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The Economic Footprint of Natural Disasters:

Demand-side or supply-side forces?

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The Economic Footprint of Natural Disasters: Demand-side or supply-side forces? *

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Abstract

This paper investigates how physical risks disrupt business cycles and hinder the role of monetary policy in stabilizing the economy. We look for evidence to determine whether the effects of natural disasters resemble demand-side shocks or supply-side shocks. We utilize data on natural disasters at both the country-quarter and country-year levels from various sources to ensure the robustness of our analysis. We find evidence that natural disasters act as supply-side shocks, exerting inflationary pressures while simultaneously contracting GDP growth and the output gap, which are persistent. This feature of natural disasters implies that monetary policy strategy becomes more challenging and uncertain following the occurrence of these events. However, these results are heterogeneous across types of disasters, groups of countries, and the severity of the disaster. In low-income countries, the effects of natural disasters are more severe. In high-income countries the non-linear effects become more important.

Keywords: Natural disasters, supply shocks, monetary policy trade-off, inflation, GDP growth, output gap.

JEL Classification: E32, E52, Q5

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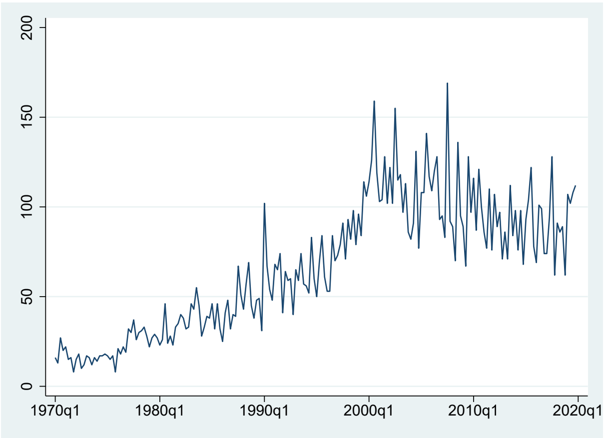
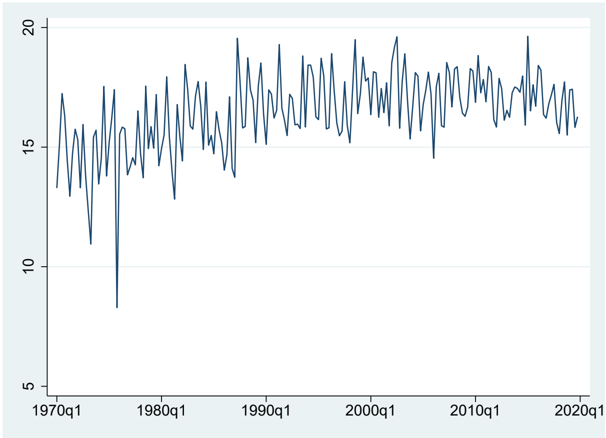
Introduction

Over time, economies around the world have been increasingly more exposed to economic losses due to natural disasters. Figure 1 displays that the frequency and intensity of these events are increasing over time, suggesting a positive trend that may persist in the future and potentially intensify further (Hoeppe, 2016; Intergovernmental Panel on Climate Change, 2023). While a growing economic exposure is a contributing factor, an intensifying climate change emerges as another significant driver (Botzen et al., 2019). These climate-related developments are injecting higher levels of uncertainty into the effectiveness of economic policy in maintaining macroeconomic and financial stability.[1]

Figure 1: *Frequency and intensity of natural disasters: quantity of disasters and affected persons.*



(a) Number of natural disasters



(b) Log of total affected persons

Source: EM-DAT. The number of total affected persons do not include the number of deaths. We count the disasters just at the start date. Period: 1970:Q1 - 2019:Q4.

