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Impact Dynamics of Natural Disasters and the Case of Pacific Island Countries

Choonsung Lim and Yue Zhou

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Prepared by Choonsung Lim and Yue Zhou

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ABSTRACT: This paper investigates the short- and medium-term economic impacts of natural disasters, focusing on Pacific Island Countries (PICs) and using global high-frequency nightlight data in addition to macroeconomic data. In this paper, we identify significant short-term effects on growth following natural disasters, which are exacerbated by high public debt and heightened climate vulnerability. Although the negative impacts generally diminish within a year for most countries, PICs face disproportionately larger and rising short-term disruptions (-1.4 percent of annual potential growth) and persistent medium-term consequences. Further analysis of PICs' fiscal, external, and real sectors following severe disasters using annual economic data reveals that weaker fiscal positions, partly driven by reduced output, may lead to an upward trend in public debt, and increased imports may deteriorate current account balances over the medium term. These findings underscore the need for robust counter-cyclical policies and proactive investments in climate resilience to mitigate the adverse effects of climate shocks and promote long-term economic stability.

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Author’s E-Mail Address:	clim2@imf.org; yzhou4@imf.org

WORKING PAPERS

Impact Dynamics of Natural Disasters and the Case of Pacific Island Countries

Prepared by Choonsung Lim and Yue Zhou[1]

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Glossary

Pacific Island Countries (PICs) comprises 13 members of the IMF, including Federated States of Micronesia (FSM), Fiji, Kiribati, Nauru, Palau, Papua New Guinea (PNG), Republic of the Marshall Islands (RMI), Samoa, Solomon Islands, Timor-Leste, Tonga, Tuvalu and Vanuatu.

Nightlight data refers to satellite imagery that captures artificial light emitted from the Earth's surface at night.

Emergency Disasters Database (EM-DAT) is a database that keeps records from 231 countries/entities, spanning the period from 1900 to 2022, with detailed information on the onset date and month of each natural disaster.

Impulse response analysis refers to the estimated effect of a one-time shock to an explanatory variable on a dependent variable over a specified time horizon.

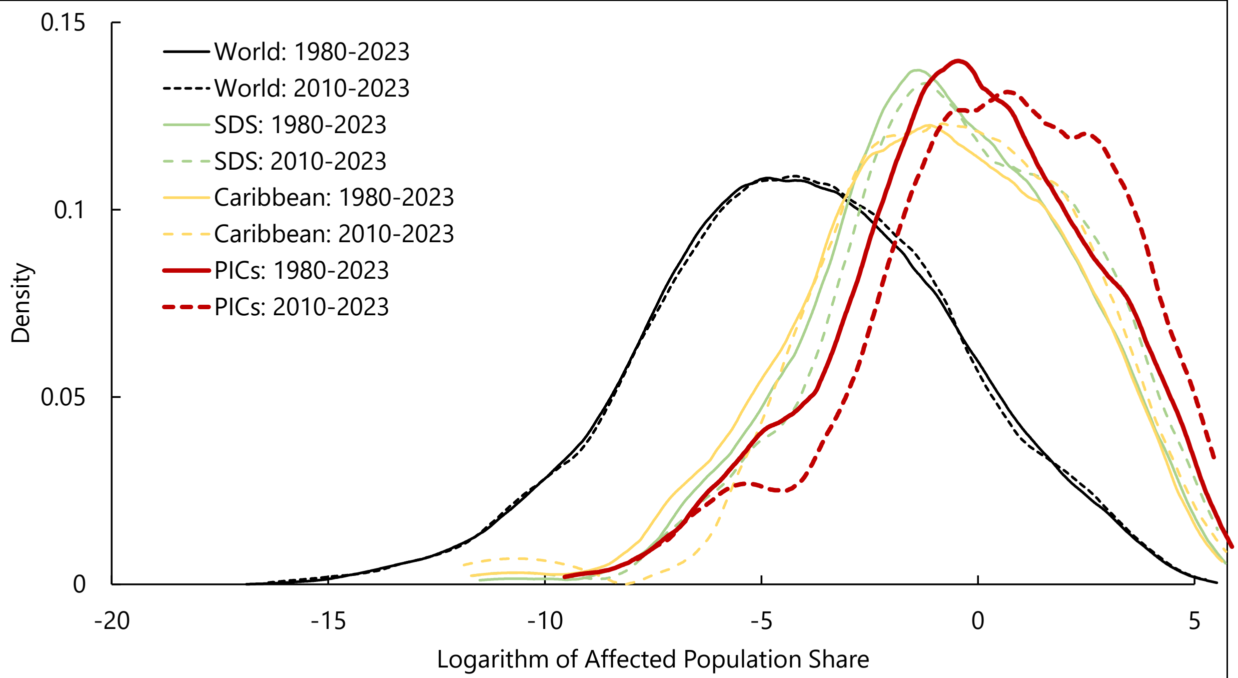
The kernel density function is a non-parametric way to estimate the probability density function of a random variable. It provides a smooth estimate of the distribution of data points in a given dataset.

External position refers to the overall balance of a country's external financial assets and liabilities. It represents the net worth of a country's international investment position (IIP), which includes all financial assets owned by residents of the country that are held abroad, minus all financial liabilities owed to foreign residents.

I. Introduction

Destructive natural disasters have become more frequent. In particular, the proportion of populations affected by such events in Pacific Island Countries (PICs) tends to be much larger than the global average and is on the rise over time (Figure 1). The level and severity of natural disasters in PICs appear to be more significant than those in Small and Developing States (SDSs) and the Caribbean.

Figure 1: Distribution of the share of population affected by natural disasters



Source: EM-DAT and IMF staff calculations.

Note: Density indicates the estimated kernel density. ln(0.00005%)=-5; ln(1%)=0; ln(100%)=4.6

However, answering the critical question of how significantly natural disasters contribute to economic fluctuations is no simple task, especially for the most vulnerable countries such as PICs. This uncertainty is partly due to the lack of accurate, high-frequency economic loss indicators and the analysis often being restricted to a limited number of (larger) countries. Furthermore, conventional GDP data falls short of meeting policy-making needs as it is typically available after a considerable delay, and its reliability is especially concerning in countries with low-income level and high vulnerability to climate impacts (Henderson et al. 2012, Klomp 2016). The substantial informal sector in many developing countries can also lead to an underestimation of the economic impact using official GDP data (Loayza 1996). These discrepancies make the conventional data inadequate for immediate decision-making purposes. In addition, despite the perception of large and persistent impact on the most vulnerable economies, there is a lack of comprehensive analysis on the medium-term dynamics of the impact in PICs. The gap in the literature warrants further analysis for gaining a thorough understanding of the effects of climate on these vulnerable nations.

To bridge these gaps, this paper pursues two avenues.

- **First, we propose the application of satellite-derived nightlight data to assess the impact dynamics of natural disasters.** This novel data source covers a wide range of World Economic Outlook (WEO) countries and is available almost in real-time, with literature suggesting complementarity with official GDP data (Henderson et al. 2012, Chen and Nordhaus 2011, Kulkarni et al. 2011). Furthermore, we have aggregated daily nightlight observations into quarterly and annual frequencies to examine the effects of natural disasters of varying types and severities. This dataset enables the examination of shorter-term (i.e., quarterly) impacts of natural disaster on economic activities for the first time for PICs, where economic data is predominantly available only on an annual basis. Additionally, the methodology not only enables the prompt availability of nightlight data at various frequencies but also enhances the body of research on the economic impacts of natural disasters. Consequently, this approach can guide more timely policy decisions in response to such disasters.

- **Second, we expand our analysis to include the longer-term horizon and a wider array of economic variables that encompass fiscal and external sectors as well as real sector.** In this part, our focus is on the impacts of severe natural disasters, using annual economic variables from 11 PICs where records of natural disasters are available from EM-DAT.[1] This analysis aims to narrow the gaps of understanding regarding the shocks from large natural disasters in PICs.

We find that while the negative impacts for the global sample diminish over a year, natural disasters have larger and rising immediate impacts on PICs and can lead to persistent effect over the medium term, undermining economic stability. Empirical results using nightlight data suggest that on average, the occurrence of natural disasters reduce PICs' potential growth by 1.4 percent every year, with heterogenous impacts depending on the types of natural disasters (earthquake, flood, storm), public debt levels, and climate adaptive capacity. The results are consistent and fall at the higher end of the range found in the literature (Cabezon et al. 2019, Lee and Zhang 2022, Lee et al. 2018). Using annual economic data, we also show that a severe natural disaster can lead to a reduction of real output by 1.7 percent in the year of occurrence, resulting in worsening fiscal and external positions in the medium term with a rising debt path.

Literature has found mixed results on the impacts of disasters on growth, with limited findings for the most vulnerable countries like PICs.[2] Noy (2009) is among the first to explore the adverse impacts of natural disasters on macroeconomic performance using annual GDP growth data. He finds significant negative impact of natural disasters on short-run macroeconomic performance, but the long-term impacts are less straightforward as reconstruction efforts can mitigate initial losses. Loayza (2012) uses global five-year average GDP data and found that severe disasters affect long-term growth. On the other hand, Fomby et al. (2013) argue the "build-back-better" effect of disasters in which some mild disasters even prompt higher growth as reconstruction boosts investment. Lee et al. (2018) focus on 12 PICs and found negative impact of natural

[1] The only PI country not included in the sample is Nauru as EM-DAT does not record any natural disaster for Nauru during the sample period.

[2] While extensive research found negative direct economic impact of natural disasters (Botzen et al. 2019), less attention has been given to the overall macroeconomic impact. The consequences of natural disasters extend beyond immediate economic losses, as they also trigger macroeconomic fluctuations through indirect channels, including infrastructure disruption and power outages.

disasters on growth, fiscal balances, and external balances. Others found that higher income level, stronger institution, and financial inclusion could mitigate the negative impacts of natural disasters[3].

Recent papers have used more innovative satellite data to overcome the shortcomings of conventional GDP data in evaluating the economic losses from natural disasters. Klomp (2016) uses satellite nightlight data to study the impact of large-scale natural disasters on economic development for 140 countries at annual frequency. He found that natural disasters cause a large drop in the luminosity compared to that estimated using the real GDP data. However, the growth dynamics at higher frequency are not fully captured by the annual data if the negative quarterly impacts are offset by faster investment during reconstruction following damages.

