows	0.13						0.12					
	x interactions	−6.58***	2.10***	−0.19				−6.61***	2.09***	−0.22			
	Net Off.Dev.Assist	−0.02						−0.02					
	x interactions	0.01	0.10**	0.03				−0.01	0.10**	0.04			
Sample	# Observations	6,812						6,812					
	# Countries	162						162					
	# Event-years	355						355					
	R^2	0.098						0.098					

Notes. Table 3 reports fixed-effects panel regressions (1960-2011) of real GDP growth on indirect disaster losses and insurance cover. Following equation (4), it tests whether insurance cover mitigates the output cost of disasters by making the growth response conditional on insurance cover (Specification A in the text). The table reports all lags (including lags of interactions) in columns and omits robust standard errors, showing significance levels as: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The growth response to losses is reported as the estimated sensitivity coefficients scaled by the log severity of disaster, as in Table 2 (following equations (1)-(3) in the text). The growth response to the cover-loss interaction is scaled analogously (following equations (4)-(5)), based on observations with positive insurance cover.

[1]For median-sized disasters, the median total loss is 3.19% of GDP, and median cover equals 12.1%

[2]For mean-sized disasters (shaded cells), the mean total loss is 15.4% of GDP, and mean cover equals 59.6%.

The panel contains 6,812 observations for 162 countries, comprising 355 disaster-years with events causing direct losses of 1% of GDP or more in a given year. Both regressions include four autoregressive lags, country fixed effects and basic controls as in Table 2, plus two groups of development controls: Access to finance (3 variables, shaded green) and Aid flows (2 variables, yellow). 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 are based on estimated impacts and four lags of the respective variables (equation (3)) for total losses, and (5) for the Cover-loss interaction term). Reported p-values are based on a non-linear Wald test.

Table 3B Risk Transfer: Un/Insured losses (Specification B)

		(1) Risk Transfer & Access and Aid						(2) Risk Transfer & 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	Response to median[1]	-1.00***	-0.54	-0.54***	0.38**	0.15	-2.35***	-0.89***	-0.50	-0.49**	0.37**	0.10	-2.10**
	Response to mean[2]	-1.96***	-1.06	-1.07***	0.75**	0.29	-4.61***	-1.75***	-0.98	-0.95**	0.72**	0.20	-4.11**
	p-value of LT-effect						0.009						0.014
Insured	Response to median[1]	0.05	0.60***	0.19	-0.12	-0.23	0.72	0.07	0.58***	0.15	-0.11	-0.21	0.73
	Response to mean[2]	0.29	3.77***	1.17	-0.77	-1.44	4.57	0.45	3.66***	0.96	-0.67	-1.32	4.59
	p-value of LT-effect						0.151						0.103
Basic controls	Growth Lags		0.19***	0.08**	0.08**	-0.01			0.18***	0.07**	0.08**	-0.01	
	Prior disasters(#)	0.16*						0.14					
	Log GDP/capita	-0.58						-0.72					
	x interactions	-0.36	-0.71**	-0.56*				-0.29	-0.72**	-0.47			
	Time trend	0.01						0.00					
	Fixed effects	country						country					
Access to finance	Access to banking	-0.004						-0.005					
	x interactions	0.04*	0.05**	0.04*				0.04**	0.05***	0.03			
	Access to insurance	-0.20**						-0.12					
	x interactions	0.30	0.28	-0.07				0.09	0.20	-0.04			
	Credit-to-GDP %	-0.02***						-0.02***					
	x interactions	0.004	0.005	0.02*				0.002	0.004	0.02**			
Aid flows	Net Aid flows	0.13						0.39					
	x interactions	-6.59***	2.17***	-0.16				-7.23***	1.56*	-0.52			
	Net Off.Dev.Assist	-0.02						-0.02					
	x interactions	0.01	0.10**	0.03				-0.004	0.09*	0.03			
Man-made crises	Banking crises							-1.69***	-2.34***	0.49	0.13	0.04	**-5.03*****
	Currency crises							-1.85***	0.11	0.66	0.66	0.95**	**0.78**
	Debt crises							-4.04***	-1.91**	-0.50	1.12*	-0.97	**-9.40*****
	Political crises							-2.28***	1.25	-0.68	0.44	-0.70	**-2.94**
	Wars							-3.44***	-1.84*	-0.49	0.37	0.01	**-8.03*****
Sample	# Observations	6,812						6,812					
	# Countries	162						162					
	# Event-years	355						355					
	R^2	0.100						0.123					

Notes. Table 2 reports fixed-effects panel regressions (1960-2011) of real GDP growth on indirect disaster losses, estimating distinct responses to insured and uninsured disaster losses (equation (6)). All lags (including lags of interactions) appear in columns, and significance levels are shown as: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The growth responses are reported as estimated sensitivities scaled by the log severity of disasters (as in equations (1)-(6)):
[1]For median-sized disasters, the median uninsured loss is 2.97%, the insured loss is 0.34% of GDP.
[2]For mean-sized disasters (shaded cells), the mean uninsured loss is 13.9%, the insured loss is 5.28% of GDP.