This paper explores the crucial role of physical risk – the risk posed by natural disasters – in disrupting business cycles and hindering macroeconomic stability. Natural disasters have direct and indirect effects on the economy. The direct effects reflect output, capital and labor force losses and the indirect effects, propagate and amplify, the initial shock. Overall, these effects are transmitted into the economy through the supply and demand channels. However, the relative importance of these channels matters for monetary policy. If natural disaster effects are led by demand-side related forces, they present no important constraints for monetary policy strategy. Conversely, if supply-side impacts from natural disasters dominate, they act as inflationary forces that at the same time dampen output, disrupting the conventional relationship between inflation and economic activity, imposing challenges to policy making. Consequently, natural disasters may render the macroeconomic state of the economy a more ambiguous signal for monetary policy decisions.

[1]For example, see Parker (2023) and Network for Greening the Financial System (2020) for an exploration of risks posed by climate change to macroeconomic stability and financial stability .

We explore this issue by answering the following question: Can we determine whether the impacts of natural disasters are more similar to demand-side shocks or supply-side shocks? By addressing this question, we contribute to the empirical literature concerning the risks that a future rise in climate-related shocks may present for short-term and medium-term monetary policy stabilization strategies.

We directly examine the macroeconomic consequences of natural disasters. We acknowledge the established link between rising temperatures and the increased frequency and intensity of extreme events (Davariashtiyani et al., 2023; Russo and Domeisen, 2023). We consider measures of natural disasters, to capture the diverse impacts of climate change within countries, avoiding the potential for oversimplification associated with focusing solely on temperature variations.

To address our research question, we leverage information on natural disasters at both country-quarter and country-year levels. Climate-related disaster data is sourced from three databases (EM-DAT, Baker et al. (2020) and Our World in Data). In particular, we focus on indicators related to the number of disasters and associated fatalities, the death rates originated by the natural disasters. We then employ a simple econometric linear model to analyze the impact of natural disasters on inflation and GDP growth. The model is estimated using either Ordinary Least Squares (OLS) or Generalized Method of Moments (GMM) depending on the model specification and potential econometric concerns.

We find robust evidence that on average the number of natural disasters and the death rate have a positive impact on inflation. In particular, on average the occurrence of one natural disaster in a quarter increases inflation by 308 basis points. However, when evaluating the impact by type of natural disaster, results are heterogeneous in direction and size. In general, epidemics, earthquakes, extreme temperatures and droughts have a positive impact on inflation. In general, the transmission of the shock is mainly through the supply channel. However, we also find that the impact of natural disasters on inflation is both asymmetric and non-linear, and may depend on the initial level of inflation. In periods of high inflation, disasters tend to be inflationary, reflecting dominant supply-side pressures. However, when inflation is lower or disasters are more persistent, the effects may become deflationary, suggesting that demand-side forces prevail.

Similarly, regarding the effects on economic activity, first, we find evidence that on average the occurrence of a natural disaster reduces annual real GDP growth by 9 basis points. In addition, this result is not homogeneous in size for different types of natural disasters. In particular, the occurrence of earthquakes has a stronger impact on annual real GDP, generating a reduction of 195 basis points. Second, we find robust evidence of a negative impact of the number of natural disasters on the output gap by around 3.5 percent, with persistent effects.

These results, which indicate the negative effects of natural disasters on both GDP growth and output gap together with positive effects on inflation indicate that natural disasters leave a footprint in the economy resembling characteristics alike to a negative supply shock. As described in Clarida et al. (1999), in the presence of these types of shocks, a trade-off between inflation and output gap emerges for monetary policy. This implies that natural disasters prompt a reassessment of the monetary policy strategy to stabilize the economy after the occurrence of these events.

We also perform robustness exercises. We group countries by income and region, following the IMF classification. Results are heterogeneous for both different regions and income levels. The positive impact of the number of natural disasters on inflation is stronger in low-income countries and for Middle East & North Africa and Sub-Saharan Africa countries. However, in high-income countries, the severity of disasters, measured by the death rate, plays a significant role in shaping inflation dynamics, as the non-linear effects of such events tend to be inflationary.