This paper contributes to the literature by studying the impact dynamics of natural disasters by applying the analysis to both short- and medium-term. Aggregating daily satellite nightlight data into quarterly observations overcomes the lack of quarterly GDP growth data in many climate-vulnerable island countries. We find that natural disasters significantly affect quarterly growth, although the negative impacts are more discernable using quarterly sample but less so in annual samples, and climate-vulnerable countries (such as PICs) tend to have more severe and persistent negative impacts than the rest of the world.

This paper also highlights the more severe and persistent negative impact of natural disasters on PICs, which are often missing in previous analysis due to lack of data. In fact, quantitative analysis suggests that the occurrence of natural disasters reduce PICs' potential growth 1.4 percent every year. These findings call for more significant adaptation measures and solid macro framework to mitigate the climate shocks in PICs.

The paper is organized as follows. Section 2 discusses the data used in the analysis. Section 3 provides descriptive analysis of natural disasters and satellite nightlight data. Section 4 presents the regression results from nightlight data on the impact dynamics of natural disasters. Section 5 shows the medium-term economic stability implications of natural disasters in PICs, using annual economic data. Section 6 concludes and discusses policy implications to tackle climate shocks, with a focus on PICs.

II. Data

In this paper, we use Emergency Disasters Database (EM-DAT) developed by World Health Organization and the government of Belgium to identify natural disasters. A disaster must meet at least one of the following criteria to be included in the database: a minimum of ten reported fatalities, at least 100 individuals reported as affected, a declared state of emergency, or an appeal for international aid.

The EM-DAT database keeps records from 231 countries/entities, spanning the period from 1900 to 2022, with detailed information on the onset date and month of each natural disaster. It also collects information on the number of people affected (injured, homeless, or requiring immediate other survival assistance such as food, water, and medical help), and an estimate of direct loss, which primarily serves as an indicator of capital loss. This paper uses the number of people affected to measure the severity of natural

[3] Others also study the impacts of disasters on inflation (Cevik and Jalles, 2023), investment (Acevedo et al., 2018), export and imports (Mohan et al., 2018).

disasters (Loyza et al. 2012). The sample used in this paper spans from 1980 to 2021, covering 192 countries and 11,869 natural disasters. However, only one third of natural disasters during the sample period report direct loss, making the direct loss variable less ideal in measuring the severity of natural disasters due to potential sample bias of non-reporting values. Instead, the number of population affected is available for most observations, which is used in the paper to measure natural disaster severity.

This paper uses nightlight intensity (Beyer et al. 2022) data to measure economic activities, which offers insights into light intensity across each 1 km^2 grid, to measure short-term economic activities, especially in PICs where quarterly GDP growth data is unavailable. The nightlight data cover 245 countries/economies between 1992 and 2013 with annual entries, including 12 PICs, and 146 countries/economies between 2013 and 2021 with monthly entries, including 5 PICs. This dataset serves as a novel tool for assessing economic dynamics in the absence of traditional economic indicators.

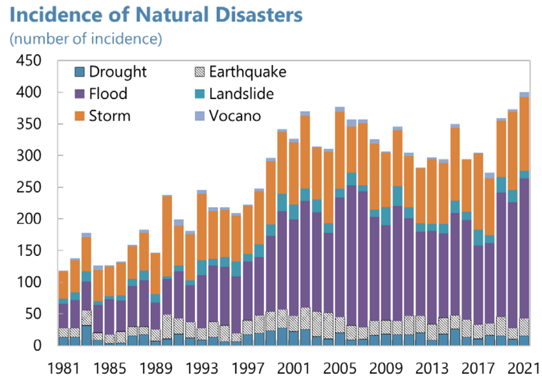
There are several advantages of using the nightlight data in measuring economic activities. First, the raw night light data after 2013 is available on daily basis and can be aggregated to quarterly levels to evaluate short-term impact of natural disasters in many developing countries without quarterly GDP data. Second, nightlight data complement the official GDP data in countries with low data capacity where official GDP is either unavailable or of lower quality. Third, nightlight captures economic activities of both the formal and informal sectors whereas official GDP generally neglects the informal sector outputs, which can be prevalent in developing countries (Melina and Schneider, 2012). There are limitations of the nightlight data, such as volatile values due to fluctuation in weather conditions. Ebener et al. (2005) argue that nightlight intensity mainly reflects non-agricultural and urban output. For a comprehensive discussion of its limitations, see Beyer et al. (2022) and Zhao et al. (2019). For control variables, we collected GDP per capita, trade openness, urban population as a share of total population, and private credit as a share of GDP from World Development Indicator.

III. Descriptive Analysis

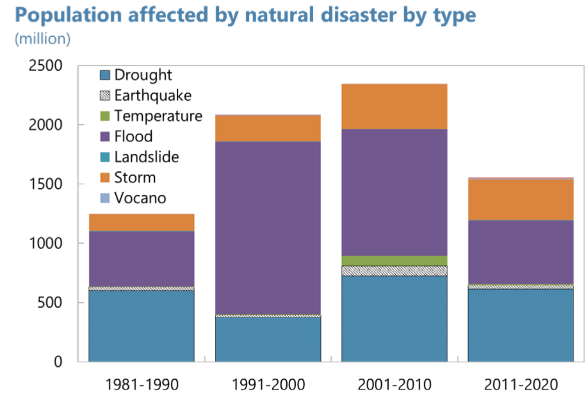
Natural disasters have remained elevated in recent decades, affecting billions of people globally. The frequency of recorded natural disasters has shown a significant upward trend since 1980. Among these, floods stand out as the most prevalent type of natural disaster, with their yearly occurrence escalating from approximately 40 instances in 1980 to over 200 in 2020 (Figure 2). Following floods, storms and earthquakes rank as the second and third most frequent natural disasters, respectively. This increase underscores a concerning escalation in the prevalence of such events, highlighting an urgent need for enhanced disaster preparedness and response strategies globally.

Consequently, there has been a significant escalation in the total number of people affected by natural disasters between 1980 and 2010, after which the trend began to show signs of moderation (Figure 3). During the 1980s, natural disasters affected approximately 1.2 billion individuals worldwide. This figure experienced a substantial rise, doubling to 2.3 billion in the 2000s, before experiencing a decrease to 1.5 billion in the 2010s. The degree of impact these disasters have on populations varies markedly across different types of disasters. Floods affect more than half of the total number of impacted individuals, making them the most significant in terms of human cost, followed by droughts and storms.

Figure 2: Incidence of natural disasters	Figure 3: Number of people affected



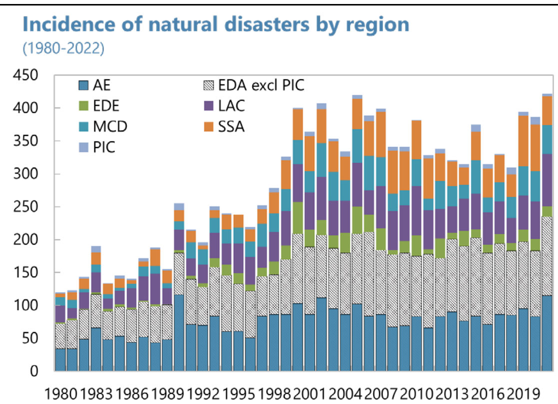
Sources: EM-DAT and IMF staff calculations.



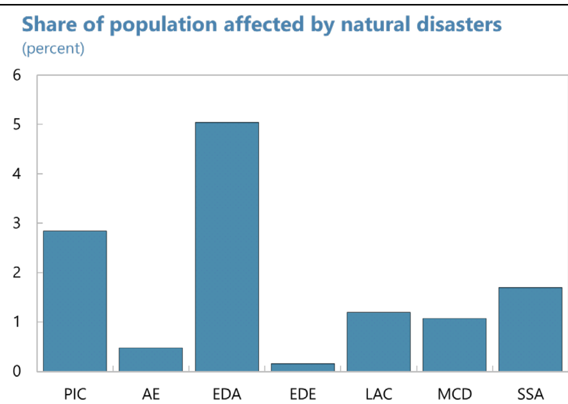
Sources: EM-DAT and IMF staff calculations.

Asia and PICs are particularly exposed to natural disasters, with significant regional disparities in the impact of natural disasters. Since the 2000s, the East and Developing Asia (EDA) region has been the hardest hit by natural disasters, experiencing over 100 incidents (Figure 4). Notably, about 5 percent of its population has been affected, a figure that can be attributed to the high population density and lower preparedness in the area (Figure 5). In PICs, on average, natural disasters affect about 3 percent of the population annually. In comparison, the Advanced Economies (AE) and Emerging and Developing Europe (EDE) regions have recorded the second and third highest numbers of natural disasters in the last two decades, respectively. However, less than 0.5 percent of their populations were impacted. While natural disasters occur less frequently in LAC, Sub-Saharan Africa (SSA), and the Middle East and Central Asia (MCD), the percentage of the population affected in these regions exceeds 1 percent. This disparity suggests that while the frequency of natural disasters varies across regions, the vulnerability of populations to these disasters also differs, reflecting the varying levels of disaster preparedness and response capabilities across different regions.

Figure 4: Incidence of natural disasters	Figure 5: Number of people affected



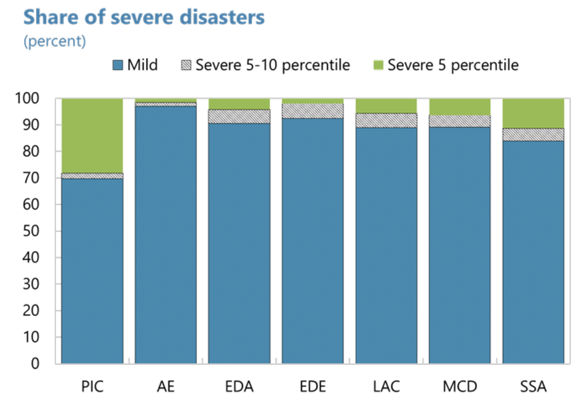
Sources: EM-DAT, WDI, and IMF staff calculations.



