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Climate change, catastrophes, insurance and the macroeconomy

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Abstract

This paper examines the role of insurance in mitigating the adverse macroeconomic effects of climate-related catastrophes. We first develop a stylised theoretical growth model which incorporates a role for natural catastrophes, climate change and insurance. This illustrates how insurance can mitigate the impact of catastrophes and articulates the potential effect of falling insurance coverage as global warming intensifies. The model also provides a basis for our empirical analysis which explores the link between insurance coverage and the macroeconomic impact of catastrophes for a sample of several thousand disaster events across 47 developed and middle income countries between 1996 and 2019. The results confirm that higher insurance coverage is associated with less severe macroeconomic consequences of disasters. With climate-related catastrophes becoming ever more frequent and severe, our findings highlight the importance of developing policies to reduce the climate insurance protection gap.

JEL classification: G22, G52, Q51, Q54

Key words: insurance protection gap; natural catastrophes; economic growth; climate change; global warming

Non-technical summary

Natural catastrophes can have significant macroeconomic implications. Global warming is likely to increase the frequency and severity of extreme weather and climate events (Intergovernmental Panel on Climate Change, 2021). Ambitious policies to tackle climate change and reduce associated catastrophe risks are clearly vital, as are adaptation measures which help to reduce the extent of damages when disaster strikes. But insurance can also play an important role in helping to mitigate the adverse macroeconomic and welfare consequences of disasters.

Yet insurance coverage for catastrophes is patchy and there is currently a substantial protection gap. For example, less than a quarter of the losses caused by natural catastrophes in the EU are currently insured, and in several countries this share is below 5%. Moreover, insurance coverage has recently been declining and may fall further due to climate change as insurers and reinsurers reduce coverage or increase premiums due to rising catastrophe risks. So the future impact of catastrophes may be greater than similar events in the past, and economic models which fail to account for this mechanism may underestimate the full magnitude of the costs of climate change.

To explore this issue, we introduce insurance into a stochastic output growth model which accounts for short and long run changes in the distribution of climatic conditions and climate-related disasters. With the term insurance, we encompass all explicit insurance coverage provided to the economy by the private insurance and reinsurance sectors, as well as by the public sector, including through public-private partnerships. The model provides three main conclusions: insurance can help mitigate the macroeconomic and welfare impact of catastrophes and greater risk pooling amplifies these benefits; climate change is likely to have an increasingly negative impact on welfare; and that impact is likely to be magnified by a lower supply of insurance which reduces insurance coverage.

The first of these theoretical findings is supported by an empirical estimation of the macroeconomic impact of past natural catastrophes across developed and middle income countries, which demonstrates the beneficial role of insurance. A catastrophe causing 1% of GDP worth of damage is estimated to reduce GDP growth by around 0.2pp in the quarter of impact. However, if a high share of damages are covered by insurance, the initial fall in GDP may be averted. In addition, we find some evidence that these GDP differentials linked to insurance coverage persist over time.

While this paper provides new insights into the interplay between climate change, insurance, the protection gap and economic output, it also highlights the need for further research. In particular, the role of governments and the potential complementary role of the private sector are key issues with practical relevance which should be further explored. Also, while this paper focuses on the reconstruction effect that shows up in measured GDP, further work is necessary to fully understand the effects on welfare. Finally, the theoretical model and empirical analyses could be extended by including dynamic adaptation and mitigation measures that can help limit the macroeconomic impact of climate change.

This work highlights the need for policies aimed at reducing the climate insurance protection gap, including by enhancing private insurance penetration and developing public-private resilience solutions (ECB-EIOPA, 2023, 2024). The cross-border nature and possible systemic implications of climate change related risks may also warrant a concerted response at the European level. For example, knowledge-sharing could enhance risk management and modelling capabilities for natural catastrophes in Europe and foster more efficient capital allocation. Also, risk pooling at regional or European level could potentially improve insurability and affordability.

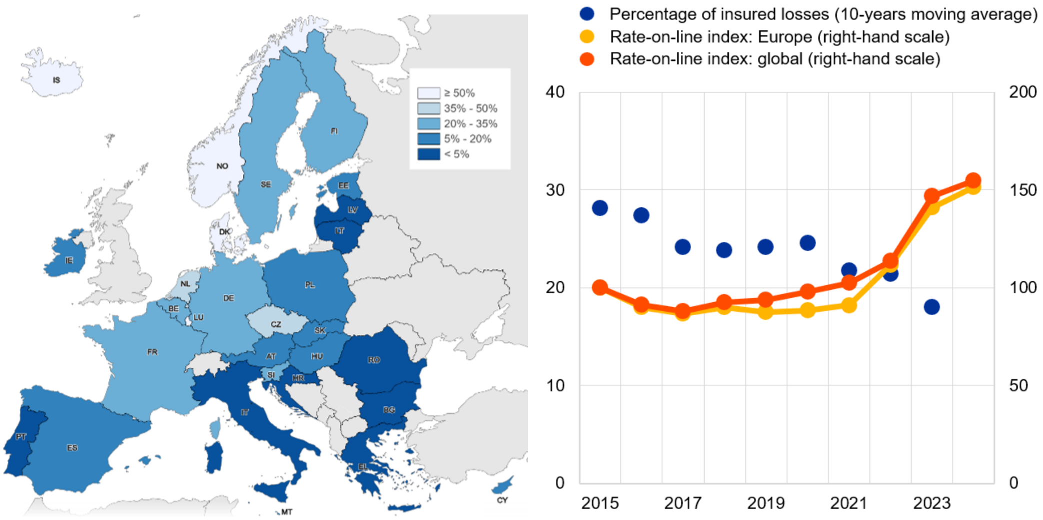
1 Introduction

Natural catastrophes can have significant macroeconomic implications (Noy (2009); Felbermayr and Gröschl (2014); Fomby et al. (2013); Klomp and Valckx (2014). Global warming is likely to increase the frequency and severity of extreme weather and climate events (Intergovernmental Panel on Climate Change, 2021; Summers et al., 2022). Ambitious policies to tackle climate change and reduce associated catastrophe risks are clearly vital, as are adaptation measures which help to reduce the extent of damages when disaster strikes. But insurance can also play an important role in helping to mitigate the adverse macroeconomic and welfare consequences of disasters (Kunreuther and Pauly, 2006; Kunreuther, 2015; Zhao et al., 2020; von Peter et al., 2024; Phan and Schwartzman, 2024).

Yet insurance coverage for catastrophes is patchy and there is currently a substantial protection gap. For example, less than a quarter of the losses caused by natural catastrophes in the EU is currently insured, and in several countries this share is below 5% (see Figure 1 and ECB-EIOPA (2024)). Moreover, insurance coverage has recently been declining and may fall further due to climate change as insurers and reinsurers reduce coverage or increase premiums due to rising catastrophe risks. So the future impact of catastrophes may be greater than similar events in the past, and economic models which fail to account for this mechanism may underestimate the full magnitude of the costs of climate change.

Figure 1: Average share of insured economic losses in Europe and property catastrophe rate-on-line indices

Notes: The chart shows the average share of insured economic losses caused by natural catastrophes in European Economic Area countries over the period 1980-2021 (map, left panel) and as the 10-year moving average across EU countries since 2015 (blue dots, right panel). The lines in the right panel show Guy Carpenter's Global and Continental Europe Property Catastrophe Rate On Line Indices (2015-2024, percentage growth). The left chart is taken from ECB-EIOPA (2024). *Sources:* EIOPA dashboard on insurance protection gap for natural catastrophes, European Environment Agency (EEA) CATDAT, Guy Carpenter and Artemis.



With this in mind, this paper examines the protective role that insurance can play in mitigating the negative macroeconomic and welfare impact of catastrophes through both a theoretical and empirical lens. Our theoretical setup exploits a stochastic output growth model which accounts for short and long run changes in the distribution of climatic conditions and climate-related disasters, along the lines of Barro (2006), Pindyck and Wang (2013) and Hong et al. (2023). A key innovation of our approach is the distinction between changes in average climatic conditions and changes in the frequency or severity of extreme climate-related catastrophes, allowing us to model their differential effects on economic growth. We also develop this model by introducing a stylised role for catastrophe insurance which can crucially help to quicken the pace of reconstruction following a disaster. Through this mechanism, we show how insurance can help to mitigate the macroeconomic and welfare impact of catastrophes. We also briefly illustrate how greater pooling of risks can increase the beneficial effects of insurance. Finally, the model allows us to articulate how climate change will probably have an increasingly negative effect on welfare through greater catastrophe risks and assess how that impact is likely to be magnified by a lower supply of insurance which reduces insurance coverage. This outcome reflects real-world dynamics, where insurance supply may contract — rather than expand — due to greater insurer risk aversion.

Our empirical analysis draws on our theoretical model. It explores the link between insurance coverage and the macroeconomic impact of catastrophes for a sample of several thousand disaster events – including floods, storms, wildfires and earthquakes – across 47 developed and middle income countries between 1996 and 2019, with the end date chosen to avoid subsequent complications linked to the Covid-19 pandemic. We apply two different empirical specifications. The first examines how the extent of insurance coverage interacts with GDP losses following disasters, also exploring rebound effects at the quarterly level. The second examines just large-scale disasters in an approach which simply splits the sample in a binary way into cases with high and low insurance coverage. The results from both approaches confirm that higher insurance coverage is associated with less severe macroeconomic consequences of disasters. For example, a catastrophe causing 1% of GDP worth of damage is estimated to reduce GDP growth by around 0.2pp in the quarter of impact. However, if a high share of damages are covered by insurance, the initial fall in GDP may be averted. In addition, we find some evidence that these GDP differentials linked to insurance coverage persist over time. In various robustness exercises, we also attempt to confront potential endogeneity concerns stemming from links between the level of insurance coverage and both a country's economic development and different types of natural disaster.

Taken together, our findings highlight the importance of developing policies to reduce the climate insurance protection gap. Well-designed policies which confront moral hazard and incentivise adaptation can help to reduce the macroeconomic and financial impact of catastrophes and enhance welfare (see ECB-EIOPA (2023, 2024) for a discussion of potential policy options). Closing the gap becomes even more important given the expected increase in the frequency and severity of climate-related catastrophes in the coming decades, an increase that will be particularly acute if the Paris Agreement targets are not met (Intergovernmental Panel on Climate Change, 2018, 2021).

To better understand how insurance can help mitigate the impact of catastrophes, it is useful to first consider how catastrophes affect the economy. When catastrophes strike, they damage capital, crops, livestock, lives and livelihoods. This destruction reduces both wealth and productive capacity. Dependent on the type of natural peril, there can be continued physical disruption – for example until floodwaters recede – as well as economic disruption through supply chains and damaged infrastructure that can far exceed the initial area of impact. Notable examples include the March 2011 earthquake and tsunami in Japan that affected automobile production nationwide (Matsuo, 2015) and the 2018 drought in Germany where low river levels disrupted transport of oil and other commoditie.

The initial phase of the disaster is usually followed by a period of rehabilitation as disruption wanes and eventually by reconstruction, which can take years to complete. In short, the overall economic impact of catastrophes extends beyond the initial direct damage (often described as "economic damage" in the insurance literature). The lost output in the months and years before full reconstruction, assuming it occurs, can far exceed the value of the initial direct damage. It can also have a negative effect on fiscal and financial stability (Lis and Nickel, 2009; Gagliardi et al., 2022; ECB-EIOPA, 2023, 2024).

Therefore, the aggregate welfare cost depends not just on the severity of the initial damage, but also on how swiftly reconstruction can be completed. Yet there is evidence that this phase can be prolonged and may even be incomplete in the absence of sufficient resources. Broadly speaking, the paradox is that reconstruction requires funds, just at a time when economic activity, profitability and wealth may be depressed. The literature points to a substantial role for external financial support for activity and reconstruction – be it from international aid or domestic fiscal transfers – in reducing the overall impact of catastrophes (McDermott et al., 2014; Hallegatte and Vogt-Schilb, 2019). Hallegatte et al. (2024) use a detailed structural macroeconomic model to estimate the medium-run impact of disasters. They show that the speed of reconstruction is a crucial factor in determining the ultimate economic cost of disasters, and that financial interventions, including insurance, play a vital role in accelerating reconstruction. Recent research focused on EU regions finds that high-income regions witness a boost to output, capital and productivity following floods, but lower-income regions witness the opposite, with prolonged periods of lower output (Usman et al., 2024).

This is also why insurance can play a protective role. Insurance payouts can help households and businesses better endure post-catastrophe disruption and underpin the reconstruction phase (Nguyen and Noy, 2020). And firm-level evidence also demonstrates the protective value of insurance (Poontirakul et al., 2017).

But climate change can affect the provision of catastrophe insurance. By affecting the frequency and intensity of compound events (multi-hazards), it poses risks for insurance reserves and capitalisation and, ultimately, for insurance supply, that can lead to non-linear amplifications of costs (Ibragimov et al., 2009). As reported by the International Association of Insurance Supervisors (IAIS) and the Sustainable Insurance Forum (SIF), rising natural catastrophes are already resulting in increased claims, affecting the premiums and availability of non-life insurance, e.g. in property, transport and liability insurance (see also Figure 1, right panel).[1] Wider research has also highlighted how the incidence of disasters, coupled with uncertainty over the degree of climate change, leads to higher reinsurance costs and premiums (Moore, 2024; Keys and Mulder, 2024; Boomhower et al., 2024). In this context, the potential presence of non-linearities and tipping points mean that the relationships between emissions, atmospheric carbon concentrations, average global temperatures and their implications for extreme weather are subject to wide bands of uncertainty.

Under severe scenarios, it is possible that the insurance market for certain climate-related

[1] See "Draft Application Paper on the Supervision of Climate-related Risks in the Insurance Sector", (October 2020).

events becomes unviable if the willingness or ability of households and businesses to pay for insurance is lower than the premium at which insurers are willing to (or able to) accept the risk transfer. For example, a study of major New Zealand cities found that even a small rise in sea levels could substantially increase flood risk and that at least partial insurance retreat was likely within the coming decade (Storey et al., 2020). And recent devastating wildfires in California and Australia have resulted in widespread reports of difficulties with insurance renewal. In some instances, managed retreat of economic activity from increasingly catastrophe-prone areas is likely to be more appropriate than seeking to increase insurance coverage and continuing to rebuild in the same places. But this does not necessarily diminish the overall value of insurance because climate change is also likely to mean that regions with previously close to no exposure to natural disasters may now face some small probability of climate-related catastrophes. Such a change would increase the potential value of insurance in these areas even if it is unlikely to be sufficient to warrant managed retreat.

Our paper relates to the literature on the macroeconomic impact of natural disasters. Theoretical research has extensively documented how climate change can affect the level of output and the economy's ability to grow in the long-term (Pindyck and Wang, 2013; Kahn et al., 2021). Notably, Albala-Bertrand (1993), Lusardi (1998), Okuyama (2003) and Loayza et al. (2012) have investigated the effects of natural disasters and climate change using neoclassical Ramsey–Solow growth models. These studies show how natural disasters can disrupt an economy's steady-state by damaging the capital stock and redirecting savings towards reconstruction efforts. This disruption typically results in an immediate and temporary drop in output, followed by a recovery phase. An even more closely related literature explores how adaptation efforts, such as building dykes or flood proofing properties, can reduce the impact of natural catastrophes when they hit, thereby mitigating their macroeconomic costs (Fried, 2022; Hong et al., 2023).[2] Phan and Schwartzman (2024) focus specifically on financial adaptation and allow for disaster insurance and catastrophe bonds in a calibrated growth model with the risks of both climate-related catastrophes and sovereign default. But they restrict attention to full insurance as a device which simply makes the country's net worth the same regardless of whether or not disaster strikes, and do not focus on the underlying mechanisms. By contrast, the extent of insurance protection takes centre stage in our model and we also pay close attention to the interplay between insurance and the speed of reconstruction after a disaster. In particular, we show how insurance benefits the economy by mitigating losses when disasters occur via reducing the recovery period and facilitating investment for reconstruction.