Also, to better evaluate any dominance of the supply or demand channel after the natural disaster, we test for the presence of second-order effects for each type of natural disaster using death rate, using the death rate, as a proxy for disaster severity and welfare costs. We find a positive first-order effect and a negative second-order effect on inflation. At lower levels of mortality, natural disasters exert a positive impact on inflation, consistent with supply-side pressures. However, as disaster severity increases, the effect becomes negative, indicating that demand-side contractions eventually outweigh supply forces. But, these results are heterogeneous, for droughts, we find a U-shaped relationship between inflation and death rate, suggesting the dominance of the demand channel for low levels of death rates, while the dominance of the supply channel for higher death rate levels. In other cases (earthquakes, volcanic activities, storms and landslides), we find evidence of an inverted U-shaped relationship. Finally, we use the cycle component of the real GDP to assess any impact of the number of natural disasters on it. In general, we find a negative impact for each natural disaster type (many of them statistically significant), except for earthquakes.

The rest of this document is organized as follows: section 1 presents the literature review. Section 2 describes the data and presents the empirical model, and we provide a preliminary assessment of the expected effects of natural disasters. Section 3 reports the regression results. In section 4 we develop the robustness exercises. Finally, section 5 concludes.

1 Literature Review

This paper is related to the literature of natural disasters and its macroeconomics effects, particularly on economic activity and inflation. Dell et al. (2014); Botzen et al. (2019) offers a good survey on the literature that studies the GDP losses from natural disasters. For example, Acevedo Mejia et al. (2019) analyze data from low-income countries and find that weather shocks significantly reduce GDP. However, effective policies can mitigate some of the negative short- and long-term effects. Notably, no policy entirely eliminates the substantial GDP losses experienced by hot-climate countries due to rising temperatures. Cavallo et al. (2013) by studying countries affected by a large disasters, and constructing synthetic controls counterfactual, show that the short-run and long-run effects on GDP growth are not very significant. Felbermayr and Gröschl (2014) find a substantial negative and robust average impact effect of disasters on growth, and Poor countries are more strongly affected than rich countries. Hsiang and Jina (2014) using panel data of 110 countries study the long-run effect of tropical cyclones on GDP. After the disaster hits national incomes decline, relative to their pre-disaster trend, and do not recover within twenty years. Avril et al. (2022); Liu et al. (2024) document that physical hazards exacerbate credit conditions, and economic losses, particularly through an increase in the external finance premium.

Parker (2023) provide an extensive survey on the different channels of impact climate shocks on potential output. The long-run impact of severe events is linked to the destruction of capital stock, incomplete recoveries (Cuaresma et al., 2007; Hallegatte and Dumas, 2009); financial frictions and bankruptcy of productive firms (Uchida et al., 2015; Basker and Miranda, 2017; Liu et al., 2024); emigration and the decline of human capital (Almond, 2006; Vigdor, 2008; Hornbeck, 2012; Caruso and Miller, 2015; Bier, 2017); disruption of efficiency and innovation slow down (Leiter et al., 2009; Noy and Strobl, 2022); uncertainty risks that changes preferences of households and businesses becoming more cautious and reducing capital investment (Isoré and Szczerbowicz, 2017; Cantelmo, 2022).

The literature documenting the inflationary consequences of natural disasters is still very recent. Parker (2017) shows heterogeneous disaster impacts on inflation using a sample of 212 countries. While severe disasters are inflationary across all economies, average disasters have negligible effects in advanced economies but remain inflationary in developing ones. Food price inflation primarily drives these effects. Disaster type also matters. Earthquakes have minimal affects on overall inflation, whereas storms, floods, and droughts trigger inflation rises, with droughts effects lasting for several years. Mukherjee and Ouattara (2021) using a panel VAR finds that temperature shocks cause persistent inflation lasting even for several years after the initial shock, for both developed and developing countries. Faccia et al. (2021) highlight the inflationary effects of extreme summer temperatures on food prices. Kotz et al. (2023) find that temperature increases in hotter months and regions have a more significant impact on inflation, affecting both headline and food prices.