Sources: EM-DAT, WDI, and IMF staff calculations.

In particular, PICs disproportionately experience more severe disasters compared to other regions. The severity of a disaster is measured by the percentage of a country's population impacted by a single disaster in relation to its total population. By defining the top 5 percentile of these events as the most severe, we calculate their proportion of total disasters within each region.[4] In PICs, a substantial 38 percent of disasters are categorized as severe, suggesting a significant impact on local populations (**Error! Reference source not found.**). SSA emerges as the second region most frequently hit by severe natural disasters, with 19 percent of such events classified as severe based on our criteria. It is closely followed by LAC, MCD, and EDA, each experiencing severe disasters in approximately 10 percent of cases.

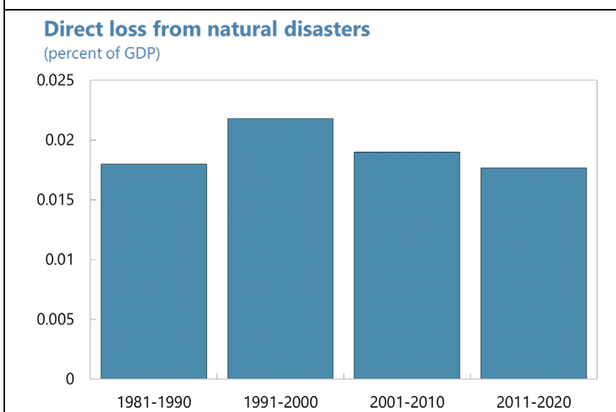
Figure 6: Share of severe disasters



Sources: EM-DAT and IMF staff calculations

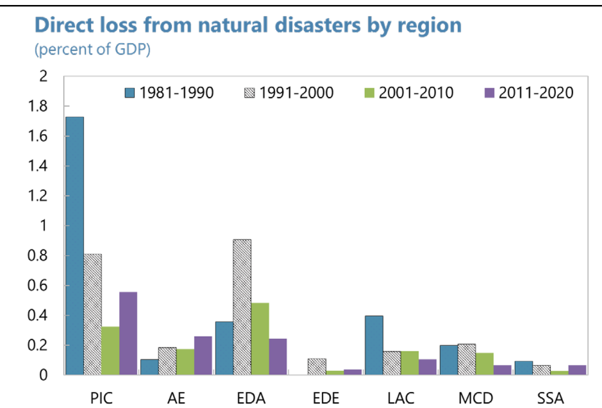
The direct damages due to natural disasters globally appears moderate, albeit only one third of the sample records direct damages. On an annual basis, these direct losses account for approximately 0.02 percent of global GDP (Figure 7). AE and EDA report the highest figures in terms of losses, with a significant factor behind this observation attributed to the abundance of estimates for direct losses available in AE compared to those in developing economies, as captured in the EM-DAT dataset. For instance, 52 percent of disaster cases in AE come with estimates of direct economic loss, whereas this figure drops to 14 percent in SSA and 22 percent in MCD (Figure 8). Overall, estimates of direct economic losses are available for only one-third of the disaster sample.

Figure 7: Direct loss from disasters, percent of GDP



Sources: EM-DAT, WEO, and IMF staff calculations.

Figure 8: Direct loss from disasters by region, percent of GDP

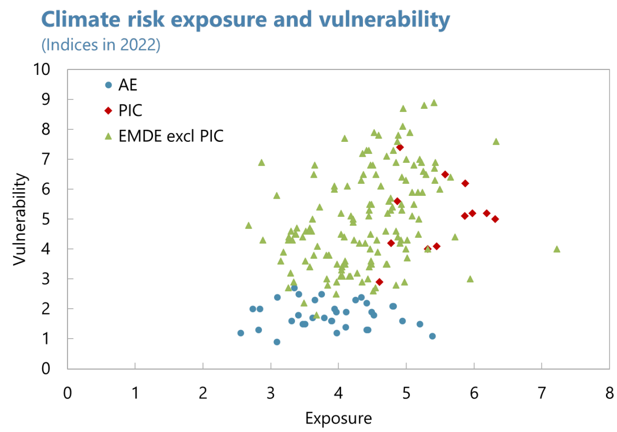


Sources: EM-DAT, WEO, and IMF staff calculations.

[4] We will discuss using the top 5 percentile cutoff to define severe disasters in section 5.

Besides the direct losses, indirect losses triggered by natural disasters tend to affect macro stability, particularly among PICs. Indirect losses from natural disasters, such as disruptions to labor markets, financial systems, and supply chains, can significantly affect macroeconomic stability (Noy, 2009). This dynamic can be particularly salient for PICs, which face a broad spectrum of hazards and possess limited capacities to absorb and rebound from such shocks (Figure 9) [5]. A natural disaster in PICs can quickly generate spillover to the whole economy and jeopardize macro stability.

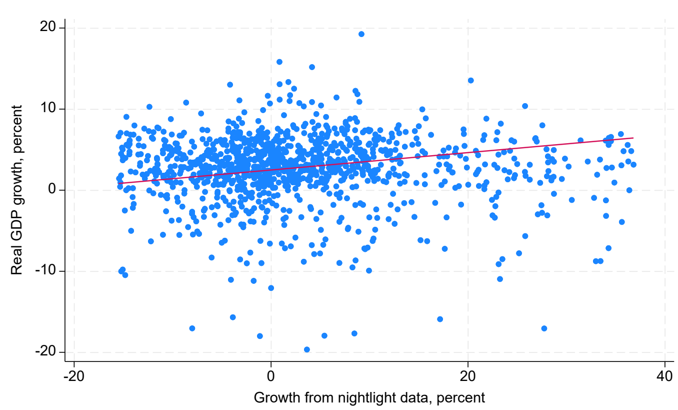
Figure 9: Climate risk exposure and coping capacity



Source: IMF INFORM, Notre Dame Global Adaption Index, and IMF staff calculations.

To evaluate the indirect economic impacts of natural disasters, we aggregate high-frequency nightlight data to quarterly and annual growth across most countries included in the World Economic Outlook (WEO). We identify a correlation between the growth rates derived from nightlight data and official GDP growth figures, with a correlation coefficient of 0.014 (Figure 10). However, this correlation varies across different income levels, with coefficients ranging from 0.028 to 0.02 in high and middle-income countries and shifting to 0.002 in low-income countries (Table A1). This variation indicates a potential discrepancy in data quality among low-income countries. Such disparities highlight the importance of leveraging nightlight data as complementary to official GDP data, particularly for assessing the economic effects of climate shocks in low-income countries, where traditional economic data may be less reliable or comprehensive.

Figure 10: GDP growth and NL intensity growth (2013-2021)



Source: WEO, DMSP/OLS, VIIRS, and staff calculations.

[5] Only Fiji, Palau, Tonga, and Samoa have the coping capacity above world average.

IV. Regression Results from Nightlight Data

Model and specification

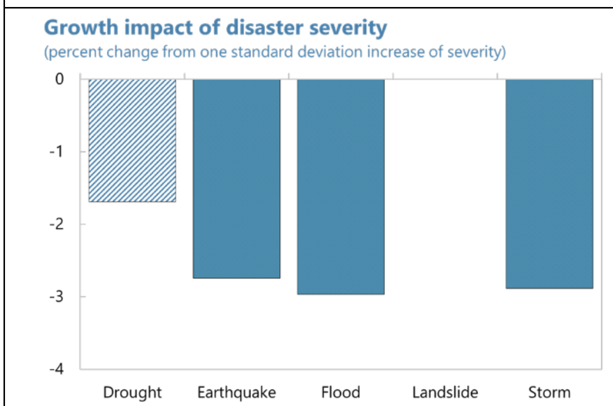
We present a dynamic model as in equation (1) to identify the impacts of natural disasters on short-term growth. Y_{it} is quarterly NL intensity growth in country i and quarter t, and lagged NL intensity growth Y_{it-1} is included on the right-hand side to account for the growth dynamics. $Disaster_{it}^{k}$ is the share of population affected by a disaster k in country i and quarter t. X_{it} is a set of control variables, including log GDP per capita, growth in trade openness, growth of urban population, and private credit. μ_i is country-specific time-invariant factors and π_t is quarterly global shocks. To avoid biased estimates in a dynamic model, we follow the literature and estimate the model with system GMM (Arellalo and Bond, 1991).

$$Y_{it} = \alpha + \gamma Y_{it-1} + \sum_{k=1}^{K} \beta^{k} Disaster_{it}^{k} + \theta X_{it} + \mu_i + \pi_t + \varepsilon \qquad (1)$$

Short-term impact

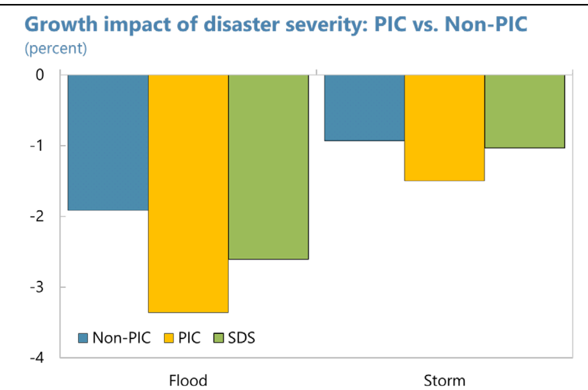
The results show that natural disasters significantly affect economic growth in the same quarter of their occurrence.[6] On average, an increase in the severity of floods and storms, the most prevalent types of natural disasters, by one standard deviation, is associated with a reduction in growth of approximately 3 percent. Earthquakes, while less frequent, still lead to a notable decrease in quarterly growth by 2.7 percent. Conversely, the impact of droughts and landslides on economic growth is statistically insignificant (Figure 11). These regression findings are detailed in Appendix Table A2.

Figure 11: Growth impacts of natural disasters



Note: quarterly nightlight growth is transformed to GDP growth using an elasticity of 1.3. Shaded bars refer to statistically insignificant coefficients.