On the empirical side, the closest paper to ours is von Peter et al. (2024). Using annual data for over 200 countries between 1960 and 2011, they find that the recovery from natural catastrophes is faster and more complete when a larger share of damages is insured, with aggregate GDP losses largely driven by the uninsured component. This is consistent with our empirical findings. However, our analysis and empirical strategy is grounded in a theoretical growth model that explicitly incorporates both climate change and insurance dynamics. This framework allows us to distinguish between gradual climate risks and acute catastrophe risks, and to articulate the mechanisms through which low and potentially declining insurance coverage can amplify the

[2]However, as Dietz and Lanz (2025) show, long-run adaptation to climate diverts resources from growth-enhancing activities and slows economic development.

macroeconomic and welfare losses from disasters. This enhances the policy relevance of our approach for assessing the climate insurance protection gap while complementing the reduced-form evidence in von Peter et al. (2024), which focuses on the persistence of the macroeconomic effect of uninsured disasters. In addition, our sample of countries is narrower and focuses only on developed and middle income countries. This allows us to use quarterly data between 1996 and 2019 and examine short-term rebound effects and persistence more carefully. Using quarterly data also allows us to distinguish the impact of multiple disasters, with potentially different levels of insurance coverage, within a given year in a single country. Excluding less developed countries reduces concerns that low insurance coverage is highly correlated with factors such as limited fiscal capacity, poor government effectiveness and low access to credit, which could otherwise confound the observed large GDP costs of disasters in such countries. Nevertheless, we still attempt to confront remaining potential endogeneity between insurance coverage, economic development and disaster types in various robustness exercises.

Our paper also relates to wider empirical research on climate-related catastrophes. Lis and Nickel (2009) and Gagliardi et al. (2022) show that large scale extreme weather events can affect public budgets and may pose risks to debt sustainability in the future under standard global warming scenarios. This can quickly spill over to financial markets, as shown for example by Auh et al. (2006) for uninsured US municipal bond returns. Natural disasters can also affect the cost of credit for firms and households in high-risk areas. Correa et al. (2022) show that, following climate change-related events, US banks charge higher spreads on loans to at-risk, yet unaffected borrowers. Weaker borrowers with the most extreme exposure to these disasters suffer the highest increase in spreads. Interestingly, there is no such effect from disasters that are not aggravated by climate change. Finally, Garmaise and Moskowitz (2009) show that imperfections in the supply of catastrophe insurance can distort real estate markets in the US by limiting the provision of bank credit and preventing positive net present value projects from being undertaken.

The remainder of the paper is structured as follows. Section 2 introduces our theoretical model of insurance, climate and the macroeconomy. Section 3 presents empirical evidence on how higher insurance coverage has been associated with a lower GDP impact from natural catastrophes in the past. Finally, Section 4 concludes and discusses policy options to reduce the climate insurance protection gap, while also minimising moral hazard and ensuring appropriate adaptation incentives.

2 A theoretical model of the macroeconomic impact of climate change with insurance

We start with a baseline growth model that incorporates disaster risk in the presence of insurance but abstracts from climate change (Section 2.1). With the term *insurance*, we encompass all explicit *ex ante* insurance coverage provided to the economy by the private insurance and reinsurance sectors, as well as by the public sector, including through public-private partnerships. Implicit public guarantees, contingent liabilities and post-disaster fiscal relief are excluded from this definition.

We then turn to the impact of climate change (Section 2.2). A key innovation of the model is the distinction between the long-term effect of gradual but persistent changes in climate variables, such as temperature and precipitation (chronic physical risks), from the short-term effect of more frequent and more severe extreme weather events, such as floods, storms, droughts and wildfires (acute physical risks). This distinction allows for a more nuanced understanding of how different climate dynamics affect economic growth. The model also captures how acute risks can affect the insurance market by reducing the supply of insurance and raising its costs, due to an increased insurer risk premium. As a result, the macroeconomic and welfare costs of climate change are likely to be greater than they would otherwise be because of this potentially growing insurance protection gap.

2.1 Modelling output in the face of natural disasters and insurance

In this section, we model the impact of natural disasters on output growth through capital, in the presence of insurance. Consider an economy in which aggregate production Y is proportional to the capital stock K: $Y = F(K)$, where we abstract from labour for simplicity.[3] The total stock of capital K in our model includes physical capital, human capital and intangible assets.[4] When disasters occur, total capital is reduced as a part of it would be destroyed or damaged. Therefore, we map changes in capital to three variables: the total amount of capital in the absence of disasters K, the amount of damaged capital upon a disaster K_d and the insurance payout K_i.

The amount of damaged capital can be expressed as $K_d = (1 - Z)K$, where Z is the undamaged share of capital or remaining fraction of capital. For simplicity, we assume that the loss given event is independent from risk adaptation (i.e. households, firms or the government cannot reduce the damage), though loss could in principle also be modelled as a function of adaptation (Fried, 2022; Hong et al., 2023), the incentives for which could, in turn, be influenced by the presence and design of insurance coverage, as we briefly discuss below. $K_i = WK_d$ is the insurance payout in the event of a disaster and is equal to the total amount of insured capital that is damaged, where W indicates the share of damaged capital covered by the insurance. The insurance payout K_i cannot be larger than the damaged capital K_d, therefore $W \leq 1$. The aggregate economic output can be written as:

$$\begin{aligned} Y = F(K, K_d, K_i) &= K - K_d + K_i \\ &= K - (1 - W)(1 - Z)K \end{aligned} \tag{1}$$

The expression $(1 - W)(1 - Z)K$ is the uninsured damage and defines the insurance protection gap. The protection gap increases as either Z falls for a given level of W (e.g. a bigger disaster that affects a larger share of capital), or as W decreases for a given level of Z (a smaller share of capital is insured). If there is no disaster, i.e. $K_d = 0$ and $Z = 1$, changes in output depend only on changes in capital. In the presence of full insurance, i.e. $K_i = K_d$ and $W = 1$, changes in output also depend on capital only, independently from damages, as insured damaged capital is rebuilt immediately . In the complete absence of insurance activity, i.e. $W = 0$, changes in output depend on changes in capital and the severity of damages, $Y = ZK$, for a given level of

[3]For example, a widely used specification for aggregate output is $Y = AK$, where A is a constant productivity.

[4]Hallegatte et al. (2024) distinguish between infrastructure and non-infrastructure capital, and between private and public capital to model productivity endogenously. In our model, we abstract from these distinctions.

disaster probability.

Output growth is constrained following a disaster because both the available capital stock decreases and resources are reallocated away from the optimum to invest in reconstruction activities (Hallegatte and Vogt-Schilb, 2019). Although a share of the productive capital stock (K_d) is inevitably damaged by the disaster regardless of insurance, we assume that the insured damaged capital (K_i) is rebuilt immediately after the event. The prompt liquidity provided by insurance can finance reconstruction activities without depleting investments and savings, thereby reducing the overall impact of the event on output. We now explore these channels in more detail.

In each period, aggregate output can be spent in consumption C, investment I and insurance premiums P: $Y = C + (I + \Phi(I, K)) + P$. Premiums are collected either by private insurance companies or by public-private partnerships and determine the degree of insurance coverage. Paying premiums marginally decreases the aggregate output of the economy, but it averts the need to pay or reallocate a large sum after disasters occur. As a result, insurance payouts help reduce the overall damages upon a catastrophe event by shortening the recovery period, as modelled in Equation (1). We do not distinguish here between public and private investments and we abstract from other adaptation spending that may reduce the damage from disasters, e.g. seawalls or land-use zoning (Hong et al., 2023). The uninsured damages at time t depend on pre-disaster insurance spending.

Investments are adjusted by a cost function $\Phi(I, K)$ that captures the effects of depreciation and the costs of installing capital: $\Phi(I, K) = \phi(i)K$, where i is the investment-capital ratio, $i = I/K$, and $\phi(i)$ is increasing and concave (Pindyck and Wang, 2013). This implies that, in the presence of adjustment costs, the capital is not perfectly liquid and cannot be used for consumption without incurring some costs, i.e. consumption and investment are not perfectly substitutable. After a disaster, damaged assets are replaced or repaired by reducing consumption and regular investment, in the absence of insurance. Following Hallegatte et al. (2007), we define two types of investments: investment towards reconstruction of the damaged capital, I_R, that increases the residual capital remaining after disasters, and investment into new capital, I_N, that would regularly increase the production capacity K (i.e. independent of disasters), such that $I = I_R + I_N$. They differ because the marginal return on reconstruction is higher than the marginal return on new capital, consistent with empirical evidence: e.g. following disasters, the construction of new buildings and infrastructure would be postponed to rebuild the damaged ones. Therefore, when capital is destroyed in a catastrophe, investment is first devoted to replacing the destroyed capital.

The time it takes to rebuild destroyed capital depends not only on the extent of the losses, but also on the cost and availability of financial tools for households and firms (Aiyagari, 1994; Hallegatte et al., 2007). In practice, the pace of reconstruction, I_R, can be limited by a lack of savings or borrowing capacity, for example, or by limited production capacity in certain sectors, such as construction. This leads to consumption losses since C would be reduced in favor of I and reconstruction periods would be much longer than what the initial amount of damage would suggest. Insurance can relax these financial constraints by quickly repaying insured damages and reducing consumption losses. Insurance payouts can finance reconstruction more quickly and efficiently than other instruments, either financial or fiscal.This is because financial instruments, such as loans, may be difficult to obtain by firms and households that just suffered from a disaster (Garmaise and Moskowitz, 2009), while fiscal relief measures are often slow and not sufficiently targeted towards the most beneficial investments and individuals or firms in need. To capture these constraints, I_R is bounded by f_{max}, the fraction of total investment that reconstruction investments can mobilize, i.e. $I_R = min\,(f_{max}I, (1-W)(1-Z)K)$.[5]

We assume that all investment is devoted to reconstruction because of the higher return of I_R with respect to I_N, and that output losses are reduced to zero exponentially with a characteristic time of reconstruction R. This implies that the economy returns to its pre-disaster state, although in practice some activities could be permanently destroyed.

Assuming that lost capital has a productivity equal to the average productivity of the capital in the economy, μ, then aggregate output losses after t_0 are given by:

$$\Delta Y(t) = \mu \Delta K e^{-\frac{t-t_0}{R}} \tag{2}$$

Here we build on the model developed by (Hallegatte and Vogt-Schilb, 2019). The model assumes that assets that were not directly damaged by the disaster continue producing with an unchanged productivity, although in reality their productivity could be reduced due to indirect effects, e.g. on the supply chain and infrastructures. The overall impact of a disaster on output is the sum of a reduction in the stock of capital and a misallocation of the residual stock compared to what would be optimal. Equation (2) can then be used to capture both the urgency to reconstruct and recover from an event, and the choice between investing in capital over the long term. The duration of the reconstruction phase therefore determines the macroeconomic cost of natural disasters. If damages can be repaired immediately, output losses will be zero, but consumption will be reduced to finance the reconstruction (i.e. $\Delta C = \Delta K$). By contrast, if there is no reconstruction, output losses will be permanent ($R = \infty$) and will be absorbed by consumption (i.e. $\Delta C = \Delta Y = \mu \Delta K$). Assuming that the productivity of destroyed capital is equal to the average pre-disaster productivity of capital, the model therefore implies that the net present value of consumption losses is larger than direct losses when reconstruction takes some time, as $\mu \Delta K > \Delta K$. In other words, consumption and welfare losses are magnified when reconstruction is delayed or slowed down.

2.1.1 The impact of natural disasters and insurance on economic growth

We now augment the standard specification of capital stock evolution in the presence of disasters (Barro, 2006; Pindyck and Wang, 2013; Hong et al., 2023) to incorporate the effects of insurance and determine what it implies for the economy's growth rate. The capital stock evolves as follows:

$$dK_t = \Phi(I_{t-}, K_{t-})dt + \sigma K_{t-} d\mathcal{B}_t - (1-W)(1-Z)K_{t-} d\mathcal{J}_t \tag{3}$$

The first term is investment, adjusted for depreciation and the costs of installing capital. The second term captures continuous shocks to capital that are standard in macroeconomic models, where $\mathcal{B}_t$ is a standard Brownian motion and the parameter σ is the diffusion volatility of the capital stock growth. The last term represents the effect of disasters on capital. Following the literature, we assume that disasters occur as discrete downward jumps to the capital stock and

[5] For simplicity, we omit that $I_R = 0$ if no disaster occurs, as Z would equal 1.

can be modelled as Poisson arrivals with a permanent impact. There is no limit to the number of these shocks, and the occurrence of one shock does not change the likelihood of another. $\mathcal{J}$ is a jump process reflecting the probability of a natural catastrophe with a fixed but unknown arrival rate, π. $t-$ denotes the pre-jump time, when insurance can be bought. Here we assume the disaster probability to be fixed, at least in the short-term, but in Section 2.2 we will allow π to vary as a function of climate change. When the jump arrives, it destroys permanently K_d, which is a stochastic fraction $(1 - Z)$ of capital K. As we will discuss in the empirical analysis, we consider large disasters to be shocks for which the drop in capital and GDP is sufficiently large. The novelty of our model is that in the presence of insurance, this fraction is reduced by $(1 - W)$ times, as also shown in Equation (1). If the catastrophe does not arrive, the third term of Equation (3) is zero. The higher the arrival rate π, for example due to climate change, the more likely that the capital stock will be hit by a disaster. Taking the first derivative of capital stock K_t, we can see that

$$dK_t/K_t = \phi(i^*)dt + \sigma d\mathcal{B}_t - (1 - W)(1 - Z)d\mathcal{J}_t \tag{4}$$

where i^* is the optimal investment-capital ratio, constant in equilibrium. The expected growth rate, denoted by $\bar{g}$, is then

$$\bar{g} = \phi(i^*)dt - \pi E(1 - W)(1 - Z) \tag{5}$$

where the second term is the expected percentage decline of the capital stock due to catastrophes. Equation (5) shows that, while insurance may crowd out investment, it enhances long-run growth by reducing the expected loss due to catastrophes $E(1–W)(1–Z)$.

Insurance premiums at time $t - 1$ mitigate the effect of disasters by insuring a share W of damages, so that the remaining share of capital after disaster conditional on the event arrival at time t, i.e. $(1–W)(1–Z) = Z + W(1–Z)$, depends on pre-disaster insurance spending. If insurance spending increases, then the benefit increases as well, but less than proportionally, i.e. insurance has decreasing returns to scale. In the next section, we therefore consider the determinants of insurance cost.