This paper is also related to the recent literature the studies the categorization of climate risks as supply or demand shocks. In particular, our paper is closely related to Ciccarelli and Marotta (2024) who using the sample of OECD countries over 1990–2019 period and a VAR model show that physical risks act as negative demand shocks while transition risks act as downward supply movements. Our paper aims to contribute to this literature by following different and simple econometric approach, and exploit a larger cross-country variation observed in developed and developing economies. Further, we source from three different datasets. We also restrict our analysis to physical risks and obtain an opposite result: physical risks act as negative supply shocks that is inflationary and contracts output. In addition, we present some evidence of compounding effects and the non linearities of natural disaster shocks.

Finally, Cevik and Jalles (2023), using a similar dataset to us of climate-induced natural disasters, Emergency Events Database (EM-DAT), study how climate shocks affect inflation and real GDP growth. They find natural disasters have a positive and negative impact on inflation and GDP growth. While they use the local projection method, we use dynamic panel regressions. Also, in contrast to them, we look for robustness using two additional data sets of disasters, include different control variables as monetary policy shocks, use interaction terms to assess the conditional impact of climate shocks, evaluate the presence of second-order effects, and most importantly, evaluate the role of the demand and supply channels in the channel transmission of the natural disasters.

2 Data and Empirical Model

2.1 Data

In this paper we use information of natural disasters from three sources: (i) The database built by Baker et al. (2020), (ii) the Emergency Events Database (EM-DAT), and (iii) Our World in Data, which is based on EM-DAT.

From the database in Baker et al. (2020) we have information of the annual occurrence of a natural disaster from 1970 to 2021. Our variable of interest takes 1 if there was at least one natural disaster in one quarter, and at most 4 if there was at least one natural disaster in each of the quarters of a year, NAT. The authors' goal is to build a measure of a natural disaster shock. Baker et al. (2020) consider only countries with certain income levels.[2]

From the base Emergency Events Database (EM-DAT), which is the base of the other two databases, we have information from 1990 to 2023 of any natural disaster that occurred and some characteristics of these as the initial and end of the event, the number of deaths, the number of people affected, etc. With this database, we built up a new measure of the number of natural disasters on a quarterly frequency, NNAT. There are 16 types of natural disasters. For the interest of this paper, we focus on natural disasters that are relatively more frequent, to have a relatively large amount of events. Thus, we end up with eight: droughts, earthquakes, epidemics, extreme temperature, flood, mass movement, volcanic activity and wildfire. To build the number of natural disasters, we consider only the beginning date of a

[2]Baker et al. (2020) works with 59 countries in their analysis. Only countries with more than $ 50 billion in nominal GDP in 2008 are considered in their analysis.

natural disaster.[3]

The third database, Our World in Data, based on EM-DAT, has information of the number of deaths and the death rates (number of deaths per 100 000 individuals) at annual frequency, from 1900 to 2022. Notice that the death rate information instead of just the number of deaths allows to control for population size. [4] In general, the three databases have information for the type of natural disaster, although a more complete classification is provided by EM-DAT database.

In addition to natural disaster data, we use country-level data at a quarterly frequency from the International Financial Statistics (IFS) database from the IMF. In particular, we use information of real GDP and the consumer price index (CPI) available. With this information, we can compute the annual real GDP growth and the real GDP cycle, as our indicators of real activity. Also, we compute the annual and quarterly inflation. To control for monetary policy intervention, we use the estimates of monetary policy shock of Choi et al. (2024).[5] The time period analyzed spans from 1970:Q1 to 2019:Q4. This is to avoid the Covid-19 period, which was exposed to several and large shocks.

Table 1 reports the descriptive statistics of our variables at the country-annual and country-quarter levels. We have an average annual inflation (π_{it}) of 8.19% and a quarterly inflation of 1.25%, both with an important level of dispersion. The mean of the natural disaster shock (NAT_{it}) is 0.24, and the average number of natural disasters (NNAT_{it}) in a quarter is 0.6. And, as expected, the MPS shock has a mean of zero and relatively small standard deviation. The death rate (DR_{it}) has a mean of 0.20 and a relatively high standard deviation. The annual real GDP growth (RGDPG_{it}) shows a mean of 3.1%. Table 1 also reports the real GDP cycle (GDPC_{it}) computed using the typical (two-sided) HP filter.[6] This represents the log deviation of the variable from its long-term value. As expected, in all cases, the means are close to zero, and the volatility is relatively higher for the credit cycle.