Figure 12: Growth impacts: PIC vs. non-PIC



Note: quarterly nightlight growth is transformed to GDP growth using an elasticity of 1.3.

Sources: EM-DAT, DMSP/OLS, VIIRS, and IMF staff calculations.

[6] We adjust the coefficient for disaster's impact on nightlight (NL) growth to measure economic growth, employing an elasticity of 1.3, as outlined by Beyer et al. (2022).

Equation (2) augments an interaction term between the severity of disaster and PIC dummy (or SDS dummy) to explore whether growth in PICs is more susceptible to natural disasters.

$$Y_{it} = \alpha + \gamma Y_{it-1} + \sum_{k=1}^{K} \beta^k Disaster_{it}^k + \sum_{k=1}^{K} \delta^k Disaster_{it}^k \cdot PIC_i + \theta X_{it} + \mu_i + \pi_t + \varepsilon \ \ (2)$$

Regression results show that natural disasters with the same magnitude have a more pronounced impact on growth in PICs than the rest of the world (Table A3). The negative growth impact of floods and storms in PICs are nearly double those observed in non-PIC countries. Further investigation through the replication of the interaction term for Small and Developing States (SDS) yielded consistent findings: the negative effects of natural disasters on growth are substantial in SDS, implying a shared susceptibility to the economic disruptions caused by natural disasters among SDS (Figure 12).

Heterogeneous effect

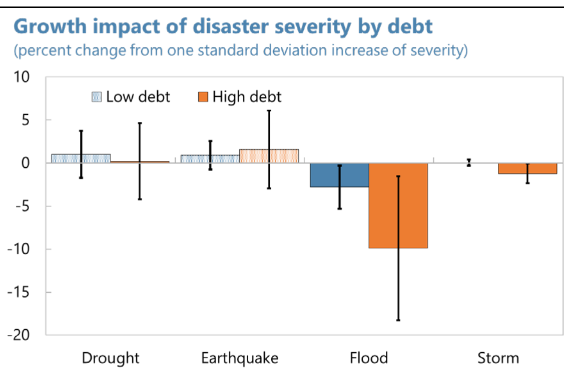
Existing macro and climate vulnerability might exacerbate the negative growth impact of natural disasters. To test this hypothesis, we augment an interaction term between a country's existing vulnerability and disaster severity. Specifically, we estimate equation (3):

$$Y_{it} = \alpha + \gamma Y_{it-1} + \beta Disaster_{it} + \delta Disaster_{it} \cdot Vulnerability_i + \theta X_{it} + \mu_i + \pi_t + \varepsilon \ \ (3)$$

Where $Vulnerability_i$ is defined as one of two dummy variables: i) it represents a country's public debt level that equals 1 if public debt is above the world average, or ii) it represents a country's adaptive capacity that equals 1 if climate adaptive capacity index is below the world average. The climate adaptive capacity index is derived from the IMF climate dashboard.

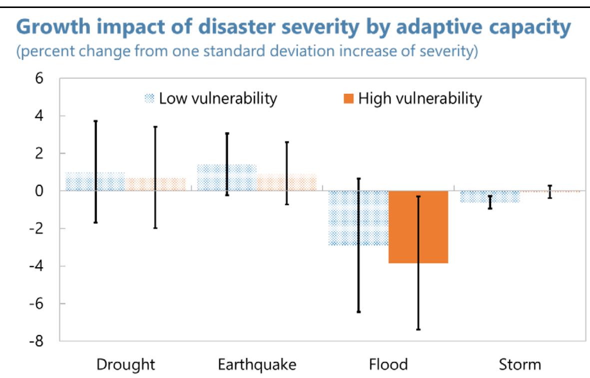
We find that pre-existing elevated public debt levels and weaker adaptive capacity exacerbate the negative impact of natural disasters on short-term growth. In countries where the public debt levels exceed the global average, a one standard deviation increase in the severity of floods correlates with a quarterly growth reduction of approximately 10 percent—a significantly larger decrease compared to countries with lower levels of public debt (Figure 13). Similarly, the adaptive capacity index measures the resources and capabilities available to respond effectively to climate impacts. A country with less adaptive capacity is subjected to more substantial negative impacts from natural disasters compared to their less vulnerable counterparts (Figure 14). Regression results are shown in Table A4.

Figure 13: Growth impacts by public debt



Note: Countries are categorized into high-debt (low-debt) group if the gross government debt is above (below) median.
Nightlight growth is transformed into GDP growth using an elasticity of 1.3.

Figure 14: By adaptive capacity



Note: Countries are categorized into high-vulnerability (low-vulnerability) group if the adapative capacity is below (above) median.
Nightlight growth is transformed into GDP growth using an elasticity of 1.3.

Sources: EM-DAT, DMSP/OLS, VIIRS, and IMF staff calculations.

Impact dynamics

While we show significant negative impact in the quarter of the occurrence of a natural disaster, a natural question is how growth evolves following the shock. In this section, we will explore the growth dynamics to illustrate a country's recovery following an occurrence of natural disaster.
By taking advantage of the high-frequency nightlight data, we are able to construct quarterly growth after disasters. Following Jorda (2005), we estimate the local projection model as in equation (4) to study the growth dynamics.

$$Y_{i,t+h} - Y_{i,t-1} = \alpha_{ih} + \gamma_{th} + \beta_h Disaster_{it} + \theta_h X_{it} + \sum_{p=1}^{h} \varphi_{hp} Disaster_{i,t+p} + \varepsilon_{i,t+h} \quad (4)$$

where $Y_{i,t+h}$ is quarterly NL intensity growth of country i in quarter t+h, with h denotes the number of quarters after the occurrence of a natural disaster; $Disaster_{it}$ is the share of population affected by a natural disaster; X_{it} includes various control variables; α_{ih} and γ_{th} control for country- and year-specific fixed effects, respectively. The subscripts i and t denote country and year, respectively.

On average, the adverse effects on growth resulting from natural disasters diminish within a year. Figure 15 illustrates the relationship between the severity of floods and storms and their cumulative impact on growth, along with a 10 percent confidence interval. The most pronounced negative impact—an approximate 3 percent decrease—occurs in the quarter during which a flood happens. The cumulative loss in growth reduces to 1.2 percent in the quarter immediately following the flood, and subsequently approaches zero by the end of the fourth quarter post-flood. A similar trajectory is observed in the aftermath of storms, where the negative influences on cumulative growth progressively diminish to zero over the course of four quarters (Figure 16).

Figure 15: Impulse response to flood

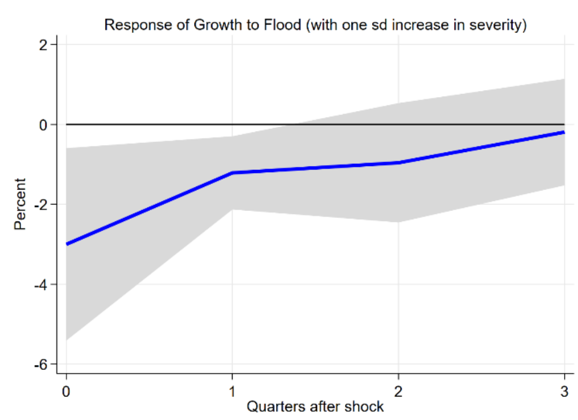
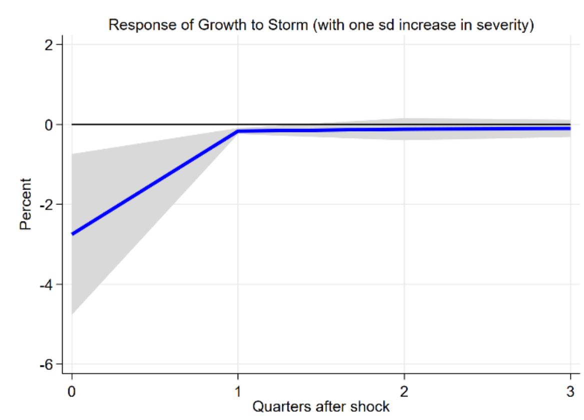


Figure 16: Impulse response to storm



Sources: EM-DAT, DMSP/OLS, VIIRS, and IMF staff calculations.

However, PICs tend to exhibit a more persistent negative impact from natural disasters. We refine equation (4) by incorporating an interaction term that juxtaposes disaster severity with PIC-specific variables. Through this approach, we delineate the impulse responses to floods and storms for both PICs and non-PIC countries (as depicted in Figure 17). In non-PIC countries, the trajectory of cumulative growth following storms and floods aligns with the previously identified pattern, where the adverse cumulative impact gradually mitigates to approximately zero over the span of one year (Figure 18). Conversely, in PICs, the negative impact on growth attributable to storms and floods is persistent, with the cumulative growth loss continuing to be evident even after three quarters post-disaster. This contrast underscores the distinct vulnerability of PICs to climate-related shocks, as they grapple with more sustained economic losses from natural disasters compared to their non-PIC counterparts. Extending the horizon with annual average of nightlight intensity reveals the impact of natural disasters can persist for multiple years in PICs (Figure 19).[7] Furthermore, we will delve into the specific channels through which climate shocks exert persistent impacts on PICs, shedding light on the underlying mechanisms of their sustained vulnerability.