2.1.2 The cost of insurance

For a given probability of an adverse event, π, insurance is beneficial in expectation, as it reduces the recovery period and facilitates investments for reconstruction. These benefits result in a reduction of (uninsured) damage after disasters. The price of insurance claims, i.e. the pre-disaster cost of insurance, is modelled as follows:

$$p(W, Z) = \alpha\pi(1 - Z)W \tag{6}$$

where α reflects the insurance risk premium and depends on the cost of capital and expense load of insurance capital providers, $\pi(1 - Z)$ is the expected damage of a disaster and $\pi(1 - Z)W$ is the amount of expected insured loss. The total cost of capital also accounts for frictional and uncertainty costs, while the expense load captures underwriting expenses, administrative costs, loss adjustment expenses, and other related charges (Cummins and Mahul, 2008). If the policyholder insures the whole capital at risk, $p(W, Z) = p(Z)$, and in the event of a shock, the policyholder receives a lump-sum payoff of one unit of consumption.

This framework allows us to model the insurance cost endogenously. The premium increases proportionally with the expected damage $\pi(1 - Z)$, which may rise due to climate change-related effects, such as higher frequency and severity of natural disasters. At the same time, for a given Z, the insured share W would decrease, under the assumption of fixed insurance supply. In addition, greater uncertainty over the loss probability distribution can lead insurers to demand a higher return on capital, increasing α, and thereby premiums. Furthermore, a higher correlation between catastrophe risks and other risks in the insurer's portfolio or rising spatial or temporal correlation across disaster risks reduces diversification benefits, raising capital needs and premiums.

Diversification constraints are captured by a supply condition: insurers are willing to supply a fixed amount of capital, S, given by $S = mKd$, where $m < 1$ is the share of economic capital allocated to insurance and $0 < d \leq 1$ is a diversification factor. Better pooling of risks increases d and therefore capacity. The insured share W must then satisfy $W \leq md/(1-Z)$. When $d < 1$, even with the same capital K, insurance supply falls relative to the case of full diversification ($d = 1$). In equilibrium, the premium becomes $p^* = \alpha d \pi m$.

This setup implies that greater disaster damage $(1 - Z)$, lower diversification d, higher catastrophe probability π, or a higher α all increase the premium, while tightening the supply constraint. The premium exceeds the expected insured loss, i.e. $p > \pi W(1 - Z)$, which holds when $\alpha > 1$. This reflects real-world pricing in catastrophe insurance markets, where high capital charges, limited reinsurance availability, and post-disaster tightening of risk tolerance raise prices above actuarially fair levels. In particular, greater uncertainty over the loss probability distribution or risk aversion among capital providers, particularly after major disasters, can further raise α (Carayannopoulos et al., 2020; Dieckmann, 2010). A high premium may then exceed what policyholders are willing to pay, reducing the effective demand for coverage. A threshold π^* may then exist beyond which insurance in economically non-viable, as too expensive for policyholders. An alternative supply specification could account for reinsurance, with $S = mKd/(1 - \rho)$, where ρ is the share of risk reinsured. For simplicity, we abstract here from the distinction between insurance and reinsurance providers. Empirically, catastrophe bond prices follow a similar relationship with expected losses (Lane and Mahul, 2008).

On the demand side, a higher disaster probability π increases the value of insurance, raising demand (Zhao et al., 2020). However, the effective amount of insurance coverage is still limited by supply constraints. If buyers are risk averse and know the capital at risk, they will insure fully ($W = 1$). But when policyholders can influence the probability or severity of losses, insurers offer only partial coverage ($W < 1$) to maintain incentives for risk reduction. In relation to catastrophe risk, moral hazard can arise when high coverage W reduces adaptation incentives in high-risk areas, potentially increasing losses (i.e. by lowering Z) and reducing the net benefit of insurance. For this reason, insurance companies often offer lower premiums to policyholders that implement climate-related adaptation measures. While our model abstracts from these behavioral dynamics, they are relevant empirically, though such effects are difficult to identify in aggregate data.

The insurance protection gap can widen for several reasons that relate both to insurance supply and demand. On the supply side, insurer risk aversion tends to rise after major disasters. Keys and Mulder (2024) find that recent property insurance premium increases reflect stronger linkages to local disaster risk. Others point to uncertainty, regulation, and asymmetric information as key drivers that limit supply through adverse selection or pricing volatility (Boomhower et al., 2024; Moore, 2024). Specifically, undiversifiable uncertainty over climate and loss distributions leads to higher and more volatile premiums and rising reinsurance costs. On the demand side, even in developed countries, some consumers remain unaware of or unwilling to purchase insurance even when it is accessible and affordable (EIOPA, 2023). However, as climate-related catastrophe risks intensify, insurance may become unaffordable or unavailable even for willing buyers. Rising disaster probabilities π, higher insurance risk premia α, and lower diversification of risks d together raise costs and reduce coverage capacity. In particular, as the constraint $W \leq md/(1-Z)$ tightens due to lower d, insurers are able to cover less capital. And at a limit, beyond the threshold π^*, insurance becomes no longer viable at any acceptable premium.

2.2 Incorporating the impact of gradual changes in climate variables on capital and insurance

Thus far, we have abstracted from the impact of climate change in the model. Climate change can affect output both via a gradual change in climatic variables and more frequent or severe natural catastrophes. In the next step, we consider the direct effects of gradual global warming on capital, that affect neither the probability nor the severity of an adverse natural event and that cannot therefore be mitigated by insurance. Then, we introduce the impact of more frequent disasters on insurance activity, i.e. on the insurance protection gap, and therefore on output.

We start by modelling the impact of gradual changes in climatic variables, such as temperature, T, and precipitation, on capital by exploiting the approach of Kahn et al. (2021). In particular, we consider the deviations from the historical norms of climatic variables.[6] In contrast to Kahn et al. (2021), we focus here on the impact of global warming, based on warming trends (i.e. changes in T), on output growth via gradual adverse effects on capital, and we abstract from the impact on labour productivity. For example, some machinery and equipment may not be able to operate as effectively above certain temperatures, or higher temperatures may accelerate the rate of depreciation of the capital stock. Gradual warming could also reduce the productivity and availability of natural resources, for example due to land desertification or rising sea levels. We abstract here from the development of new technologies that could mitigate these effects over time.

The historical norms are regarded as capital neutral, in the sense that if climate variables remain close to their historical norms, they are not expected to have any gradual long-term effects on capital. In this step, we also assume that K_d and K_i are not affected by gradual changes in climate related variables.

Specifically, we consider capital as a function of changes in temperature: $K(x_t) = K_t \omega_0 exp(-\omega x_t)$, where $x_t = (T - T^*_{t-1})$, ω_0 is a positive constant and the exponential function is a multiplicative shifter of capital, with ω being the sensitivity of physical capital to climate change, and also assumed to be positive, so that climate change adversely affects the capital stock. The histori-

[6] As an alternative to deviations from historical norms $(T - T^*)$, we could consider the variability of climatic variables relative to historical norms $(T - T^*)/\sigma_T$.

cal norms T^* are assumed to be fixed to reflect the average temperature. We then obtain the following output function:

$$Y_t = F(K_t, K_{dt}, K_{it}, x_t) = K_t \omega_0 exp(-\omega x_t)[1 - (1 - W)(1 - Z)] \tag{7}$$

Equation (7) shows that if there is no deviation of temperatures from historical norms (so that $x_t = 0$), output would be the same as in Equation (1). But if changes in temperature directly affect capital, without changing the probability or severity of a disaster, then the output in Equation (7) is smaller than in Equation (1), given that $exp(-\omega x_t) < 1$. In short, regardless of the provision of insurance, output and welfare are likely to be lower in the presence of climate change.

Global warming is also likely to affect output by making natural catastrophes more frequent or more severe. This affects output directly by increasing losses from disasters, and indirectly via the widening insurance protection gap. The direct effect can occur even if the protection gap does not widen. Here, we focus on the indirect effect of an increase in disaster probability, π, on insurance coverage. As an alternative, we could also consider the effect of an increase in severity, Z. As shown in Equation (6), insurance premiums would increase as a consequence of increased disaster risk and insurance coverage would decline, a process called insurance retreat in the literature. Alternatively, insurers could introduce terms in insurance policies that transfer part of the risk to the policy holder (partial retreat) (Storey et al., 2020).

We modify Equation (6) to account for changes in insurance premiums due to climate change:

$$p(W, Z, x) = \alpha \pi (1 - Z) W exp(\psi x_t) \tag{8}$$

where ψ is the sensitivity of disaster probability to climate change, reflecting changes in the frequency of extreme events under climate change. If there is no deviation of climate variables from historical norms ($x = 0$), insurance on physical capital will depend on the insurance risk premium and expected damages as in Equation (6), and the output model collapses to equation (1). If climate change increases insurance costs, a positive ψ would be associated to higher premiums and therefore lower insurance coverage, i.e. a higher protection gap.

$$Y_t = F(K_t, K_{dt}, K_{it}, x_t) = K_t \omega_0 exp(-\omega x_t)[1 - (1 - W exp(-\psi x_t))(1 - Z)] \tag{9}$$

Given the inverse relationship between insurance cost and coverage, the sensitivity of the disaster probability enters the expression with a negative sign. As above, the historical norms are regarded as insurance neutral, in the sense that if climatic variables remain close to their historical norms, they are not expected to have any effects on the probability of the adverse natural event and therefore on insurance. If insurance coverage is negatively affected by climate change, the output in Equation (7) is larger than in Equation (9) because $exp(-\psi x_t) < 1$ if $\psi > 0$. If there is no insurance, equations (7) and (9) are equivalent.

Overall, the theoretical model provides several important conclusions. First, disasters are costly and influence output through their increasing frequency or severity. Insurance can help mitigate the impact of disasters by relaxing financial constraints and accelerating the rebuild, thereby reducing the overall welfare loss, in line with the findings of Hallegatte et al. (2024). Second, a gradual increase in temperatures above historic norms can result in lower productivity and lower output overall, for which insurance can offer little protection. Finally, an increase in the probability of natural hazards can result in a widening of the insurance protection gap, which exacerbates the detrimental effect of increasing climate-related catastrophes on capital, output, growth and welfare.

3 Empirical evidence of the impact of the protection gap

In this section, we empirically test predictions from the theoretical model for aggregate output, specifically the growth Equation (5).[7] Abstracting from the stochastic properties of that equation, it implies that the growth rate of an economy is adversely affected by damage from natural disasters, but insurance can play a role in mitigating their impact. More formally, for a given period t and country c, Equation (5) can be rewritten as:

$$g_{c,t} = \phi_{c,t} - \pi_c E(1 - W_{c,t})(1 - Z_{c,t}) = \phi_{c,t} - \pi_c E(1 - Z_{c,t}) + \pi_c E W_{c,t}(1 - Z_{c,t}) \tag{10}$$

where $\phi_{c,t}$ is the growth rate in economy c and period t without any disaster damage (i.e. when $Z_{c,t} = 1$), $(1{-}Z_{c,t})$ is the share of capital damaged by a disaster (or a set of disasters) occurring in country c and period t, and $W_{c,t}$ is the corresponding share of the damaged capital covered by insurance.

Furthermore, decomposing $\phi_{c,t}$ into a country fixed effect α_c and a time fixed effect θ_t and adding a random error term $\epsilon_{c,t}$, we derive the following empirical specification:

$$g_{c,t} = \alpha_c + \theta_t + \beta_1(1 - Z_{c,t}) + \beta_2 W_{c,t}(1 - Z_{c,t}) + \epsilon_{c,t} \tag{11}$$

In line with equation (10), we expect $\beta_1 < 0$ and $\beta_2 > 0$, i.e. a negative effect of the disaster damages on GDP growth and a (somewhat) offsetting positive GDP growth effect if (some of) these disaster damages are covered by insurance. We estimate this empirical specification in Section 3.2.

To account for the non-linearities in the theoretical model, we also derive a complementary empirical specification from Equation (11) by transforming the continuous variables $1 - Z_{c,t}$ and $W_{c,t}$ into dummy variables to distinguish between large-scale natural disasters with low and high shares of insured losses. The coefficient for large-scale natural disasters with a low share of insured losses is then expected to be negative (as in the case of β_1) and the coefficient for large-scale natural disasters with a high share of insured losses is expected to be higher (less negative) than this coefficient (derived from $\beta_1 + \beta_2$). This alternative empirical specification is estimated in Section 3.3.

[7] The sub-components of GDP growth such as consumption and investment are generally more volatile and the dynamics thereof more complicated.

3.1 Data

3.1.1 Data on quarterly GDP growth

For the dependent variable, we use quarterly data on real GDP growth rates from Eurostat and complement them with data from the OECD, which provides us with a sample of 47 countries. This naturally skews the sample towards more developed economies. The sample does include some emerging market economies (including Brazil, India, Indonesia, Russia and South Africa), but not any country classified as low income by the World Bank. This helps to mitigate some concerns about the coverage of the data on disasters we use and about our results being influenced by the level of a country's economic development (see Section 3.2.2 for further discussion of both these points).

By focusing on GDP growth rates, our empirical analysis follows the theoretical model and the approach of most other studies in this field (e.g., Noy (2009); Felbermayr and Gröschl (2014); Fomby et al. (2013); Klomp and Valckx (2014); von Peter et al. (2024)). Yet GDP growth is only an imperfect proxy for capturing the overall welfare consequences of catastrophes, since it captures changes to the flow of activity rather than changes to the stock of wealth.

3.1.2 Data on disaster damage and (un)insured losses

To proxy the share of capital damaged by natural disasters and the share of damaged capital covered by insurance, we use EMDAT, an international disasters database collected by the Centre for Research on the Epidemiology of Disasters.[8] The EMDAT database contains information about individual disaster events across the globe since 1980. Owing to a somewhat lower coverage in early years, we drop events before 1996. Our sample ends at the end of 2019 to avoid complications associated with the highly unusual growth patterns during the Covid-19 pandemic. For example, the severe floods which hit parts of Germany and some neighbouring countries in the summer of 2021 came at the same time as pandemic re-opening effects significantly boosted growth.

We start from the worldwide sample in EMDAT and focus on four types of natural disasters: climatological (405 events), geophysical (505 events), hydrological (2,179 events) and meteorological (1,913 events) (see Table 1).[9] The most common events are floods (38% of all events) and storms (31%), followed by earthquakes (8%), extreme temperatures (7%) and wildfires (5%). A typical drought results in the largest damages (median around $760mn), followed by an extreme temperature event (median $\tilde{\$}$300mn), a storm (median $\tilde{\$}$160mn) and a wildfire (median $\tilde{\$}$140mn). While earthquakes display a relatively limited median damage (around $90mn), the distribution is highly skewed to the right by events with exceptionally large damages, resulting in the largest mean among all types of events (around $2,650 mn).[10] Although geophysical disasters such as earthquakes are independent of climate change, we include them in our analysis to increase the sample size, especially in relation to very large disasters (see Table A1 in the Annex for a list of the largest disasters relative to a country's GDP in our sample).

[8] Available from www.emdat.be.

[9] These are the disaster types most studied in the literature. This excludes: technological disasters, which are typically factory and transport accidents and therefore generally small and localised, biological disasters, which in general have a smaller initial impact on capital (although, as the Covid-19 pandemic showed, there can be substantial indirect impacts) and extra-terrestrial disasters (a meteor strike in Russia).

[10] All values in this paragraph are in constant 2010 USD.