The panel is the same as for Table 3A (see notes). In addition to Access to finance (green) and Aid flows (yellow), column (2) also includes 5 types of man-made crises (orange). 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 (equation (3)), with reported p-values based on a non-linear Wald test.

Table 4 The Cost of Disasters across Different Physical Types

		(1) Full sample				(2) All but rich countries			
		Geophys	Meteorol	Hydrol	Climatl	Geophys	Meteorol	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	-1.02^{**}	-2.69^{**}	-0.99^{**}	-0.53	-1.10^{**}
	Lag 1	-1.58	-0.47	0.15	-0.49	-2.43	-0.48	0.14	-0.50
	Lag 2	-1.16	-0.24	-0.42	-0.78^{*}	-1.94	-0.33	-0.44	-0.86^{*}
	LT-effect in % GDP	**-6.62^{*}**	**-2.36^{**}**	**-0.95**	**-3.14^{***}**	**-9.06^{*}**	**-2.31^{**}**	**-1.07**	**-3.16^{***}**
	LT-effect p-value	0.09	0.02	0.37	0.00	0.07	0.02	0.32	0.00
	Mean loss in % GDP	*27.6*	*17.5*	*6.8*	*6.8*	*32.1*	*19.6*	*7.2*	*7.1*
	Impact on growth	-4.10^{**}	-2.16^{**}	-0.71	-1.68^{**}	-5.31^{**}	-2.14^{**}	-0.90	-1.73^{**}
	LT-effect in % GDP	**-13.11^{*}**	**-5.11^{**}**	**-1.60**	**-5.20^{***}**	**-17.9^{*}**	**-5.02^{**}**	**-1.80**	**-4.96^{***}**
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	0.43^{**}	0.04	-0.23^{*}	-0.37^{*}	0.70^{**}	0.01	-0.24^{*}	-1.41^{**}
	Lag 1	0.51	1.63^{***}	0.18	1.42^{***}	0.95	1.34^{***}	0.18^{*}	5.81^{***}
	Lag 2	0.60^{*}	-0.28	0.08	-0.24	1.12^{**}	-0.21	-0.03	-1.95^{***}
	LT-effect in % GDP	**2.12^{**}**	**1.92^{*}**	**0.04**	**1.12^{**}**	**3.55^{**}**	**1.47^{**}**	**-0.11**	**3.14^{**}**
	LT-effect p-value	0.03	0.06	0.88	0.01	0.02	0.05	0.43	0.01
	Mean loss in % GDP	*7.49*	*6.85*	*0.29*	*0.77*	*9.72*	*6.29*	*0.23*	*2.21*
	Impact on growth	4.07^{**}	0.10	-0.63^{*}	-0.59^{*}	6.97^{**}	0.04	-0.93^{*}	-1.41^{**}
	LT-effect in % GDP	**20.3^{**}**	**4.58^{*}**	**0.10**	**1.78^{**}**	**35.5^{**}**	**4.31^{**}**	**-0.43**	**3.14^{**}**
Extended controls	Growth Lag 1	0.20^{***}				0.18^{***}			
	Lag 2	0.08^{**}				0.04^{*}			
	Prior disasters (#)	0.12				0.13			
	Time trend	-0.00				-0.01			
	Log GDP/capita	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	**-4.40^{***}**				**-3.31^{**}**			
	Currency crises: Impact	-2.15^{***}				-2.19^{***}			
	LT-effect	**-2.38^{*}**				**-2.54^{**}**			
	Debt crises: Impact	-3.92^{***}				-3.97^{***}			
	LT-effect	**-8.82^{***}**				**-8.76^{***}**			
	Political crises: Impact	-2.34^{***}				-2.65^{***}			
	LT-effect	**-2.47^{*}**				**-3.22^{***}**			
	Wars: Impact	-3.52^{***}				-4.00^{***}			
	LT-effect	**-7.42^{***}**				**-8.32^{***}**			
Sample	# Observations	7,109				4,950			
	# Countries	162				114			
	R^2	0.137				0.089			

Notes. Table 4 reports two regressions (1960-2011) based on equation (6) in the text, allowing for distinct estimates specific to each physical type: geophysical, meteorological, hydrological, or climatological disasters (Table 1). For reference, the *rows in italics* report the number of events and their severity, based on disasters of this physical type causing direct losses of 1% of GDP or more in a given year. Shaded rows represent *mean* severities. Column (1) reports full-sample results with all controls (Table 3B column 2); column (2) excludes high-income countries. All long-term effects (LT-effect, in bold) are based on the estimated impacts and four lags (equation (3)). Controls marked "included" enter contemporaneously in levels and interacted with a disaster dummy and with two lags (see notes to Tables 2 and 3). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A1 Variable Definitions and Data Sources