Figure 17: Impulse response to flood

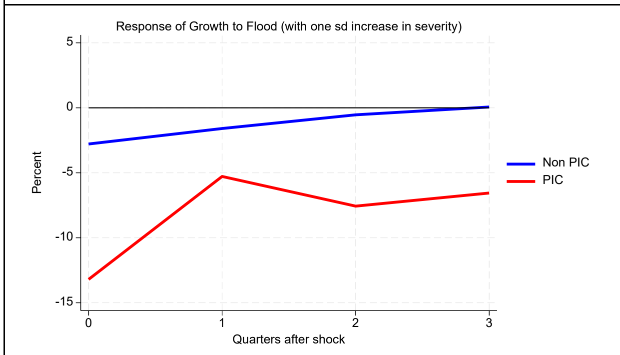


Figure 18: Impulse response to storm

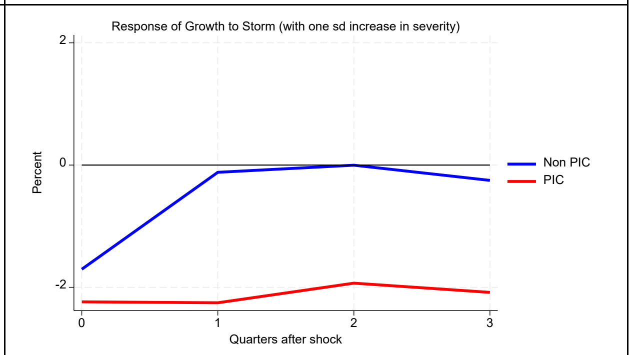
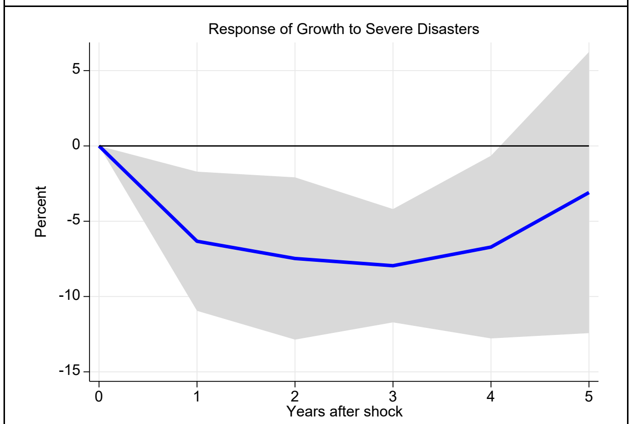


Figure 19: Impulse response of nightlight intensity growth in PICs



Sources: EM-DAT, DMSP/OLS, VIIRS, and IMF staff calculations.

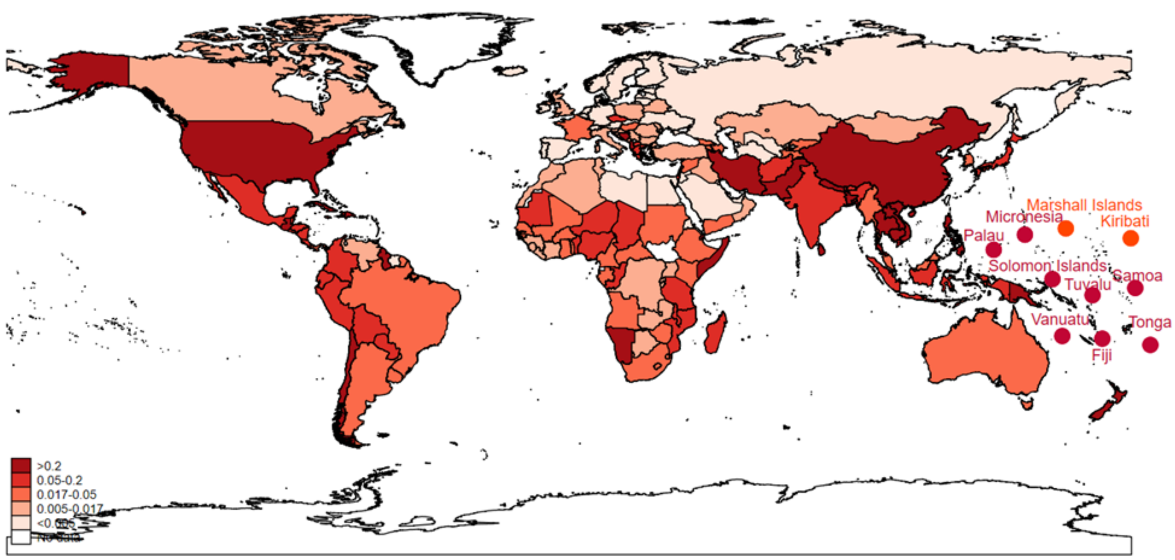
Based on the analysis above, we have developed a global heatmap to illustrate each country's expected potential growth losses due to natural disasters (Figure 19). We follow Cabezon et al. (2019) to calculate the expected potential growth loss from natural disasters. Specifically, we use the estimated coefficients for natural disasters from equation (1) using the global sample, which identify the impact of natural disasters on growth for all countries with all else being equal, multiplied by the historical frequency and severity

[7] It's worth noting that the official GDP data and NL data generate different impacts quantitatively though the results are qualitatively similar. This might partly reflect that the official GDP data do not fully capture the economic loss from natural disaster shocks.

of such disasters for each country (the expected potential loss is different from the actual losses incurred from disasters, as it only evaluates the impact of natural disasters while holding all other factors equal for all countries).[8] We then classify countries into five distinct groups based on their exposure levels, employing a color gradient where a darker color indicates greater exposure.

The heatmap shows that many Asian and Pacific countries have high expected potential growth loss due to natural disasters. A significant portion of the region is depicted in dark red on exposure maps, indicating they fall into the highest loss category, characterized by losses exceeding 0.2 percent of quarterly growth, with the average quarterly potential growth loss exceeding 0.3 percent in PICs during the sample period (Figure 20)

Figure 20: Heatmap of Economic Exposure to Natural Disasters



Source: EM-DAT, WEO, WDI, and IMF staff calculations.

We further assess the evolution of expected potential growth loss to natural disasters in PICs. We divide the sample into three distinct time periods, 1960-1979, 1980-1999, and 2000-2019. The difference among these time periods are the frequency and severity of natural disaster, and all other factors are controlled at the world average level. We then take the medium potential growth losses from the region and convert to annual losses to facilitate easier interpretation.[9]

For PICs, the median expected potential growth loss induced by natural disasters reached 1.4 percent per year between 2000 and 2019. In other words, the medium to long-term potential growth in PICs is estimated to be lowered by at least 1.4 percent due to natural disasters (which assumes that they have improved their resilience to the world's average). The result is consistent and falls at the higher end of the

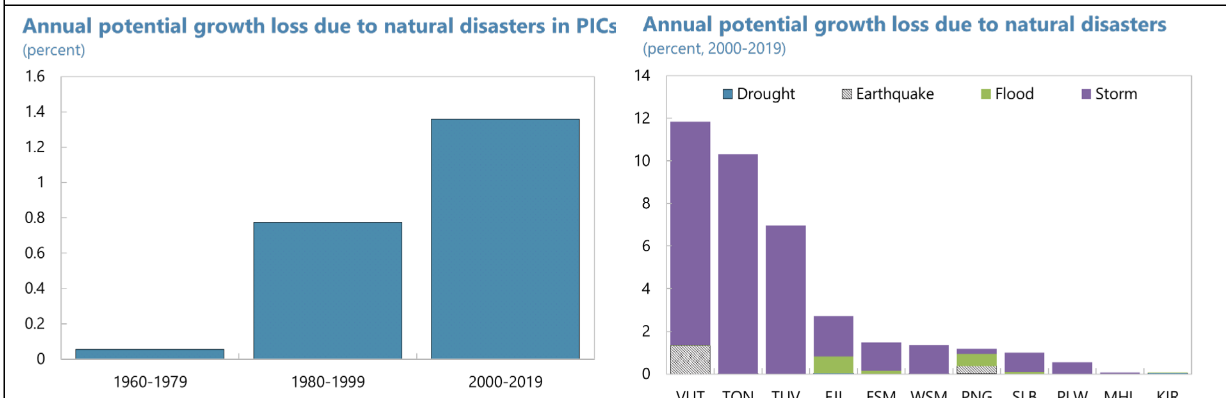
[8] The expected potential growth loss for PICs is a conservative estimate. If we use the coefficients of growth on disasters estimated from the PIC sample (Figure 17 and 18), the expected growth loss would be larger.

[9] We use the average frequency and severity of natural disasters in each quarter to estimate a country's exposure to natural disasters. This assumption implies a recurrent average natural disaster in each quarter, and hence a recurrent loss in each quarter at the same magnitude. We also assume that PICs managed to close the gaps in macroeconomic and climate adaptive capacity.

range found in the literature.[10] Therefore, PICs need greater adaptation efforts than other countries to effectively mitigate the negative impacts of natural disasters. There are also large variations in economic exposure to natural disasters among PICs. For example, Vanuatu and Tonga face an annual loss of expected potential growth of over 10 percent if the current pattern of natural disasters persists in frequency and severity. Conversely, the loss of potential growth from natural disasters is relatively lower in Kiribati and the Marshall Islands, thanks to less frequent and severe occurrences of these events. Storms are the major source of potential growth loss in PICs, while floods and earthquakes are more specific to a few PICs.

In addition, PICs have experienced an increasing loss of expected potential growth in the past decades (Figure 21). The median annual loss of potential growth from natural disasters grew from 0.8 percent between 1980 and 1999 to the current 1.4 percent between 2000 and 2019, reflecting the increasing frequency and severity of natural disasters in the region. Going forward, PICs face even greater pressure to raise their growth potential if the occurrence and severity of natural disasters continue to increase.

Figure 21: Annual potential growth loss due to natural disasters in PICs



Sources: IMF staff calculations.
Note: Median loss due to natural diasters in the PICs sample.

Sources: EM-DAT and IMF staff calculations.

[10] For example, using official GDP data and a panel vector autoregressive (VAR) analysis, Cabezon et al. (2019) find that natural disasters reduce annual growth in PICs by 0.7 percent. Lee and Zhang (2022) and Lee et al. (2018) find severe natural disasters have a negative impact on growth ranging from 1.4 to 1.9 percent in PICs, regardless of their frequency.