Table 1: Types of disasters and associated damages (monetary values in constant 2010 USD)

Event type	# events	Percent	Damage: mean	Damage: median
Climatological	**405 (191) [46]**	**8.1 (7.8) [7.6]**	**$1,061 mn**	**$237 mn**
Drought	147 (76) [7]	2.9 (4.2) [0.8]	$1,419 mn	$762 mn
Wildfire	258 (115) [39]	5.2 (3.7) [6.8]	$825 mn	$138 mn
Geophysical	**505 (224) [67]**	**10.1 (21.4) [5.3]**	**$2,472 mn**	**$93 mn**
Earthquake	419 (208) [67]	8.4 (21.3) [5.3]	$2,653 mn	$93 mn
Mass movement (dry)	8 (1) [0]	0.2 (0.0) [0.0]	$7 mn	$7 mn
Volcanic activity	78 (15) [0]	1.6 (0.1) [0.0]	$119 mn	$76 mn
Hydrological	**2,179 (843) [173]**	**43.6 (24.7) [20.0]**	**$759 mn**	**$108 mn**
Flood	1,910 (802) [168]	38.2 (24.5) [19.0]	$791 mn	$118 mn
Landslide	269 (41) [5]	5.4 (0.2) [0.6]	$149 mn	$23 mn
Meteorological	**1,913 (990) [356]**	**38.2 (46.1) [67.0]**	**$1,208 mn**	**$169 mn**
Extreme temperature	363 (37) [8]	7.3 (2.1) [1.1]	$1,435 mn	$304 mn
Storm	1,550 (953) [348]	31.0 (44.1) [66.0]	$1,199 mn	$163 mn
Total	**5,002 (2,248) [642]**	**100.0 (100.0) [100.0]**	**$1,153 mn**	**$136 mn**

Sources: EMDAT and authors' calculations.
Notes: The figures in round [squared] brackets refer to the number of events and corresponding percentages, for which data on total damage [(un)insured losses] are available. To derive these figures, we undertake two cleaning steps. First, for 45 events, for which insured losses are available (amounting to around $15 bn) but total damage data are missing, we set insured losses to missing values. Second, for 23 events, for which insured losses exceed total damage, we set total damage equal to insured losses if this excess is smaller than 25% of total damage (11 events) and we set both insured losses and total damage to missing values otherwise (12 events).

While the database includes over 5,000 disaster events across the globe for the period of our analysis, information on financial damages is only available for about 2,250 disasters. Within those, a split between insured and uninsured losses is available only for around 640 events, which skews our sample coverage towards more storms (66%) and fewer floods (19%), followed by wildfires (7%) and earthquakes (5%) (see squared brackets in Table 1). But those disasters with the split are generally much larger and thus also likely to be more relevant in terms of macroeconomic impact. In particular, the average financial damage for disasters where insured losses are available is around $3,100 million, which is almost ten times higher than the average damage of disasters where the split between insured and uninsured damages is unavailable (around $370 million; see Table 2).

To increase the number of events for our empirical analysis, we impute insured and uninsured losses for most events where data on total damages are available. The values are imputed based on country-specific regression models, where the dependent variable is the share of insured losses in total damages and the explanatory variables include the log of total damage and dummies for nine different types of disaster (drought, earthquake, extreme temperature, flood, landslide, mass movement, storms, volcanic activity, and wildfire; see also Table 1) to the extent applicable for a given country. For some countries, the model cannot be estimated owing to a low number of observations, resulting in around 250 events with damage data but no imputed values for insured/uninsured losses (see Table 2).[11] In the empirical exercises in Sections 3.2 and 3.3, we present results based on both the smaller sample where both insured and uninsured losses are available in the data and the wider sample which also includes catastrophes where the split is imputed.

[11]Results of the imputation exercise are available upon request.

Table 2: Results of data imputation for insured and uninsured losses (monetary values in constant 2010 USD)

	Damages	Insured	Uninsured	# events	Damage: mean
Original dataset					
Information on (un)insured losses	$2.0 tr	$0.7 tr	$1.3 tr	642	$3,108 mn
Information on total damage only	$0.6 tr	-	-	1,606	$372 mn
No information on damage	-	-	-	2,754	-
Total				5,002	-
Dataset with imputed values					
Information on (un)insured losses	$2.6 tr	$0.8 tr	$1.7 tr	2,016	$1,267 mn
Information on total damage only	<$0.1 tr			232	$163 mn

Sources: EMDAT and authors' calculations.
Notes: Imputation is based on country-specific regressions, where the share of insured losses is regressed on the log of total damage and dummies for nine different types of disaster (drought, earthquake, extreme temperature, flood, landslide, mass movement, storms, volcanic activity, and wildfire; see also Table 1) to the extent applicable for a given country. If the imputed value of the share of insured losses is below zero (55 events) or above one (98 events), we set it to missing.

3.1.3 Merged panel dataset

The GDP growth data are quarterly, while the EMDAT disaster data are recorded on a per-disaster basis. To align the two, we aggregate the disaster data into a quarterly-country panel dataset. Specifically, we proxy the share of capital damaged by disasters in country c and quarter t by the share of financial damages from (all) disasters in that quarter and country relative to country GDP lagged by one year. We obtain the GDP level data from the World Development Indicators (WDI) and use constant 2010 USD for the calculation. The share of the damaged capital covered by insurance ($1{-}Z_{c,t}$) is then proxied as the share of insured financial losses per quarter in total disaster damages per quarter.[12]

The mean (median) disaster cost per quarter is 0.25% (0.029%) of GDP in the full EMDAT sample, which declines to 0.16% (0.028%) of GDP for our sample of 47 countries where quarterly GDP data are available (see Table A2 in the Annex). The lower mean in our sample reflects the fact that quarterly GDP data are mainly available for developed countries, where natural disasters have typically had a smaller impact relative to GDP in the past. In this smaller sample, the disaster damage exceeds 1% of GDP for only 15 observations (see Table A1 in the Annex). At the same time, the share of insured losses per quarter is somewhat higher in the sample with quarterly GDP data (median at 47%) compared to the world-wide EMDAT sample (median at 41%) since insurance coverage tends to be higher in developed countries than in emerging ones (see also Section 3.2.2).

Overall, the insured share displays a large heterogeneity both across our 47 countries and across disasters within countries. The average country share ranges from below 5% (e.g. Colombia, Croatia, Greece, Korea) to over 65% (e.g. Denmark, France, Luxembourg; see Table A2 in Annex).

[12]For the treatment of missing values, see Annex Section A.1.

3.2 Estimating linear effects: continuous disaster damage and insured share

In this section, we first estimate our baseline model in Equation (11) with disaster damages and the share of insured losses (interacted with disaster damages) being the two key explanatory variables of interest for explaining GDP growth (Section 3.2.1). In addition to estimating the contemporaneous GDP growth effects of these variables, we also investigate lagged effects (i.e., assuming a disaster hit in the previous quarter) to try to capture potential rebound effects. We then discuss the potential endogeneity of our key variables of interest in Section 3.2.2 and test the robustness of our results to different disaster types, different treatment of missing values and exclusion of two countries with extremely large disaster damages (Section 3.2.3 and Sections A.1 and A.2 in the Annex). Potential non-linear effects of the two key explanatory variables of interest are then estimated in Section 3.3, where we transform these initially continuous variables into dummy variables.

3.2.1 Baseline results

Using a panel regression with standard errors clustered by country, we estimate Equation (11) and report the results in Table 3. We start by focusing in column (1) on the sample for which insured and uninsured losses are split in the underlying dataset. The sign of the coefficients is as expected, with greater damages from disasters being significantly associated with a lower growth rate but with this effect being mitigated by a higher share of insured losses. The statistical significance of both coefficients improves when we use the larger sample with imputed data in column (2), while the size of the coefficients remains almost unchanged.

Table 3: Panel estimates with the share of insured losses - simultaneous effects

Dependent variable	**quarterly GDP growth rate (in %)**					
Sample	**(1) Original**	**(2) Imputed**	**(3) Original**	**(4) Imputed**	**(5) Original**	**(6) Imputed**
Damages as a share of GDP (%)	-0.24*	-0.23*	-0.25**	-0.24**	-0.22*	-0.18
	(0.07)	(0.05)	(0.01)	(0.02)	(0.08)	(0.11)
Damages as a share of GDP (%) * Share of insured losses (%)	0.0036*	0.0037**	0.0039**	0.0038**	0.0034**	0.0027*
	(0.06)	(0.04)	(0.01)	(0.01)	(0.04)	(0.08)
Lag of GDP growth (%)					-0.042	-0.015
					(0.68)	(0.88)
Country fixed-effects	Y	Y	Y	Y	N	N
Quarterly fixed-effects	Y	Y	N	N	Y	Y
Quarterly-country groups fixed-effects	N	N	Y	Y	N	N
Observations	3,100	3,595	3,100	3,595	3,064	3,552
R-squared	0.207	0.192	0.314	0.296	0.202	0.186

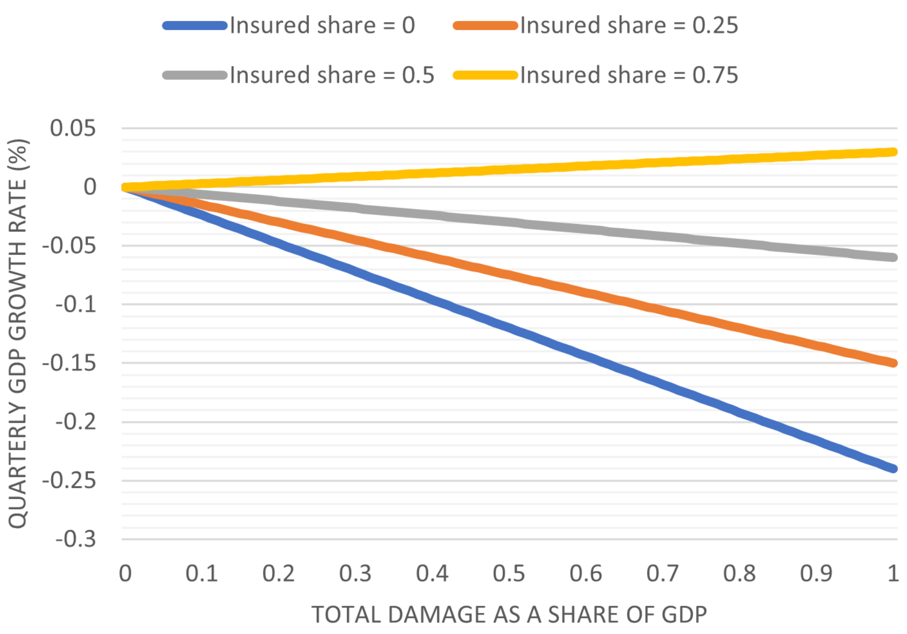
Notes: Panel regression using standard errors clustered by country. *, **, *** denote significance at the 10, 5 and 1% confidence level. p-values are reported in parentheses. In columns (3) and (4), the following country groups (defined in line with country groups in the IMF's World Economic Outlook database) are used: (i) the euro area, (ii) other advanced Europe (Czech Republic, Denmark, Iceland, Norway, Sweden, Switzerland, United Kingdom), (iii) other other advanced economies (Australia, Canada, Israel, Japan, Korea, New Zealand, United States), (iv) emerging and developing Europe (Bulgaria, Croatia, Hungary, Poland, Romania, Russian Federation, Turkey) and (v) other emerging and developing countries (Brazil, Chile, Colombia, Costa Rica, India, Indonesia, Mexico, South Africa).

Since the general macroeconomic environment can differ materially across the globe, quarterly fixed effects might not be fully sufficient to control for the variation in GDP growth rates over time. Therefore, we allow the quarterly fixed effects to vary across five country groups and report the results in columns (3) and (4). Using these more granular quarterly fixed effects, the significance of the coefficients of interest increases in both the original and the imputed samples, while their size changes only slightly. To further check the robustness of the results, we include the lagged dependent variable in columns (5) and (6), while excluding the country fixed-effects to avoid obtaining a biased fixed-effects estimator. For both variables of interest, we obtain coefficients whose size and significance mostly slightly decrease compared to the baseline model in columns (1) and (2). At the same time, the estimates further indicate the mitigating effect of the higher share of insured losses on the GDP growth rate when a disaster hits.

Turning to the economic interpretation of the coefficients, the estimates in column (1) suggest that if a large disaster of 1% of GDP hits a country, the quarterly GDP growth rate declines by 0.24 percentage points in case of no insurance coverage (e.g. from the median of 0.72% in our sample to 0.48%; see Figure 2). However, if 25% of the losses are insured, the GDP growth rate is estimated to only decline by around 0.15 percentage points. The effect is even smaller, at around 0.06 percentage points, if half of the losses are insured. For unusually high shares of insured losses – e.g. a 75% insured share corresponding to the 90th percentile of the distribution – our empirical model even suggests an almost immediate (within quarter) rebound in GDP growth.

Figure 2: The estimated impact of natural disasters on the quarterly GDP growth rate by size of damage and insured share.

Notes: Based on estimates in column (1) of Table 3



To further investigate such potential rebound effects, we test the effect of lagged disaster damage and insurance coverage on the quarterly GDP growth rate in Table 4 in the Annex. This model specification confirms our results for contemporaneous effects: damages from disasters are associated with a lower GDP growth rate, while this effect is mitigated by insurance. In addition, across most model specifications, the results suggest that, on average, there is a rebound in GDP growth one quarter after a disaster happens (coefficients of further lags are estimated as insignificant). However, while reconstruction activity is recorded as positive in GDP growth numbers, in reality it does not represent a gain to welfare since it takes away available output that could otherwise be used for improving the current capital stock, or for consumption (see Hallegatte and Przyluski (2010) for a more detailed description of estimating the costs of catastrophes).

Table 4: Panel estimates with the share of insured losses - rebound effects

Dependent variable	**quarterly GDP growth rate (in %)**					
Sample	**(1) Original**	**(2) Imputed**	**(3) Original**	**(4) Imputed**	**(5) Original**	**(6) Imputed**
Damages as a share of GDP (%)	-0.25*	-0.24*	-0.26**	-0.23**	-0.23*	-0.20*
	(0.08)	(0.06)	(0.04)	(0.03)	(0.09)	(0.08)
→ Lag 1	0.28***	0.18*	0.23***	0.18	0.29***	0.23**
	(0.00)	(0.05)	(0.00)	(0.13)	(0.00)	(0.02)
Damages as a share of GDP (%) * Share of insured losses (%)	0.0041**	0.0039**	0.0046**	0.0037**	0.0036*	0.0031*
	(0.05)	(0.04)	(0.01)	(0.02)	(0.05)	(0.05)
→ Lag 1	-0.0044***	-0.0025	-0.0026***	-0.0018	-0.0043***	-0.0032**
	(0.00)	(0.12)	(0.01)	(0.35)	(0.00)	(0.04)
Lag of GDP growth (%)					-0.090	-0.040
					(0.38)	(0.70)
Country fixed-effects	Y	Y	Y	Y	N	N
Quarterly fixed-effects	Y	Y	N	N	Y	Y
Quarterly-country groups fixed-effects	N	N	Y	Y	N	N
Observations	2,352	2,967	2,352	2,967	2,342	2,950
R-squared	0.227	0.210	0.339	0.323	0.229	0.205

Notes: Panel regression using standard errors clustered by country. *, **, *** denote significance at the 10, 5 and 1% confidence level. p-values are reported in parentheses. For country groups used in columns (3) and (4), see Table 3.

3.2.2 Potential endogeneity of insured share and disaster damage linked to a country's economic development

We now present some robustness checks to allay concerns that our baseline model is unable to fully isolate the effects of our two key explanatory variables of interest – insured share and disaster damage – on GDP growth due to the potential endogeneity arising from differences between richer and poorer countries in our sample. Although our sample only contains countries with available quarterly GDP data and is thus more homogeneous compared to worldwide samples used in other related studies (e.g., von Peter et al. (2024)), the variation in income per capita is still substantial, with India and Luxembourg being the poorest and richest countries in our sample.