Dep. variable: y_{it} = annual growth rate of real GDP, in %	World Bank (WDI), complemented by 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 premiums, % 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}	$v_{it} = \ln(U_{it}/GDP_{it} + 1)$
Insurance cover (insured losses in % of total direct losses)	$cover_{it} = 100 * T_{it}/L_{it}$

Table A2 Robustness Experiments

		(0) Table 3B	(1) Indicator	(2) Cutoff	(3) Log-levels	(4) Post-1980	(5) GDP/capita	(6) GNI
Uninsured disaster losses	*Median loss*	*2.97%*	*1*	*1.66%*	*$204mn*	*2.92%*	*2.97%*	*2.97%*
	Impact on growth	−0.89***	−1.14***	−0.59***	−1.02***	−0.98***	−0.87***	−0.90***
	Lag 1	−0.50	−0.06	−0.30	−0.48	−0.62	−0.48	−0.73*
	Lag 2	−0.49**	−0.51**	−0.33**	−0.68**	−0.34	−0.42**	−0.50**
	Lag 3	0.37**	0.35	0.26**	0.39	0.27	0.38**	0.47**
	Lag 4	0.10	−0.05	0.10	0.02	0.09	0.23	0.29
	LT-effect in % of GDP	**−2.10****	**−2.11****	**−1.28****	**−2.64****	**−2.45****	**−1.65***	**−1.89****
	Mean loss	*13.9%*	*1*	*9.6%*	*$2745mn*	*13.4%*	*13.9%*	*13.9%*
	Impact on growth	−1.75***	−1.14***	−1.42***	−1.51***	−1.92***	−1.70***	−1.76***
	LT-effect in % of GDP	**−4.11**	**−2.11**	**−3.08**	**−3.92**	**−4.77**	**−3.23**	**−3.70**
Insured disaster losses	*Median loss*	*0.34%*		0.23%	$110mn	0.34%	0.34%	0.34%
	Impact on growth	0.07		0.01	0.35	0.10	0.03	0.10
	Lag 1	0.58***		0.39***	1.47**	0.59***	0.57***	0.60***
	Lag 2	0.15		0.06	1.02**	−0.11	0.10	0.14
	Lag 3	−0.11		−0.07	−0.70*	−0.03	−0.16	−0.14
	Lag 4	−0.21		−0.16	−0.69	−0.25*	−0.25*	−0.21
	LT-effect in % of GDP	**0.73**		0.34	2.17	0.47	0.41	0.67
	Mean loss	*5.28%*		*3.49%*	*$1626mn*	*5.60%*	*5.28%*	*5.28%*
	Impact on growth	0.45		0.07	0.55	0.67	0.18	0.61
	LT-effect in % of GDP	**4.59**		**2.49**	**3.40**	**3.06**	**2.60**	**4.24**
Man-made crises and development controls	Growth Lag 1	0.18***	0.18***	0.18***	0.18***	0.21**	0.22***	0.20***
	Lag 2	0.07**	0.07**	0.08**	0.07**	0.06***	0.05	0.04
	Lag 3	0.08**	0.08**	0.08**	0.08**	0.05***	0.02	0.03
	Lag 4	−0.01	−0.01	−0.01	−0.01	0.03	0.01	0.02
	Prior disasters (#)	0.14	0.10	0.10	0.12	0.16	0.14	0.20*
	Log GDP/capita	included	included	included	included	included	included	included
	Country fixed effects	included	included	included	included	included	included	included
	Access to banking	included	included	included	included	included	included	included
	Access to insurance	included	included	included	included	included	included	included
	Credit-to-GDP %	included	included	included	included	included	included	included
	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	6,644
	# Countries	162	162	162	162	162	162	162
	# Event-years	355	355	556	355	294	347	348
	R^2	0.123	0.120	0.121	0.122	0.140	0.137	0.136

Notes. The table reports robustness experiments based on the more final development specification (Table 3B column 2) reproduced in column (0), using the same sample (1960-2011) and groups of controls with interactions and lags, except that:

(1) uses a disaster **indicator** (ignoring severity): 1 for years where disasters cost 1% GDP or more, and 0 otherwise
(2) returns to losses as % of GDP, with a lower **cutoff** (0.5% instead of 1% of GDP) to include more disasters
(3) replaces severity by the **level of losses,** expressed in constant 2011 US dollars (not scaled by GDP), in logs
(4) starts the sample after **1980** (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 GDP growth by growth in Gross National Income (**GNI**) where available.

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 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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