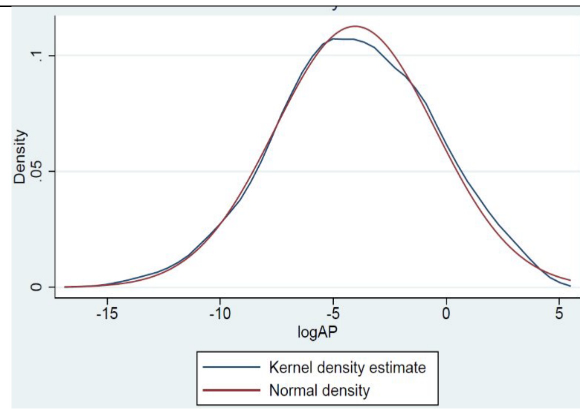
V. Medium-term Impacts on PICs Economic Stability

This section extends the scope to the medium-term implication of natural disasters on economic stability in PICs. Specifically, we look into the medium-term impact of severe natural disasters on fiscal/external positions as well as growth, using annual economic data from WEO. To capture medium-term dynamics of impacts, a local projection model (Jorda 2005, Teulings and Zubanov 2014[11]) is specified as follows:

$$y_{i,t+h} - y_{i,t-1} = \alpha_{ih} + \gamma_{th} + \beta_h Disaster_{it} + \theta_h X_{it} + \sum_{p=1}^{h} \varphi_{hp} Disaster_{i,t+p} + \varepsilon_{i,t+h} \quad (5)$$

where $y_{i,t}$ is log of GDP or GDP per capita, or external/fiscal variables (in percent of GDP); $Disaster_{it}$ is a severe natural disaster dummy; X_{it} includes various control variables such as a lag of population, inflation, trade openness and $\Delta y_{i,t}$, and terms of trade growth of Australia and the U.S. interacted with the trade share with these two countries to capture global trade activity closely related to the Pacific islands; α_{ih} and γ_{th} control for country- and year-specific fixed effects, respectively. The subscripts *i* and *t* denote country and year, respectively. The data covers 11 Pacific Island countries[12], and the sample period for regression is 1994 through 2019, based on data availability.

Figure 22: Distribution of the affected population share



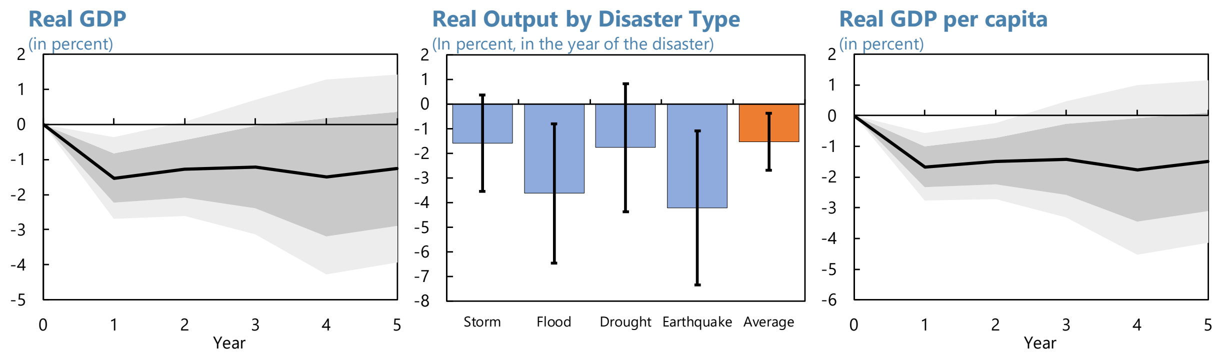
Note: X-axis represents the log of the affected population share. Blue line represents the kernel density function estimated with global natural disaster observation during 1980-2023, while red line indicates the normal distribution.
Source: EM-DAT, WEO and staff calculations.

A severe natural disaster is defined as a 5-percent right tail event in the distribution of the share of affected population (Figure 22). The share of affected population appears to be log-normally distributed in the global sample pooled over the horizon of 1980-2023. The natural disaster dummy equals to 1 if the log of the affected population share is greater than 4.2 (around 65 percent of population). If the information of affected population is missing, the distribution of the damage-to-GDP ratio is applied, following Lee et al. (2018). The selection of the top 5 percentile is supported by ad-hoc evidence indicating that the impact of natural disasters increases nonlinearly at that threshold (see Appendix Figure A1).

[11] Using the methodology by Teulings and Zubanov (2014), the local projection equation is augmented with the leads of the independent variable between forecast horizon 't' and 't+h' in order to correct for the bias of the coefficient estimates.
[12] Fiji, Kiribati, Marshall Islands, Micronesia, Palau, Papua New Guinea, Samoa, Solomon Islands, Tonga, Tuvalu, and Vanuatu are included, based on data availability.

The findings indicate that the adverse consequences of natural disasters on growth in PICs extend into the medium term (Figure 23).[13] Specifically, severe natural disasters reduce real GDP by 1.5 percent in the year of occurrence, and this reduction is sustained into the second year. Impacts from earthquakes and floods turn out more significant than those from storms and droughts. These negative impacts, on average, appear to persist over the medium term, suggesting long-term ramifications of natural disasters in PICs, while wider confidence intervals suggest that the recovery pattern can be heterogeneous. For real income per capita, a similar, but clearer, dynamic, indicating a sustained negative effect, is also observed**.**

Figure 23: Cumulative Impulse Response of Real GDP and Income per capita



Source: WEO, EM-DAT, and IMF staff calculations.

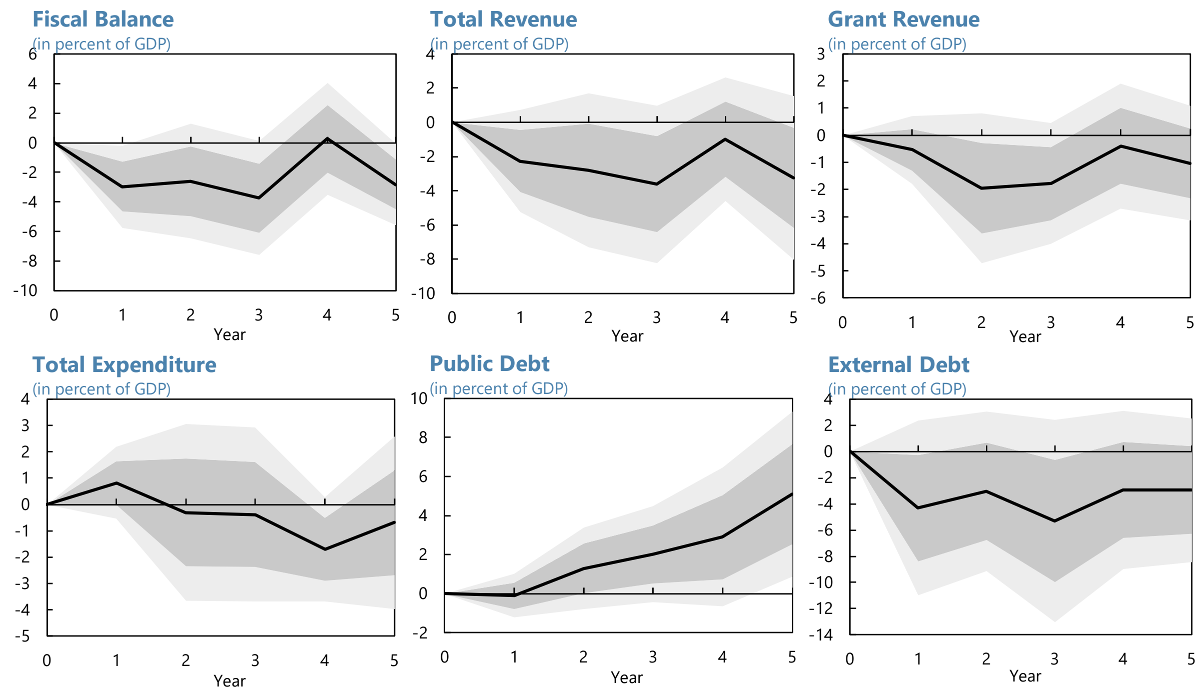
Note: Shades represent 68 percent and 90 percent confidence interval. Bar chart represents the estimated impact of each disaster type in the year of occurrence, with a vertical line indicating 90 percent confidence interval.

Fiscal balances also appear to deteriorate following severe disasters, primarily due to sustained losses in revenue (Figure 24). On average, countries experience a persistent reduction in revenue ranging between 2-4 percent of GDP starting from the year the disaster occurs, although the estimates are not statistically insignificant. Total expenditure, reflecting reconstruction and social spending, increases by 0.8 percent of GDP in the first year, but no substantial alteration in expenditure is observed over the medium term. Consequently, the fiscal balance is reduced by around 3 percent of GDP for three years following the shock. Additionally, the weakened fiscal positions seem to contribute to an escalation in public debt, which increases by 5.1 percent of GDP in the fifth year after a severe disaster. Meanwhile, we could not find clear evidence suggesting increased grants flowing into PICs in the aftermath of a severe natural disaster at the 95th percentile,[14] but more severe disasters turn out to be different. That is, there is an indication that grant inflow might escalate with the increasing severity of disasters (Figure 25). This suggests that the top 5 percentile whose threshold is 95th percentile might not be sufficiently severe to empirically capture the flow of grants.

[13] Table A5 shows the estimation results for the year of occurrence, including control variables.

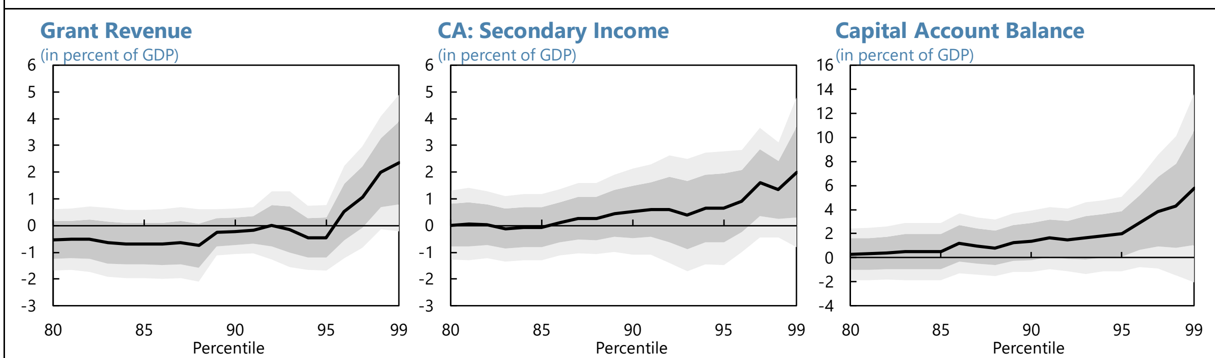
[14] This holds through year 5. Robustness check, either by splitting the sample periods or by adding years since the Covid pandemic, does not substantially change this result. We found positive impacts on secondary income (Figure 26) and capital account (Table A5 column 13) in balance of payment in the year of a disaster, but they are not statistically significant.