There are two key concerns related to the difference in the economic development of countries. The first is that our model may suffer from an omitted variable bias arising from the possibility that the share of insured losses correlates with a country's economic and/or financial development – which could also influence economic recovery after a disaster. For instance, better access to private credit in richer countries could accelerate economic recovery in a similar way to insurance. Similarly, better government effectiveness could help facilitate faster reconstruction of public infrastructure. Although the use of country-fixed effects helps to address this concern by controlling for non-time-varying cross-country differences in GDP growth, it may not fully account for such concerns in the context of GDP growth recoveries, which follow specific disasters occurring in countries at particular points in time.

Panel A of Table 5 shows several country-specific characteristics from the WDI dataset that capture the economic, financial or educational development of a country and its government effectiveness, divided by countries with a high (above median) and low (below median) share of insured losses (see Table A4 in the Annex for individual country data). The average of all these variables is higher for countries with a high share of insured losses. For example, average GDP per capita reaches almost $50,000 in countries with a high share of insured losses compared to only around $30,000 in countries with a low share of insured losses. In addition, panel B of Table 5 reports significant positive correlations between the share of insured losses and all of these variables, except secondary education. The correlation is particularly strong for government effectiveness, domestic credit to the private sector and GDP per capita (coefficients of 0.63, 0.55 and 0.53 respectively).[13]

Table 5: Comparison of country characteristics by insurance coverage

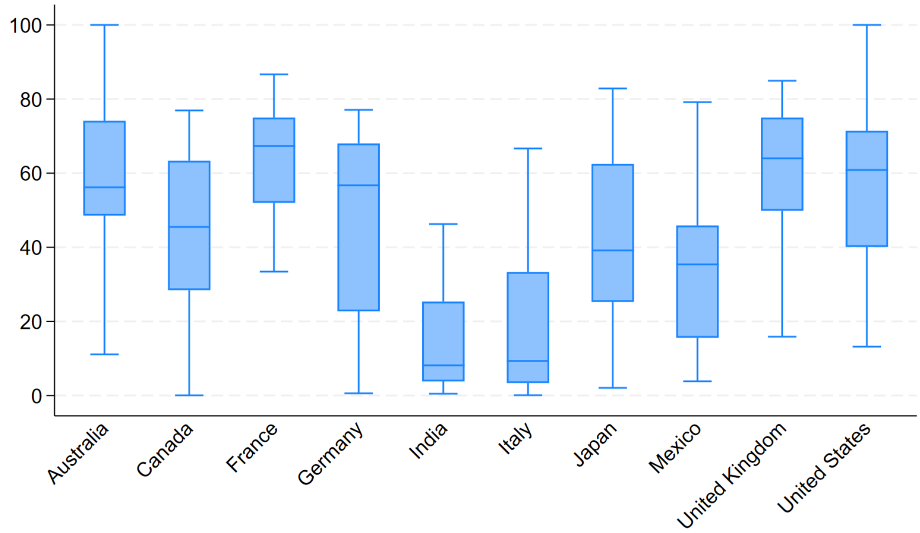
	A. Countries with insurance coverage:		B. Correlation with insurance coverage:	
	low	high	coefficient	p-value
Share of insured losses (%)	17	52	–	–
Adults educated to upper secondary level (%)	60	72	0.21	0.18
Adults owning bank account	74	91	0.40	0.01
Domestic credit to private sector (% of GDP)	66	110	0.55	0.00
GDP per capita (PPP, 2021 International $)	29,749	49,015	0.53	0.00
Government effectiveness	0.57	1.39	0.63	0.00

Sources: EMDAT, WDI and authors' calculations.
Notes: In panel A, countries are split by the average share of insured losses per country, with high insurance coverage countries being those above the median and low insurance coverage being those below (see Table A4 in the Annex for individual country data). Out of our sample of 47 countries, information on insurance coverage is not available for three countries (Finland, Iceland and Romania), which are excluded. Country-specific characteristics are averages for available data over the period 1996–2019. Bank account ownership also includes accounts with a mobile money app. Government effectiveness is standardised, such that a score of 1 represents one standard deviation above the global average. Panel B reports the correlation between the (average) share of insured losses per country and the respective country-specific characteristics (both coefficients and corresponding p-values are reported).

At the same time, it is important to highlight that there remains considerable heterogeneity in the share of insurance coverage within individual countries, with some variation over time and material differences across different disaster types. For example, zooming in on the top ten countries with the most disasters, the insured share of individual disasters ranges from below 20% to over 75% for seven out of the ten countries (see Figure 3). Time-series charts (see Figure A1 in Annex) indicate that there is some variation in the insured share within some of these countries over time, albeit often without a clear time trend or a time trend that does not seem to be a dominant determinant of the within-country variation (i.e. there is not much evidence of insurance market growth in most of these countries).

[13] We do not find any significant correlation between our second explanatory variable, disaster damage as share of GDP, and these country-specific characteristics. Therefore, we also do not discuss related endogeneity concerns.

Figure 3: Boxplots of insured share for the ten countries with most disasters



Notes: Includes the ten countries from Table A2 in Annex with the largest number of quarters for which data on insured losses are available. Boxplots shows the median, the 25th and 75th percentiles and the adjacent values (i.e., the largest/lowest values that are no further away from the nearest quartile than 1.5 times the interquartile range). *Sources:* EMDAT and authors' calculations.

To study the variation in the insured share between different types of disasters, we assign to each quarter the type of disaster that causes the most damage. For instance, if there were two floods with damage of $500 million each and one storm with damage of $1300 million, we would assign the dominant disaster type in that quarter to be a storm. Using this approach and looking at quarters with available data on insured share, the most common dominant disaster types are storms (203 quarters), floods (136 quarters), earthquakes (54 quarters) and wildfires (36 quarters). There are only 15 quarters where other types of disaster (e.g., drought, extreme temperature, landslide) are more damaging. Examining the ten countries with the most disasters, the insured share varies significantly within countries across the dominant types of disasters (see Table A3 in the Annex). For example, in Japan and the United States, insurance coverage is much higher for storms than for floods and earthquakes, but in Mexico, earthquakes have the highest insurance coverage.

This wide dispersion of insurance shares within countries and across disaster types provides some comfort that our results are not solely driven by differences in country characteristics between countries that have on average high or low rates of insurance. In particular, there is considerable variation in the share of insured losses beyond that driven by economic development.

The second concern relates to a potential measurement error due to reporting bias in EM-DAT data, which generally offer better coverage for richer countries (Felbermayr and Gröschl, 2014).[14] As a result, both total damages and insured losses may be under-reported for poorer

[14]Endogeneity might also arise from reverse causality – but there is little reason for this concern as it is unclear how GDP growth would influence either disaster damage as a share of GDP or the post-disaster share of insured losses. For disaster damage, this is supported by the fact that the (unconditional) correlation between real GDP growth and disaster damage as a share of GDP is highly insignificant. The correlation between real GDP growth and the share of insured losses is slightly negative (-0.15) and significant at 5%, which likely reflects the fact that poorer countries tend to have generally stronger GDP growth and a lower share of insured losses (see Table 5). This does not support the hypothesis that e.g. stronger GDP growth (recovery) induces a higher insurance coverage.

countries in our sample, which could create a selection bias. It is worth noting that this coverage bias is particularly concentrated in the pre-2000 period, and since September 2023 EM-DAT has referred to pre-2000 data as "historic data" (Centre for Research on the Epidemiology of Disasters, 2025). Given that our sample period falls mostly after that date, this bias is less of an issue than for those studies that cover many decades prior to 2000 (e.g., Noy (2009)).

Still, Table 6 shows that the missing values for both total damages and insured losses appear more often in countries with lower education levels, lower financial development, lower GDP per capita and lower government effectiveness. These differences are more pronounced when considering missing values for insured losses (Panel B of Table 6) than missing values for disaster damage (Panel A of Table 6). This is not surprising given the larger number of missing values for insured losses than for total damage data (see Table 2). At the same time, the disparities in these country characteristics are always statistically significant, regardless of whether we look at disasters with missing damage or missing insured loss data.[15] In addition, it is worth noting that the differences in country characteristics between missing and non-missing insured loss data in Panel B of Table 6 (e.g. GDP per capita at around $32,000 vs $48,000) are quite similar to the differences reported in Panel A of Table 5 for countries with low and high insurance coverage (e.g., GDP per capita at around $30,000 vs $49,000).

Table 6: Comparison of country characteristics by data availability

	A. Missing damage?		**B. Missing insured loss?**	
	Yes	No	Yes	No
Adults educated to upper secondary level (%)	56	67	57	74
Adults owning bank account	72	77	71	86
Domestic credit to private sector (% of GDP)	81	113	85	138
GDP per capita (PPP, 2021 International $)	31,362	38,868	31,701	48,141
Government effectiveness	0.65	0.95	0.67	1.30

Sources: EMDAT, WDI and authors' calculations.
Notes: The table shows averages of country-specific characteristics, calculated by averaging across individual disaster events reported in EMDAT, separately for cases where data on total damages and insured losses are missing and where they are available. Two-sample t-tests suggest that the differences between all these averages (e.g. between average GDP per capita when data on damages are missing and when they are available) are statistically significant at any conventional significance level. For more details about the WDI data, see the notes to Table 5.

In an attempt to at least partially address these two concerns, we run several robustness checks in which we split our countries into two sub-samples by various country-specific characteristics to further homogenise them. We first examine country splits based on the three WDI variables that exhibit the highest correlation with the share of insured losses in Table 5. Specifically, we split countries into those with (i) low and high GDP per capita; (ii) low and high domestic credit to the private sector; and (iii) low and high government effectiveness.[16] The results are presented in columns (5) to (10) of Tables 7 (simultaneous effects) and 8 (with rebound effects). By and large, our baseline results continue to hold for all of these country splits, even if significance drops in some cases and coefficients sometimes become insignificant, which is not surprising given that the large drop in the sample size reduces statistical power.

[15] The differences are somewhat less pronounced for imputed insured loss data than for initially reported insured loss data - but they remain significant.
[16] For the list of countries in each group, see Table A5 in the Annex.

These robustness exercises mitigate concerns that our baseline findings are affected by endogeneity linked to a country's economic development. Instead, they suggest that the within country variation in insured share across disasters and to some extent over time, as discussed above, may partly underpin our baseline results. However, the share of insured losses is also quite heterogenous across both developed and middle income countries. For example, countries like Italy, Austria, Norway and Portugal have a low (below median) share of insured losses, while South Africa and Costa Rica have a high (above median) share (see Table A4 in the Annex), suggesting that there are other important determinants of average insurance coverage beyond the economic development of a country. These can be various, involving both demand and supply side factors. However, policies such as whether or not a country has a government-supported natural catastrophe insurance scheme are also important. Such schemes tend to support insurance coverage (see OECD (2021); ECB-EIOPA (2024)), which is also confirmed in our data: the average share of insured losses in countries with such schemes is 53%, compared to 32% for countries without such schemes. In addition, there are ten countries with an insurance scheme in the group of countries with high insurance coverage (Belgium, Spain, Japan, the Netherlands, the United States, Australia, the United Kingdom, New Zealand, France and Denmark), while only two countries with a scheme belong to the group with low insurance coverage (Turkey and Norway; see Table A4 in the Annex).[17] On the other hand, the existence of an insurance scheme is not strongly linked to the economic development of a country as our sample includes many high-income countries (e.g., Canada, Germany, Sweden and Luxembourg) that do not have an insurance scheme in place.[18] This suggests that one somewhat exogenous factor which might be partially explaining our baseline results is whether or not a country has a government-backed natural catastrophe insurance scheme.

In this context, we run another robustness exercise which splits countries into those with a low and high average share of insured losses. The share in the first group with low coverage varies from below 5% in Colombia, Croatia and Greece to 30-34% in Norway, Austria and Mexico; while it ranges from 35-40% in Belgium, Czechia, Spain and Poland to over 65% in Luxembourg and Denmark in the second group with a high share. Hence, there still remains considerable heterogeneity in insurance coverage within the two country groups. Columns (3) and (4) in Tables 7 and 8 suggest that our results are also generally robust to splitting countries into those with low and high insurance coverage. The estimated coefficients have the expected signs and are mostly significant at 10%.

3.2.3 Further robustness checks

We carry out three further robustness checks on our baseline results to address additional potential concerns. The first concern is that the economic implications of disasters may differ by disaster type (e.g. floods often destroy physical infrastructure but heatwaves rarely do), and that households and businesses more commonly hold insurance against certain disaster types. By consequence, the results in the baseline may be driven by differences between the impact of

[17] At the time of writing, Italy is in the process of implementing a scheme, but this is not relevant for our analysis, which is based on 1996-2019 data.

[18] The insurance schemes tend to share the same objective: they all aim to enhance societal resilience against disasters. They typically do so by improving risk awareness and prevention, while increasing insurance capacity through more affordable (re)insurance (see (ECB-EIOPA, 2024)).

Table 7: Robustness to sample splits - simultaneous effects

Dependent variable	quarterly GDP growth rate (in %)									
	(1) Original	(2) Imputed	(3) Original	(4) Imputed	(5) Original	(6) Imputed	(7) Original	(8) Imputed	(9) Original	(10) Imputed
Country sample:	**Baseline sample**		**Low insurance coverage**		**Low income**		**Low credit**		**Low government effectiveness**	
Damages (% of GDP)	-0.24*	-0.23*	-0.56*	-0.31	-0.60***	-0.38**	-0.62***	-0.47***	-0.57***	-0.45**
	(0.07)	(0.05)	(0.07)	(0.11)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)
Damages (% of GDP) * Insured share (%)	0.0036*	0.0037**	0.020*	0.0096	0.021***	0.011**	0.016	0.011*	0.012	0.0096***
	(0.06)	(0.04)	(0.08)	(0.11)	(0.01)	(0.03)	(0.11)	(0.07)	(0.23)	(0.01)
Observations	3,100	3,595	1,343	1,594	1,361	1,606	1,419	1,642	1,340	1,593
R-squared	0.207	0.192	0.281	0.246	0.297	0.258	0.308	0.270	0.304	0.263
Number of countries	47	47	22	22	23	23	23	23	23	23
Country sample:	**Baseline sample**		**High insurance coverage**		**High income**		**High credit**		**High government effectiveness**	
Damages (% of GDP)	-0.24*	-0.23*	-0.60***	-0.53***	-0.29*	-0.26	-0.13***	-0.14***	-0.14***	-0.15***
	(0.07)	(0.05)	(0.00)	(0.00)	(0.08)	(0.17)	(0.00)	(0.00)	(0.00)	(0.00)
Damages (% of GDP) * Insured share (%)	0.0036*	0.0037**	0.0076***	0.0069***	0.0038*	0.0036	0.0022***	0.0024***	0.0021***	0.0024***
	(0.06)	(0.04)	(0.00)	(0.00)	(0.06)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	3,100	3,595	1,522	1,766	1,739	1,989	1,681	1,953	1,760	2,002
R-squared	0.207	0.192	0.245	0.233	0.206	0.201	0.205	0.195	0.209	0.201
Number of countries	47	47	22	22	24	24	24	24	24	24

Notes: Panel regression with country and quarterly fixed effects using standard errors clustered by country. *, **, *** denote significance at the 10, 5 and 1% confidence level. [-values are reported in parentheses. For country samples used in columns (3) - (10), see Tables A4 and A5 in the Annex.

disasters that are commonly insured and those that are not. Related to this is the concern that the baseline sample includes some disasters which are not typically covered by insurance such as extreme temperature, mass movement (dry) and landslides (see Table 1). In Tables A6 and A7 in the Annex, we report two additional types of regressions. First, in columns (3) and (4), we add to the baseline model fixed effects for each of the four disaster types with most observations of insured loss data (storms, floods, earthquakes and wildfires), as well as a fixed effect covering 'other disasters'. Second, we drop from the sample the category of 'other disasters', which overlaps strongly with those disaster types that typically have very low insurance coverage (columns (5) and (6)). In each case, these modifications only lead to negligible changes in the results.

The second concern relates to disasters for which we have no data for damages. Here we check the impact on our results from dropping quarters where there are catastrophes, but no damage data, or by setting small-scale disasters to zero (effectively imposing that they have no empirical macroeconomic effect). In both cases, the results remain significant and qualitatively similar (see Section A.1 in the Annex).

The final robustness check is to eliminate Chile and New Zealand from our sample. These countries were hit by massive earthquakes, which are by far the largest catastrophes in our sample in terms of damage as a share of GDP. There is, therefore, a concern that these outliers may skew our results. However, we find that excluding these countries, individually or jointly, increases the size and also generally the significance of the coefficients of interest (see Section A.2 in the Annex).

Table 8: Robustness to sample splits - rebound effects

Dependent variable	quarterly GDP growth rate (in %)									
	(1) Original	(2) Imputed	(3) Original	(4) Imputed	(5) Original	(6) Imputed	(7) Original	(8) Imputed	(9) Original	(10) Imputed
Country sample:	**Baseline sample**		**Low insurance coverage**		**Low income**		**Low credit**		**Low government effectiveness**	
Damages (as % GDP)	-0.25*	-0.24*	-0.64***	-0.51***	-0.65**	-0.40**	-0.63***	-0.54***	-0.57***	-0.54***
	(0.08)	(0.06)	(0.00)	(0.00)	(0.02)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)
→ Lag 1	0.28***	0.18*	0.22	0.071	0.18	-0.070	0.24	0.037	0.32	0.017
	(0.00)	(0.05)	(0.72)	(0.89)	(0.67)	(0.72)	(0.71)	(0.90)	(0.59)	(0.95)
Damages (as % GDP) * Insured share (%)	0.0041**	0.0039**	0.0084***	0.0066***	0.022**	0.012**	0.0097*	0.011*	0.0049	0.0098**
	(0.05)	(0.04)	(0.00)	(0.00)	(0.03)	(0.05)	(0.08)	(0.06)	(0.31)	(0.01)
→ Lag 1	-0.0044***	-0.0025	-0.0026	-0.0011	0.00057	0.0094	-0.0019	0.0040	-0.0072	0.0075
	(0.00)	(0.12)	(0.73)	(0.86)	(0.97)	(0.15)	(0.90)	(0.61)	(0.66)	(0.22)
Observations	2,352	2,967	1,160	1,498	961	1,231	1,048	1,281	928	1,204
R-squared	0.227	0.210	0.258	0.244	0.356	0.315	0.355	0.323	0.360	0.325
Countries	47	47	22	22	23	23	23	23	23	23
Country sample:	**Baseline sample**		**High insurance coverage**		**High income**		**High credit**		**High government effectiveness**	
Damages (as % GDP)	-0.25*	-0.24*	-0.63*	-0.36*	-0.30	-0.25	-0.14***	-0.14***	-0.15***	-0.15***
	(0.08)	(0.06)	(0.10)	(0.09)	(0.15)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
→ Lag 1	0.28***	0.18*	0.15	-0.14	0.20	-0.15	0.28***	0.25***	0.26***	0.23***
	(0.00)	(0.05)	(0.74)	(0.49)	(0.63)	(0.58)	(0.00)	(0.00)	(0.00)	(0.00)
Damages (as % GDP) * Insured share (%)	0.0041**	0.0039**	0.023	0.011*	0.0045*	0.0038*	0.0027***	0.0025***	0.0027***	0.0026***
	(0.05)	(0.04)	(0.11)	(0.10)	(0.06)	(0.05)	(0.00)	(0.01)	(0.00)	(0.00)
→ Lag 1	-0.0044***	-0.0025	0.0019	0.013*	-0.0031	0.0013	-0.0039***	-0.0033***	-0.0038***	-0.0034***
	(0.00)	(0.12)	(0.90)	(0.06)	(0.56)	(0.68)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	2,352	2,967	986	1,263	1,391	1,736	1,304	1,686	1,424	1,763
R-squared	0.227	0.210	0.322	0.289	0.214	0.208	0.217	0.205	0.219	0.208
Number of countries	47	47	22	22	24	24	24	24	24	24

Notes: Panel regression with country and quarterly fixed effects using standard errors clustered by country. *, **, *** denote significance at the 10, 5 and 1% confidence level. p-values are reported in parentheses. For country samples used in columns (3) - (10), see Tables A4 and A5 in the Annex.

3.3 Estimating non-linear effects: large-scale disasters with low and high shares of insured losses

Equation (11) suggests that the effects of disaster damages and the insured share (interacted with disaster damages) are both linear. But non-linear effects are likely to be particularly relevant for large-scale disasters. And the macroeconomic benefits from insurance protection could also be non-linear in the extent of coverage. To account for possible non-linearities, we also estimate an alternative empirical specification in which we use two dummy variables to capture large-scale natural disasters with high and low shares of insured losses respectively.

In line with the definition of small-scaled disasters in Annex Section A.1, we define large-scale disasters to be disasters with total damage exceeding the 75th percentile of the distribution of total damage data (0.11% of GDP). Regarding the share of insured losses, we define it to be high (low) if it is above 40% (below 40%) in the original sample, while we use the threshold of 35% in the imputed sample. We select the thresholds of 40% and 35% as they broadly correspond to the median share of insured losses across all disasters in the respective samples.

The move from continuous explanatory variables to dummy variables has various effects on the estimations in terms of the sample size and the effective number of observations that drive the results. In particular, because large-scale disasters only represent a quarter of all the disaster observations used in the previous empirical setup, we are left with many fewer observations that capture the actual effect of disasters, which might lead to less significant results.[19] In addition, the smaller number of large-scale disasters increases the already high variance of post-disaster quarterly GDP data. Combined with the fact that an annual growth rate perspective might be more relevant for large-scale disasters due to potentially drawn out rebound effects, this empirical setup therefore uses the annual GDP growth rate in each quarter (calculated as the year-on-year difference in the log of GDP) as the dependent variable and includes up to three lags of the two dummy variables.

The results presented in Table 9 confirm the adverse effect on the GDP growth rate from large-scale natural disasters when insurance coverage is low. In the larger sample with imputed values, this adverse effect is estimated to drag on the annual GDP growth rate for up to three quarters after the disaster (see also Figure 4). For large-scale disasters with a high share of insured losses, the GDP growth rate is estimated to be higher and does not deviate significantly from its long-term trend, in line with the theoretical model. This suggests that higher insurance coverage is associated with stronger GDP growth after large disasters, with the effect potentially persisting for several quarters. The can probably be attributed to insurance payouts supporting reconstruction. We further note that we obtain these results despite the fact that we do not fully control for some potentially confounding effects that could further mitigate the effect of disasters such as a potential post-disaster fiscal intervention, which is likely to be correlated with low insurance coverage.

[19]Note that the issue with missing values addressed in Annex Section A.1 now becomes less important as the (un)availability of insured share becomes irrelevant for small-scale disasters. Moreover, it is sufficient to have data on damage of one large-scale disaster to classify that quarter into a quarter with a large-scale disaster, regardless of whether damage data on other disasters in that quarter are available.

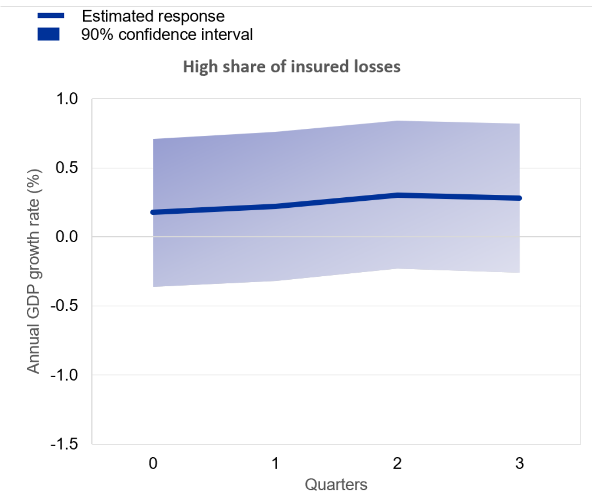
Table 9: Panel estimates for large-scale disasters with low and high shares of insured losses

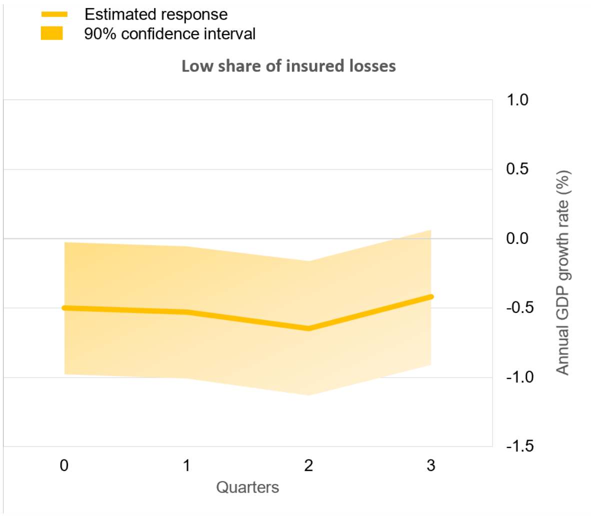
Dep. var.	**annual GDP growth rate (in %)**							
Sample	**(1) Original**	**(2) Imputed**	**(3) Original**	**(4) Imputed**	**(5) Original**	**(6) Imputed**	**(7) Original**	**(8) Imputed**
Large scale disaster with a high share of insured losses								
→ Lag 0	-0.38	0.12	-0.34	0.12	-0.35	0.16	-0.39	0.18
	(0.43)	(0.72)	(0.52)	(0.71)	(0.52)	(0.62)	(0.50)	(0.58)
→ Lag 1			-0.58	0.19	-0.48	0.18	-0.38	0.22
			(0.26)	(0.55)	(0.38)	(0.57)	(0.50)	(0.50)
→ Lag 2					-0.12	0.35	-0.069	0.30
					(0.82)	(0.27)	(0.90)	(0.35)
→ Lag 3							0.15	0.28
							(0.79)	(0.40)
Large scale disaster with a low share of insured losses								
→ Lag 0	-0.65*	-0.49*	-0.65	-0.48*	-0.73	-0.48*	-0.81	-0.50*
	(0.10)	(0.09)	(0.14)	(0.10)	(0.12)	(0.10)	(0.11)	(0.08)
→ Lag 1			-0.17	-0.53*	-0.22	-0.54*	-0.17	-0.53*
			(0.71)	(0.07)	(0.66)	(0.06)	(0.75)	(0.07)
→ Lag 2					0.20	-0.64**	0.27	-0.65**
					(0.71)	(0.03)	(0.63)	(0.03)
→ Lag 3							0.73	-0.42
							(0.24)	(0.15)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarterly FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,823	4,302	3,381	4,170	3,047	4,057	2,774	3,950
R-squared	0.355	0.341	0.380	0.353	0.393	0.361	0.402	0.366

Notes: Panel regression using standard errors clustered by country. *, **, *** denote significance at the 10, 5 and 1% confidence level. p-values are reported in parentheses. Large-scale natural disasters refer to disasters with total damage larger than the 75th percentile of the distribution of total damage data (0.11% of GDP). In the original sample, the share of insured losses is high (low) if it is above 40% (below 40%). In the imputed sample, the share of insured losses is high (low), if it is above 35% (below 35%). The thresholds of 40% and 35% broadly correspond to the median share of insured losses across all disasters in the respective samples.

Figure 4: The impact of large-scale natural disasters with low and high shares of insured losses on the annual GDP growth rate.

Notes: Based on estimates in column (8) of Table 9. For the quarter including the date(s) of the disaster (t=0) and the three subsequent quarters, the y-axis measures the percentage point impact of the disaster on the year-on-year annual growth rate at the end of that quarter.





4 Conclusions and policy implications

Climate change is likely to bring about a marked increase in catastrophe risk globally. The theoretical and empirical results presented in this paper demonstrate that the macroeconomic impact of that increase is not pre-determined. Setting aside adaptation efforts and mitigation measures to transition to a low-carbon economy and thereby limit the extent of global warming, insurance also has a key role to play in mitigating the macroeconomic impact of future catastrophes. Our theoretical model illustrates how insurance can help to reduce the overall welfare loss from catastrophes by accelerating reconstruction and limiting the period of lower output. And we find empirically that higher insurance coverage is associated with a lower impact of natural catastrophes on GDP.

Yet the insurance protection gap in Europe and elsewhere is already substantial, and there are several reasons to suspect it may widen as a result of climate change. More frequent and more severe disasters may act to reduce the supply of private insurance, whilst simultaneously making insurance more valuable from a welfare perspective. While full insurance coverage at all times and everywhere is unlikely to be socially optimal, the relatively low levels of current insurance coverage highlight the need for policies to reduce the climate insurance protection gap. Options include enhancing private insurance penetration, deepening catastrophe bond markets and developing public-private resilience solutions (ECB-EIOPA, 2023). More ambitiously, risk pooling across countries or regions could further improve insurability and affordability (ECB-EIOPA, 2024) .

For all such policies, effective design is vital to minimise moral hazard, set appropriate incentives and ensure that greater insurance coverage brings clear welfare benefits. In this respect, insurers can provide incentives for risk reduction and adaptation by promoting risk awareness and providing risk-based incentives linked to premiums via impact underwriting – an underwriting and pricing strategy aimed at incentivising policyholders to implement ex ante (structural) measures and reduce exposure to climate-related hazards (see Linnerooth-Bayer et al. (2019) and EIOPA (2021)). For instance, they can offer premium reductions for insuring buildings in flood-prone areas if they meet certain flood protection standards. Another approach to reducing risk exposure is managed retreat, which involves restricting or avoiding human activity in high-risk areas.[20] In some circumstances, this may be better for welfare than providing insurance which could perversely incentivise building in high-risk areas. Underinsurance can also be induced by a moral hazard problem, whereby the public sector often bears the residual risk, thus creating expectations that it will eventually cover the losses from the next natural catastrophe. One solution is to align the responsibility for providing disaster relief with the responsibility for implementing relevant regulations such as those relating to spatial and land use planning. Evidence from the United States suggests that subsidies for investment in adaptation may also help. In particular, Fried (2022) shows that while disaster aid may discourage adaptation, federal subsidies for investment in adaptation more than offset this moral hazard issue. Finally, mandatory insurance take-up in public-private partnerships can help mitigate both moral hazard and adverse selection issues (see ECB-EIOPA (2023) and ECB-EIOPA (2024) for a fuller discussion of these aspects).

[20] For example, the Netherlands' "Room for the River" programme aimed to reduce flood risk by relocating dykes further inland, allowing rivers to spread across larger areas.