Figure 24: Cumulative Impulse Response of Fiscal Positions



Source: WEO, EM-DAT, and IMF staff calculations.
Note: Shades represent 68 percent and 90 percent confidence interval.

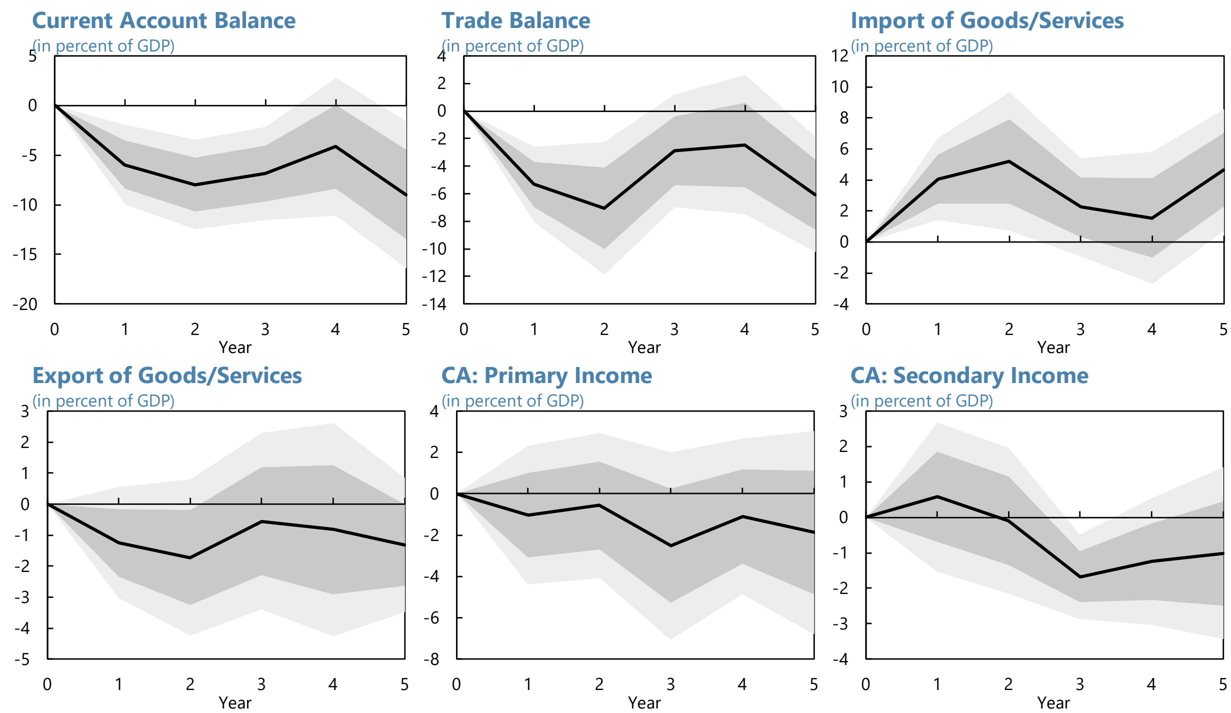
Figure 25: Impact on Donor Activities by Severity of Natural Disasters



Source: WEO, EM-DAT, and IMF staff calculations.
Note: Line represents the estimated impact in the year of occurrence for each severity threshold. Shades represent 68 percent and 90 percent confidence interval.

The results indicate worsening external positions after a severe disaster as well (Figure 26). Specifically, the current account balance experiences a decline of 6 percent of GDP in the aftermath of a severe disaster, which further deteriorates to 9.0 percent of GDP after 5 years. This pattern is primarily attributed to a marked increase in imports, indicating that PICs are compelled to depend on imports to compensate for disruptions in domestic production. Although there is an expected decrease in exports on average, the estimates are statistically insignificant, likely due to the diversity in the significance and primary industry of exports among PICs.

Figure 26: Cumulative Impulse Response of External Positions



Source: WEO, EM-DAT, and IMF staff calculations.

Note: Shades represent 68 percent and 90 percent confidence interval.

VI. Conclusion

The increasing frequency and severity of natural disasters in PICs have raised concerns over economic stability in the region. However, there is hardly consensus regarding the magnitude of economic impacts of natural disasters, partly due to lack of accurate growth measurements. Furthermore, the absence of real-time economic indicators presents a significant challenge in promptly evaluating the economic ramifications of a natural disaster, and consequently, provides limited guidance for developing effective policy responses.

Using nightlight data, we study the impact of natural disasters on growth in the short-run and illustrate the growth dynamics flowing disasters. The economic impacts of a natural disaster are significant in the quarter of occurrence, with idiosyncratic impacts dependent on a country's macro stability and climate adaptive capacity. While on average, the negative impacts diminish over a year, natural disasters have larger short-term impacts on PICs and can lead to persistent effect over the medium term, undermining economic stability. Furthermore, increasing exposure to climate-related natural disasters and inadequate coping mechanisms underscore the urgent need for robust disaster resilience strategies in PICs.

This paper carries three policy suggestions for PICs to tackle climate challenges.

- First, given PICs' exposure to natural disasters, near-term policies should prioritize the implementation of appropriate counter-cyclical measures to mitigate the adverse effects of such events. This entails building fiscal buffers for counter-cyclical policies.

- Second, in the long term, a solid macroeconomic framework, investment in adaptation, mainstreaming adaptation in PFM, and strengthening financial infrastructure (e.g., developing insurance and contingency funding) can reduce climate vulnerability and funding constraints, and help address climate shocks (Massetti and Bellon 2022). These strategies encompass, but are not limited to, scaling up investments in adaptation in a fiscally prudent manner and the development of insurance and contingency financing mechanisms.

- Third, this paper demonstrates that using high frequency and real-time nightlight data can enhance the timeliness of assessing the economic impacts of natural disasters and formulating appropriate policy responses.

Appendix

Table A1. Coefficient of real GDP growth on NL intensity growth

	High income	Upper middle	Lower middle	Low income	Total
Coef between GDP and NL	0.028***	0.020**	-0.002	0.002	0.014***

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

Table A2. Short-term impact of natural disasters on NL intensity growth		
Measurement of disaster	Severity	Incidence
VARIABLES	Dep Var: NL Intensity Growth	
L.NL growth	0.137**	-0.049
	(0.058)	(0.030)
Drought	-0.420	-1.960
	(0.390)	(4.457)
Earthquake	-4.672*	-0.804
	(2.661)	(3.544)
Flood	-1.774**	-3.553**
	(0.865)	(1.594)
Landslide	-2,037.354	-3.319
	(17,138.615)	(4.463)
Storm	-5.113**	-5.174**
	(2.273)	(2.419)
D. Trade openness	0.512***	0.168
	(0.196)	(0.154)
D. Urban population	-2.112***	-1.401***
	(0.683)	(0.455)
Ln(GDP per capita)	-1.789**	-0.996
	(0.823)	(0.650)
Private credit	0.008	0.010
in percent of GDP	(0.019)	(0.015)
Constant	-32.649	0.458
	(43.000)	(6.582)
Observations	2,270	2,150
Number of id	96	96

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The signs of control variables are consistent with the literature.

Table A3. Idiosyncratic short-term impact of natural disasters in PICs and SDSs		
	(1)	(2)
	PIC	SDS
VARIABLES	Dep Var: NL intensity growth	
L.NL intensity growth	0.068	0.139**
	(0.047)	(0.056)
Drought	0.086	-0.117
	(0.230)	(0.377)
Earthquake	0.155	-0.323
	(0.265)	(0.390)
Flood	-1.143***	-0.911***
	(0.384)	(0.276)
Storm	-1.658***	-0.290
	(0.607)	(1.406)
Drought*PIC/SDS	2.438	1.877
	(2.707)	(1.438)
Earthquake*PIC/SDS	-0.454	0.169
	(1.661)	(3.335)
Flood*PIC/SDS	-0.869	-0.643
	(2.074)	(3.320)
Storm*PIC/SDS	-1.006*	-1.548
	(0.574)	(4.816)
D. Trade openness	0.241*	-0.129
	(0.135)	(0.290)
D. Urban population	-0.597*	-0.854*
	(0.326)	(0.496)
Ln(GDP per capita)	-0.909	-1.112
	(0.562)	(0.805)
Private credit	0.032**	0.040
in percent of GDP	(0.014)	(0.025)
Constant	-16.735*	-23.611
	(9.730)	(17.503)
Observations	2,935	2,343
Number of id	120	123