Overall, exploring the interplay between mitigation measures, adaptation efforts and insurance in limiting the macroeconomic impact of climate-related catastrophes is a fruitful area for future research. But tackling the structural causes of the climate insurance protection gap now and in the future has the potential to provide substantial macroeconomic and welfare benefits.

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A Annex

Table A1: Large disasters

Country	**Year**	**Quarter**	**Damage (% of GDP)**	**Share of insured losses (%)**	**Type/name of large disaster**
Chile	2010	1	14.5	27	Chile Earthquake
New Zealand	2011	1	9.9	80	Christchurch Earthquake
New Zealand	2010	3	4.5	77	Christchurch Earthquake
New Zealand	2016	4	2.1	54	Kaikōura Earthquake
New Zealand	2011	2	2.0	67	Canterbury Earthquake
Turkey	1999	3	5.2	10	İzmit Earthquake
Japan	2011	1	3.6	18	Tōhoku Earthquake
Czech Republic	2002	3	1.9	50	Flood
Czech Republic	1997	3	1.7	17	Flood
Poland	1997	3	1.8	13	Flood
Latvia	2005	1	1.6	12	Cyclone Erwin
United States	2005	3	1.2	51	Hurricane Katrina
Colombia	1999	1	1.2	5	Colombia Earthquake
Denmark	1999	4	1.2	81	Cyclone Anatol
Indonesia	2004	4	1.0	5	Indian Ocean Earthquake

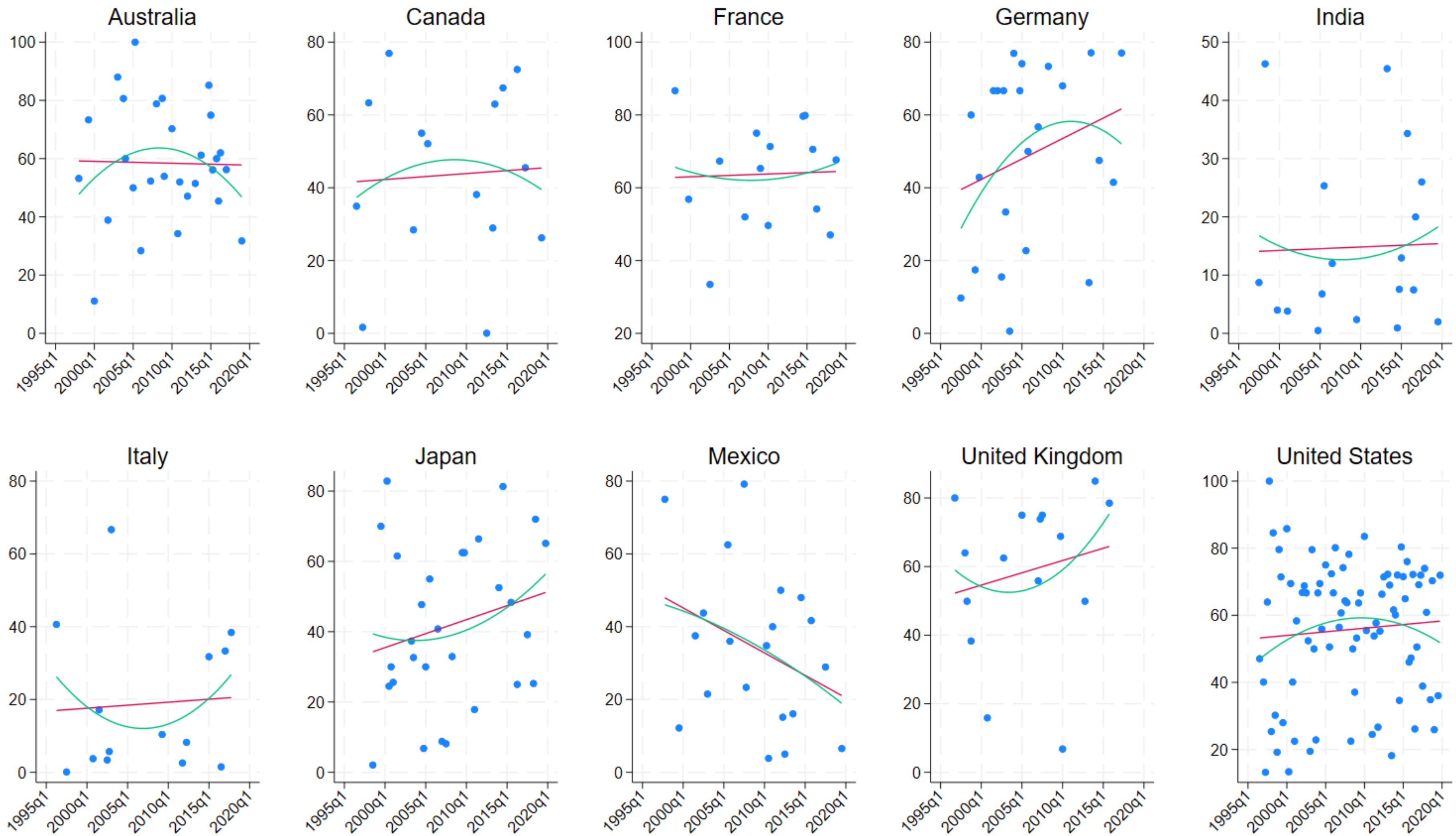
Sources: EMDAT, WDI and authors' calculations.
Notes: The table lists disasters with damage over 1% of GDP, for which data on both damage and insured losses are available. Only countries with quarterly GDP data are considered.

Table A2: Total damage and insurance coverage by country

Countries with quarterly GDP	Number of quarters with total damage (with insured losses)	Total damage (% of GDP)		Share of insured losses (%)	
		mean	median	mean	median
Australia	50 (28)	0.08	0.040	58.5	56.2
Austria	14 (4)	0.14	0.088	30.9	21.0
Belgium	9 (4)	0.03	0.017	35.6	35.0
Brazil	27 (3)	0.03	0.008	22.8	5.0
Bulgaria	10 (1)	0.30	0.019	13.4	13.4
Canada	24 (15)	0.06	0.017	43.6	45.5
Chile	20 (6)	0.86	0.106	26.9	28.3
Colombia	15 (3)	0.17	0.005	3.6	4.0
Costa Rica	11 (2)	0.33	0.145	60.6	60.6
Croatia	6 (1)	0.32	0.183	3.7	3.7
Cyprus	1 (1)	0.04	0.043	60.0	60.0
Czech Republic	13 (8)	0.35	0.072	37.8	40.6
Denmark	3 (2)	0.57	0.466	74.9	74.9
Estonia	1 (1)	0.80	0.795	20.0	20.0
Finland	0 (0)	–	–	–	–
France	26 (15)	0.06	0.010	63.8	67.3
Germany	30 (23)	0.05	0.013	48.9	56.7
Greece	11 (1)	0.37	0.136	4.5	4.5
Hungary	10 (2)	0.10	0.055	29.3	29.3
Iceland	2 (0)	0.29	0.289	–	–
India	61 (18)	0.10	0.049	14.8	8.2
Indonesia	49 (10)	0.13	0.008	15.1	4.8
Ireland	5 (2)	0.06	0.083	48.9	48.9
Israel	5 (1)	0.08	0.062	6.2	6.2
Italy	34 (14)	0.08	0.023	18.8	9.3
Japan	46 (29)	0.15	0.012	41.9	39.2
Korea, Rep.	23 (3)	0.10	0.021	5.2	4.0
Latvia	2 (1)	0.83	0.825	12.3	12.3
Lithuania	3 (1)	0.27	0.103	20.0	20.0
Luxembourg	1 (1)	0.06	0.061	67.7	67.7
Mexico	43 (20)	0.10	0.028	34.0	35.4
Netherlands	9 (6)	0.04	0.014	55.2	63.4
New Zealand	22 (8)	0.90	0.038	60.9	63.2
Norway	1 (1)	0.04	0.036	30.8	30.8
Poland	11 (3)	0.26	0.023	39.0	12.9
Portugal	11 (5)	0.32	0.089	24.6	8.6
Romania	14 (0)	0.21	0.095	–	–
Russian Federation	39 (3)	0.02	0.007	12.7	5.0
Slovak Republic	8 (2)	0.20	0.139	49.2	49.2
Slovenia	6 (1)	0.28	0.234	10.0	10.0
South Africa	23 (5)	0.05	0.024	51.6	49.1
Spain	26 (11)	0.05	0.009	38.3	40.3
Sweden	3 (2)	0.26	0.058	49.1	49.1
Switzerland	15 (10)	0.11	0.067	53.7	51.7
Turkey	13 (6)	0.49	0.048	19.0	8.0
United Kingdom	25 (15)	0.06	0.026	58.6	64.0
United States	93 (81)	0.07	0.030	55.8	60.9
All countries with quart. GDP	874 (379)	**0.16**	**0.028**	**43.5**	**47.4**
All countries in EMDAT	1,190 (423)	**0.25**	**0.029**	**40.2**	**40.6**

Sources: EMDAT, WDI and authors' calculations.
Notes: The figures in parentheses refer to the number of quarters for which data on the share of insured losses are available. The mean and median of total damage refers to all total damage data available (i.e. not only to total damage for which insured losses are available).

Figure A1: Share of insured losses (%) over time for the top ten countries with the most disasters



Sources: EMDAT and authors' calculations. *Notes:* Includes the ten countries from Table A2 with the largest number of quarters for which data on insured losses are available. The red and green lines show linear and quadratic fits respectively.

Table A3: Average share of insured losses (%) by type of disaster for the top ten countries with the most disasters

Country	All disasters	Storms	Floods	Earth-quakes	Wild-fires	Other disasters
Australia	58.5	60.3	52.4	–	64.8	–
	(28)	(14)	(10)	(0)	(10)	(0)
Canada	43.6	50.8	36.8	–	49.6	–
	(15)	(4)	(9)	(0)	(3)	(0)
France	63.8	66.3	63.1	–	–	–
	(15)	(7)	(9)	(0)	(0)	(0)
Germany	48.9	63.3	20.1	66.7	–	25.3
	(23)	(14)	(6)	(1)	(0)	(2)
India	14.8	17.9	15.6	2.15	–	13.3
	(18)	(5)	(11)	(2)	(0)	(1)
Italy	18.8	24.5	23.0	10.7	–	–
	(14)	(2)	(7)	(5)	(0)	(0)
Japan	41.9	60.5	23.9	25.4	–	81.3
	(29)	(18)	(5)	(12)	(0)	(1)
Mexico	34.0	32.9	17.8	33.8	–	57.5
	(20)	(12)	(2)	(4)	(0)	(2)
United Kingdom	58.6	58.8	60.9	50.0	–	–
	(15)	(9)	(8)	(1)	(0)	(0)
United States	55.8	62.4	42.5	22.1	54.8	56.8
	(81)	(78)	(23)	(4)	(13)	(5)
All 10 countries with most disasters	47.3	57.8	38.9	24.2	58.1	49.5
	(258)	(163)	(90)	(29)	(26)	(11)
All 47 countries with quarterly GDP	43.5	55.0	37.1	25.5	50.6	46.7
	(379)	(203)	(136)	(54)	(36)	(15)

Sources: EMDAT and authors' calculations.
Notes: Classification into the different disaster types is based on the most damaging disaster which occurred in a given quarter. Shows the ten countries from Table A2 with the largest number of quarters for which data on insured losses are available. The number of the quarters for which such data are available is reported in parentheses. This number might be lower for all disasters compared to the sum of the different disaster types, owing to potential missing values in non-dominant disaster types (see Annex Section A.1 for more details on the treatment of missing values).

Table A4: Countries with low and high insurance coverage

Countries with low insurance coverage

	Country	Mean insurance coverage	Insurance scheme?
1	Colombia	3.6	No
2	Croatia	3.7	No
3	Greece	4.5	No
4	Korea, Rep.	5.2	No
5	Israel	6.3	No
6	Slovenia	10.0	No
7	Latvia	12.3	No
8	Russian Federation	12.7	No
9	Bulgaria	13.4	No
10	India	14.8	No
11	Indonesia	15.1	No
12	Italy	18.8	No
13	Turkey	19.0	Yes
14	Estonia	20.0	No
15	Lithuania	20.0	No
16	Brazil	22.8	No
17	Portugal	24.6	No
18	Chile	26.9	No
19	Hungary	29.3	No
20	Norway	30.8	Yes
21	Austria	30.9	No
22	Mexico	34.0	No

Countries with high insurance coverage

	Country	Mean insurance coverage	Insurance scheme?
1	Belgium	35.6	Yes
2	Czechia	37.8	No
3	Spain	38.3	Yes
4	Poland	39.0	No
5	Japan	41.9	Yes
6	Canada	43.6	No
7	Ireland	48.9	No
8	Germany	48.9	No
9	Sweden	49.1	No
10	Slovak Republic	49.2	No
11	South Africa	51.6	No
12	Switzerland	53.7	Yes
13	Netherlands	55.2	No
14	United States	55.8	Yes
15	Australia	58.5	Yes
16	United Kingdom	58.6	Yes
17	Cyprus	60.0	No
18	Costa Rica	60.6	No
19	New Zealand	60.9	Yes
20	France	63.8	Yes
21	Luxembourg	67.7	No
22	Denmark	74.9	Yes

Sources: EMDAT, OECD (2021), ECB-EIOPA (2024) and authors' calculations.
Notes: Countries are split by the average share of insured losses per country, with high insurance coverage countries being those above the median and low insurance coverage being those below. Out of our sample of 47 countries with quarterly GDP, information on insurance coverage is not available for three countries (Finland, Iceland and Romania), which are excluded. The indicator for an insurance scheme being in place or not is based on natural catastrophe risk insurance programmes included in Table 2.1 in OECD (2021) and Section 2 in ECB-EIOPA (2024).

Table A5: Various country splits

	Low income		Low credit		Low gov. effectiveness	
	Country	**Mean**	**Country**	**Mean**	**Country**	**Mean**
1	India	4,729	Mexico	22	Russia	-0.42
2	Indonesia	8,494	Romania	23	Indonesia	-0.31
3	South Africa	13,141	Colombia	34	Romania	-0.18
4	Colombia	13,630	Indonesia	35	Brazil	-0.18
5	Brazil	16,304	Poland	37	Colombia	-0.17
6	Costa Rica	17,620	Hungary	40	India	-0.04
7	Bulgaria	19,610	Russia	40	Bulgaria	0.01
8	Turkiye	19,695	India	41	Mexico	0.11
9	Mexico	20,437	Bulgaria	43	Turkiye	0.14
10	Chile	22,608	Lithuania	44	Costa Rica	0.29
11	Romania	23,374	Czechia	45	South Africa	0.35
12	Latvia	23,700	Brazil	46	Croatia	0.46
13	Poland	25,039	Slovakia	49	Greece	0.50
14	Lithuania	26,445	Costa Rica	50	Italy	0.52
15	Slovakia	26,449	Turkiye	57	Poland	0.56
16	Croatia	27,156	Latvia	58	Latvia	0.68
17	Hungary	27,447	Croatia	61	Hungary	0.69
18	Russia	28,986	Slovenia	62	Slovakia	0.71
19	Estonia	30,137	Belgium	62	Lithuania	0.74
20	Korea, Rep.	34,007	Israel	68	Czechia	0.89
21	Greece	34,009	Estonia	71	Korea, Rep.	0.94
22	Portugal	35,657	Italy	80	Estonia	0.95
23	Slovenia	35,700	Finland	81	Slovenia	0.96

	High income		High credit		High gov. effectiveness	
1	Israel	36,469	Luxembourg	87	Chile	1.06
2	Czechia	36,730	Germany	91	Portugal	1.08
3	Cyprus	39,218	Greece	91	Israel	1.21
4	New Zealand	40,690	France	91	Cyprus	1.21
5	Japan	41,088	Austria	91	Spain	1.22
6	Spain	41,978	Chile	97	Japan	1.42
7	United Kingdom	46,711	Ireland	98	France	1.48
8	France	48,296	Sweden	99	Ireland	1.50
9	Italy	49,382	Canada	105	United States	1.56
10	Australia	50,431	Netherlands	111	Germany	1.59
11	Finland	51,269	Australia	112	Belgium	1.60
12	Canada	51,769	Korea, Rep.	114	United Kingdom	1.65
13	Sweden	53,204	South Africa	120	Austria	1.68
14	Belgium	54,195	Norway	122	Australia	1.68
15	Germany	54,377	Iceland	126	Iceland	1.69
16	Iceland	54,633	Portugal	129	Luxembourg	1.74
17	Austria	57,769	Spain	133	New Zealand	1.75
18	United States	59,302	United Kingdom	140	Canada	1.80
19	Netherlands	59,575	Denmark	144	Netherlands	1.85
20	Denmark	59,860	Switzerland	151	Sweden	1.86
21	Ireland	63,550	New Zealand	153	Norway	1.88
22	Switzerland	71,739	Japan	176	Switzerland	1.94
23	Norway	82,110	United States	178	Denmark	2.00
24	Luxembourg	123,370	Cyprus	192	Finland	2.06

Sources: EMDAT, World Bank's WDI and authors' calculations.
Notes: The split into low and high income countries is based on average GDP per capita (PPP, 2021 International $) per country over the period 1996–2019. The split into low and high credit is based on average domestic credit to the private sector as a percentage of GDP. Government effectiveness is standardised, such that a score of 1 represents one standard deviation above the global average. Mean refers to the country average of the corresponding variable over the sample period.

Table A6: Robustness to types of disaster - simultaneous effects

Dependent variable	**quarterly GDP growth rate (in %)**					
	Baseline approach		**With disaster type fixed effects**		**Without 'other disaster types'**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sample	**Original**	**Imputed**	**Original**	**Imputed**	**Original**	**Imputed**
Damages as a share of GDP (%)	-0.24*	-0.23*	-0.23*	-0.25*	-0.24*	-0.23*
	(0.07)	(0.05)	(0.10)	(0.06)	(0.07)	(0.06)
Damages as a share of GDP (%) * Share of insured losses (%)	0.0036*	0.0037**	0.0037*	0.0035**	0.0037*	0.0036**
	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)
Country fixed-effects	Y	Y	Y	Y	Y	Y
Quarterly fixed-effects	Y	Y	Y	Y	Y	Y
Disaster type fixed-effects	N	N	Y	Y	N	N
Observations	3,100	3,595	3,100	3,595	3,096	3,547
R-squared	0.207	0.192	0.208	0.193	0.208	0.192

Notes: Panel regression using standard errors clustered by country. *, **, *** denote significance at the 10, 5 and 1% confidence level. p-values are reported in parentheses. Regressions in columns (3) and (4) include fixed effects for the four most common dominant types of disaster (i.e., storm, flood, earthquake and wildfire) and 'other disasters'. None of these fixed effects is estimated to be significant at the 10% confidence level. In columns (5) and (6), the sample includes only the four most common dominant types of disaster (i.e., storm, flood, earthquake and wildfire), while observations where 'other disaster types' are found to be dominant are dropped.

Table A7: Robustness to types of disaster - rebound effects

Dependent variable	**quarterly GDP growth rate (in %)**					
	Baseline approach		**With disaster type fixed effects**		**Without 'other disaster types'**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sample	**Original**	**Imputed**	**Original**	**Imputed**	**Original**	**Imputed**
Damages (as % GDP)	-0.25*	-0.24*	-0.25	-0.25*	-0.25*	-0.24*
	(0.08)	(0.06)	(0.10)	(0.08)	(0.08)	(0.07)
→ Lag 1	0.28***	0.18*	0.28***	0.18*	0.28***	0.19**
	(0.00)	(0.05)	(0.00)	(0.07)	(0.00)	(0.03)
Damages (as % GDP) * Insured share (%)	0.0041**	0.0039**	0.0041**	0.0036*	0.0041**	0.0039**
	(0.05)	(0.04)	(0.05)	(0.07)	(0.05)	(0.04)
→ Lag 1	-0.0044***	-0.0025	-0.0044***	-0.0026	-0.0043***	-0.0026*
	(0.00)	(0.12)	(0.00)	(0.11)	(0.00)	(0.09)
Country fixed-effects	Y	Y	Y	Y	Y	Y
Quarterly fixed-effects	Y	Y	Y	Y	Y	Y
Disaster type fixed-effects	N	N	Y	Y	N	N
Observations	2,352	2,967	2,352	2,967	2,346	2,891
R-squared	0.227	0.210	0.228	0.211	0.228	0.210

Notes: Panel regression using standard errors clustered by country. *, **, *** denote significance at the 10, 5 and 1% confidence level. p-values are reported in parentheses. Regressions in columns (3) and (4) include fixed effects for the four most common dominant types of disaster (i.e., storm, flood, earthquake and wildfire) and 'other disasters'. None of these fixed effects is estimated to be significant at the 10% confidence level. In columns (5) and (6), the sample includes only the four most common dominant types of disaster (i.e., storm, flood, earthquake and wildfire), while observations where 'other disaster types' are found to be dominant are dropped.

A.1 Robustness to the treatment of missing values

When aggregating the EMDAT event-level data into the quarterly-country panel dataset, we make certain choices on how to treat missing values in the data. Specifically, we face two types of missings: (i) missing data on the insured share of disaster damages and (ii) missing data on disaster damages. Although the imputation exercise described in Section 3.1 reduces the amount of missing values on the insured share, it still leaves us with relatively many quarters, which suffer from the unavailability of the (original or imputed) insured share for some disasters.[21]

In the results presented so far, we drop from the panel dataset quarters, where insured share is not available for at least one event with a known disaster damage, while we keep quarters, for which we have incomplete information on the total disaster damage. To test for the robustness of this choice, we estimate our baseline model on a smaller sample, from which we drop quarters with incomplete information on total disaster damage. Columns (3) and (4) of Table A8 show that estimating the model with country and quarterly fixed effects on such a smaller sample yields slightly lower estimates compared to the baseline results (see columns (1) and (2) of Table A8) - but the coefficients gain in significance and maintain the expected signs.

Table A8: Robustness to the treatment of missing values - simultaneous effects

Dependent variable	**quarterly GDP growth rate (in %)**					
	Baseline approach		**Drop quarters with incomplete damages**		**Small-scaled disasters set to 0**	
Sample	**(1) Original**	**(2) Imputed**	**(3) Original**	**(4) Imputed**	**(5) Original**	**(6) Imputed**
Damages as a share of GDP (%)	-0.24*	-0.23*	-0.15***	-0.12***	-0.26*	-0.23*
	(0.07)	(0.05)	(0.01)	(0.01)	(0.06)	(0.07)
Damages as a share of GDP (%) * Share of insured losses (%)	0.0036*	0.0037**	0.0023***	0.0020***	0.0039**	0.0035*
	(0.06)	(0.04)	(0.01)	(0.01)	(0.05)	(0.06)
Country fixed-effects	Y	Y	Y	Y	Y	Y
Quarterly fixed-effects	Y	Y	Y	Y	Y	Y
Observations	3,100	3,595	3,007	3,242	3,604	3,639
R-squared	0.207	0.192	0.210	0.205	0.190	0.190

Notes: Panel regression using standard errors clustered by country. *, **, *** denote significance at 10, 5 and 1% confidence level. P-values are reported in parentheses.

Another consideration we do is that we can increase the sample size, if we assume that small-scaled disasters are unlikely to have a significant effect on GDP growth. This partially eliminates the issue of missing values for insured share, as it becomes irrelevant for these events whether the information on insured share is available or not. Specifically, we consider disasters to be small-scaled, if the damages are smaller than the 75th percentile of the distribution of total damage data (0.11% of GDP) and for these small-scaled disasters, we set damages equal to 0. The estimates in columns (5) and (6) of Table A8 are very similar to those in columns (1) and (2), which further confirms the robustness of our results.

[21] Note that the choices about the treatment of missing data that need to be made are the same, regardless of whether the data on insured share are the original ones or those complemented by the imputed values.

In Table A9, we then report the results for our baseline model with rebound effects (using again the specification with country and quarterly fixed effects). Similarly to the model with contemporaneous effects only, the size of the estimated coefficients slightly decreases in the small sample, when quarters with incomplete damage data are excluded (columns (3) and (4)), while the estimates are very similar to the baseline results for the sample, where damages of small-scaled disasters are set to 0 (columns (5) and (6)).

Table A9: Robustness to the treatment of missing values - rebound effects

Dependent variable	**quarterly GDP growth rate (in %)**					
	Baseline approach		**Drop quarters with incomplete damages**		**Small-scaled disasters set to 0**	
Sample	**(1) Original**	**(2) Imputed**	**(3) Original**	**(4) Imputed**	**(5) Original**	**(6) Imputed**
Damages as a share of GDP (%)	-0.25*	-0.24*	-0.16**	-0.11*	-0.25*	-0.25*
	(0.08)	(0.06)	(0.02)	(0.07)	(0.08)	(0.07)
→ Lag 1	0.28***	0.18*	0.28***	0.23***	0.28***	0.27***
	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
Damages as a share of GDP (%) * Share of insured losses (%)	0.0041**	0.0039**	0.0027**	0.0018*	0.0040*	0.0040**
	(0.05)	(0.04)	(0.01)	(0.09)	(0.05)	(0.05)
→ Lag 1	-0.0044***	-0.0025	-0.0044***	-0.0035***	-0.0043***	-0.0041***
	(0.00)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
Country fixed-effects	Y	Y	Y	Y	Y	Y
Quarterly fixed-effects	Y	Y	Y	Y	Y	Y
Observations	2,352	2,967	2,274	2,562	2,958	3,009
R-squared	0.227	0.210	0.231	0.222	0.210	0.211

Notes: Panel regression using standard errors clustered by country. *, **, *** denote significance at 10, 5 and 1% confidence level. P-values are reported in parentheses.

A.2 Robustness to outliers: earthquakes in New Zealand and Chile

As already discussed in Section 3.1, the distribution of the data on disaster damages is fairly skewed to the right by disasters with exceptionally large damages. In Table A1, we list 15 large disasters whose damage exceeds 1% of GDP.[22] Nine of these disasters are earthquakes and four of them hit New Zealand between 2010 and 2016. Given the short time span between the earthquakes in New Zealand, where adverse affects on GDP might interfere with each other, we test the robustness of our results to the inclusion/exclusion of these large disasters by dropping the full time series of a country rather than dropping selected quarters only.

More specifically, we drop from our sample two countries: Chile and New Zealand. This is because Chile was hit by by far the largest disaster in our sample, the 2010 Chile earthquake and tsunami, whose damage reached almost 15% of GDP. New Zealand was then hit by the devastating earthquakes in Christchurch in 2010 and 2011, with the respective damages reaching almost 5% and 10% of GDP, and the Canterbury and Kaikōura earthquakes in 2011 and 2016 respectively, where both earthquakes caused damages of around 2% of GDP.

[22]The table displays only disasters for which data on both damage and insured losses are available.

The results are reported in Table A10 and suggest that our estimates of the contemporaneous effects are fairly robust to the exclusion of both countries, either individually (columns (3)-(6)) or jointly (columns (7)-(8)). In fact, in all of these cases, the estimates of both coefficients of interest (damages and insured share) increase in size and mostly also in significance. From this perspective, our baseline estimates of the contemporaneous effects can be considered fairly conservative.

Table A10: Robustness to outliers - simultaneous effects

Dependent variable	**quarterly GDP growth rate (in %)**							
	Baseline approach		**Excluding Chile**		**Excluding New Zealand**		**Excluding Chile and New Zealand**	
Sample	**(1) Orig.**	**(2) Imp.**	**(3) Orig.**	**(4) Imp.**	**(5) Orig.**	**(6) Imp.**	**(7) Orig.**	**(8) Imp.**
Damages (% of GDP)	-0.24*	-0.23*	-0.52***	-0.44**	-0.48**	-0.36**	-0.55***	-0.46**
	(0.07)	(0.05)	(0.00)	(0.01)	(0.04)	(0.03)	(0.00)	(0.01)
Damages (% of GDP) * Insured share (%)	0.0036*	0.0037**	0.0069***	0.0060***	0.014*	0.0095**	0.010**	0.0087**
	(0.06)	(0.04)	(0.00)	(0.01)	(0.07)	(0.05)	(0.04)	(0.02)
Country fixed-effects	Y	Y	Y	Y	Y	Y	Y	Y
Quarterly fixed-effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,100	3,595	3,042	3,521	3,025	3,506	2,967	3,432
R-squared	0.207	0.192	0.210	0.193	0.210	0.195	0.212	0.196

Notes: Panel regression using standard errors clustered by country. *, **, *** denote significance at 10, 5 and 1% confidence level. P-values are reported in parentheses.

The results of estimating rebound effects (in addition to contemporaneous effects) are reported in Table A11. Interestingly, the rebound effects cease to be significant, when estimated on the sample without either Chile (columns (3) and (4)) or New Zealand (columns (5) and (6)) or both (columns (7) and (8)). At the same time, the estimates of contemporaneous effects again tend to increase in both size and significance, so that they successfully pass this robustness check.

Table A11: Robustness to outliers - rebound effects

Dependent variable	**quarterly GDP growth rate (in %)**							
	Baseline approach		**Excluding Chile**		**Excluding New Zealand**		**Excluding Chile and New Zealand**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Sample	**Orig.**	**Imp.**	**Orig.**	**Imp.**	**Orig.**	**Imp.**	**Orig.**	**Imp.**
Damages (% of GDP)	-0.25*	-0.24*	-0.57***	-0.47**	-0.57**	-0.39**	-0.62***	-0.50***
	(0.08)	(0.06)	(0.00)	(0.01)	(0.04)	(0.04)	(0.01)	(0.01)
→ lag	0.28***	0.18*	0.15	-0.0023	0.24	-0.017	0.12	-0.095
	(0.00)	(0.05)	(0.70)	(0.99)	(0.12)	(0.90)	(0.79)	(0.69)
Damages (% of GDP) * Insured share (%)	0.0041**	0.0039**	0.0077***	0.0065***	0.018*	0.010*	0.013**	0.0092**
	(0.05)	(0.04)	(0.00)	(0.01)	(0.06)	(0.07)	(0.03)	(0.03)
→ lag	-0.0044***	-0.0025	-0.0026	-0.00029	-0.0029	0.0059	-0.0027	0.0055
	(0.00)	(0.12)	(0.60)	(0.92)	(0.58)	(0.19)	(0.68)	(0.23)
Country fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Quarterly fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,352	2,967	2,315	2,905	2,292	2,882	2,255	2,820
R-squared	0.227	0.210	0.229	0.212	0.232	0.215	0.233	0.216

Notes: Panel regression using standard errors clustered by country. *, **, *** denote significance at 10, 5 and 1% confidence level. P-values are reported in parentheses.

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