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

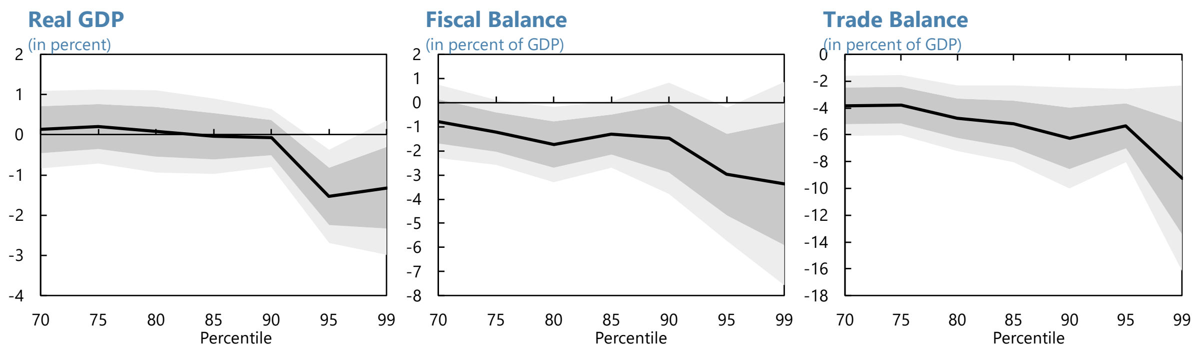
Table A4. Idiosyncratic impact by macro and climate vulnerability		
	(1)	
	Public Debt	Climate Vulnerability
VARIABLES	Dep Var: NL intensity growth	
L.NL intensity growth	0.230***	0.224***
Population affected by	(0.053)	(0.053)
Drought	0.248	0.251
	(0.407)	(0.654)
Earthquake	1.573	2.410
	(1.702)	(4.591)
Flood	-1.675*	-1.722
	(0.907)	(1.170)
Landslide	130.818	-105.834
	(87.173)	(358.265)
Storm	0.091	-1.052
	(0.368)	(3.073)
Drought*vulnerability	-0.199	-0.075
	(0.773)	(0.762)
Earthquake*vulnerability	1.084	-0.810
	(4.967)	(4.913)
Flood*vulnerability	-4.231	-0.564
	(3.148)	(1.725)
Landslide*vulnerability	-84.130	234.860
	(233.497)	(367.326)
Storm*vulnerability	-2.235*	0.955
	(1.229)	(3.092)
Constant	33.037***	32.993***
	(5.803)	(5.804)
Observations	2,734	2,734
Number of id	121	121
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Table A5. Impacts of Severe Natural Disasters in the Year of Occurrence

	Real Sector		Fiscal Sector				External Sector							Debts	
Dependent variables:	Log of Real GDP (1)	Log of Real GDP per capita (2)	Fiscal Balance (3)	Total Revenue (4)	Grants Revenue (5)	Total Expenditure (6)	Current Account (7)	Trade Balance (8)	Imports (9)	Exports (10)	Secondary Income, net (11)	Primary Income, net (12)	Capital Account (13)	Public Debt (14)	External Debt (15)
Severe Disaster (Y/N)	-1.529*	-1.672**	-2.979	-2.265	-0.540	0.814	-5.957**	-5.324***	4.055**	-1.246	0.582	-1.028	1.979	-0.103	-4.323
	(0.707)	(0.667)	(1.680)	(1.817)	(0.756)	(0.828)	(2.455)	(1.662)	(1.596)	(1.084)	(1.279)	(2.033)	(1.877)	(0.675)	(4.051)
AR(1)	0.105	0.135	-0.341***	-0.380*	-0.358***	-0.372***	-0.063	0.131	0.188	0.031	-0.499***	-0.345***	0.007	0.243***	-0.300***
	(0.117)	(0.122)	(0.083)	(0.179)	(0.060)	(0.068)	(0.074)	(0.108)	(0.114)	(0.122)	(0.080)	(0.066)	(0.123)	(0.053)	(0.031)
Log of Population (t-1)	3.522	4.343*	-2.628	-2.778	-2.567	-0.142	13.636	8.685	-8.090	1.167	-0.384	4.821	-4.344	1.151	-1.258
	(2.110)	(2.292)	(5.095)	(6.746)	(2.646)	(4.432)	(9.824)	(11.091)	(11.817)	(2.515)	(3.963)	(5.460)	(3.739)	(2.244)	(7.439)
Log of Inflation (t-1)	-12.204	-7.946	-4.240	0.824	-3.375	4.843	15.322	-1.442	-6.837	-5.699	10.643	-0.383	-18.203	-3.217	-25.949*
	(7.045)	(8.380)	(8.235)	(8.277)	(5.498)	(11.029)	(16.399)	(23.727)	(19.374)	(7.376)	(9.196)	(15.025)	(16.722)	(11.652)	(13.802)
Trade Openness (t-1)	-0.008	-0.015	-0.047	-0.144**	-0.088***	-0.098**	0.230	0.369*	-0.468**	-0.074**	-0.044***	-0.048	-0.151*	-0.021	-0.157***
	(0.014)	(0.015)	(0.062)	(0.061)	(0.015)	(0.037)	(0.129)	(0.170)	(0.160)	(0.026)	(0.012)	(0.030)	(0.072)	(0.032)	(0.040)
Terms of Trade growth of AUS x Share of trade with AUS	-38.788	-46.686	37.292	3.704	-8.666	-30.441	-71.541	-96.029	106.090	12.245	29.025	2.444	54.710	-29.453	9.497
	(35.413)	(35.520)	(71.499)	(83.707)	(23.349)	(41.975)	(91.443)	(108.707)	(118.156)	(25.261)	(24.370)	(51.717)	(58.464)	(28.944)	(72.690)
Terms of Trade growth of US x Share of trade with US	187.995**	216.422***	-10.103	-107.820	-45.207	-109.317	177.534	129.850	-185.745	-63.355	-100.063	12.949	-266.915	-41.099	-104.623
	(51.164)	(56.783)	(80.892)	(153.231)	(66.319)	(130.595)	(285.110)	(363.716)	(399.582)	(65.586)	(99.800)	(119.186)	(179.929)	(69.355)	(136.850)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	242	240	238	238	230	238	242	240	240	240	236	236	220	213	200
Number of Groups (Countries)	11	11	11	11	11	11	11	11	11	11	11	11	11	10	9
R2-within	0.217	0.225	0.189	0.254	0.276	0.242	0.177	0.267	0.329	0.183	0.329	0.221	0.178	0.285	0.261

All dependent variables are differenced from the previous year. Estimation is done using fixed effect (within) regression. Standard errors, clustered at a country level, in parentheses. Constant and dummies are not reported. * p<0.10, ** p<0.05, *** p<0.01

Figure A1: Nonlinear Impact of Natural Disasters by Threshold for Tail Events



Note: Line represents the estimated impact in the year of occurrence for each severity threshold. Shades represent 68 percent and 90 percent confidence interval.

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E. and Topalova, P., 2020. The effects of weather shocks on economic activity: what are the channels of impact?. *Journal of Macroeconomics*, *65*, p.103207.

Arellano, M. and Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, *58*(2), pp.277-297.

Bellon, M. and Massetti, E., 2022. Planning and mainstreaming adaptation to climate change in fiscal policy. *IMF Staff Climate Note 2022/003*, International Monetary Fund, Washington, DC.

Beyer, R.C., Hu, Y. and Yao, J., 2022. Measuring quarterly economic growth from outer space. *IMF Working Paper*, International Monetary Fund, Washington, DC.

Botzen, W.W., Deschenes, O. and Sanders, M., 2019. The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*.

Cabezon, E., Hunter, L., Tumbarello, P., Washimi, K., and Wu, Y., 2015. Enhancing Macroeconomic Resilience to Natural Disasters and Climate Change in the Small States of the Pacific. *IMF Working Papers*, 15/124, International Monetary Fund, Washington.

Chen, X. and Nordhaus, W.D., 2011. Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, *108*(21), pp.8589-8594.

Cevik, S. and Jalles, J.T., 2023. Eye of the Storm: The Impact of Climate Shocks on Inflation and Growth. *IMF Working Paper*, International Monetary Fund, Washington, DC.

Ebener, S., Murray, C., Tandon, A. and Elvidge, C.C., 2005. From wealth to health: modelling the distribution of income per capita at the sub-national level using night-time light imagery. *International Journal of Health Geographics*, *4*, pp.1-17.

Fomby, T., Ikeda, Y. and Loayza, N.V., 2013. The growth aftermath of natural disasters. *Journal of applied econometrics*, *28*(3), pp.412-434.

Hansen, B.E., 1999. Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of econometrics*, *93*(2), pp.345-368.

Henderson, J.V., Storeygard, A. and Weil, D.N., 2012. Measuring economic growth from outer space. *American economic review*, *102*(2), pp.994-1028.

International Monetary Fund. African Dept., 2016. *Regional Economic Outlook, October 2016, Sub-Saharan Africa*. International Monetary Fund.

Jordà, Ò., 2005. Estimation and inference of impulse responses by local projections. *American economic review*, *95*(1), pp.161-182.

Klomp, J., 2016. Economic development and natural disasters: A satellite data analysis. *Global Environmental Change*, *36*, pp.67-88.

Kulkarni, R., Haynes, K.E., Stough, R.R. and Riggle, J.D., 2011. Revisiting night lights as proxy for economic growth: A multi-year light based growth indicator (LBGI) for China, India and the US. *GMU School of Public Policy Research Paper*, (2011-12).

Lee, D., and Zhang, H., 2022. The economic impact of disasters in Pacific island countries: estimation and application to economic planning. *Climate and Development*, *15*(3), 251–267. https://doi.org/10.1080/17565529.2022.2077690

Lee, D., Zhang, H. and Nguyen, C., 2018. The economic impact of natural disasters in Pacific Island countries: Adaptation and preparedness. *IMF Working Paper*, International Monetary Fund, Washington, DC.

Loayza, N.V., 1996, December. The economics of the informal sector: a simple model and some empirical evidence from Latin America. In *Carnegie-Rochester conference series on public policy* (Vol. 45, pp. 129-162). North-Holland.

Loayza, N.V., Olaberria, E., Rigolini, J. and Christiaensen, L., 2012. Natural disasters and growth: Going beyond the averages. *World Development*, *40*(7), pp.1317-1336.

Marto, R., Papageorgiou, C., and Klyuev, V., 2017. Building Resilience to Natural Disasters: An Application to Small Developing States. *IMF Working Paper*, 17/223, International Monetary Fund, Washington.

Mohan, P.S., Ouattara, B. and Strobl, E., 2018. Decomposing the macroeconomic effects of natural disasters: A national income accounting perspective. *Ecological economics*, *146*, pp.1-9.

Noy, I., 2009. The macroeconomic consequences of disasters. *Journal of Development economics*, *88*(2), pp.221-231.

Teulings, C.N. and Zubanov, N., 2014. Is economic recovery a myth? Robust estimation of impulse responses. *Journal of Applied Econometrics*, *29*(3), pp.497-514.

Zhao, M., Zhou, Y., Li, X., Cao, W., He, C., Yu, B., Li, X., Elvidge, C.D., Cheng, W. and Zhou, C., 2019. Applications of satellite remote sensing of nighttime light observations: Advances, challenges, and perspectives. *Remote Sensing*, *11*(17), p.1971.

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