[3]For example, if a natural disaster lasts more than one quarter, we account for this on NNAT only in the quarter that appears.

[4]The data is available in: https://ourworldindata.org/

[5]Notice that the original MPS estimation, is at a monthly frequency, so MPS is added up at the quarterly frequency in this work.

[6]We set the value of the smooth parameter to 1600 (the default value).

Table 1: *Descriptive statistics*

Variables	Obs	N	Mean	S.D.	Minimum	Maximum
Annual frequency						
π_{it} (%)	1296	30	8,19	9,89	-5,70	67,35
NAT$_{it}$	1296	30	0,24	0,62	0,00	4,00
DR$_{it}$	4607	122	0,20	0,74	0,00	9,66
RGDPG$_{it}$ (%)	5026	79	3,07	3,04	-13,70	13,56
Quarterly frequency						
π_{it} (%)	9885	115	1,25	1,89	-5,73	20,06
NNAT$_{it}$	9885	115	0,59	1,16	0,00	8,00
MPS$_{it}$ (%)	9885	115	0,00	0,04	-0,20	0,19
GDPC$_{it}$ (%)	2320	46	0,18	1,82	-11,30	10,18

Source: Baker et al. (2020), EM-DAT, Our World in Data, International Financial Statistics (IFS), IMF. Own elaboration. N: number of countries. S.D.: Standard deviation. We omit observations with extreme values: For annual inflation, we keep -10% $\leq \pi_{it} \leq$ 70%. For quarterly inflation, we keep -6% $\geq \pi_{it} \leq$ 25%. For the number of total natural disaster, we keep NNAT$_{it}$ < 9. We keep -0.20% $\leq$ MPS$_{it}$ $\leq$ 0.20%, DR$_{it}$ $\leq$ 10, -15% $\leq$ RGDPG$_{it}$ $\leq$ 15%, -12% $\leq$ GDPC$_{it}$ $\leq$ 12%.

Table 2 reports the descriptive statistics of the number of natural disasters and death rate by natural disaster type for the 1970-2019 period. It shows that on average floods and storms are the most frequent natural disasters, while earthquakes and storms are those that produce on average the largest death rates. In addition, droughts and mass movements are less frequent, and droughts and volcanic activity generate smaller death rates.

Table 2: *Descriptive statistics by type of natural disaster*

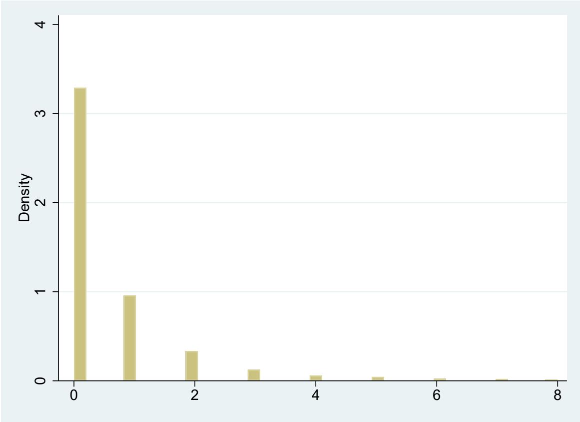
Variables	Obs	N	Mean	S.D.	Minimum	Maximum
			Number of natural disasters - Quarterly frequency			
Drought	9948	115	0,02	0,14	0,00	2,00
Earthquake	9947	115	0,05	0,28	0,00	4,00
Epidemic	9948	115	0,05	0,24	0,00	4,00
Extreme Temperature	9948	115	0,04	0,20	0,00	2,00
Flood	9926	115	0,23	0,60	0,00	5,00
Mass Movement	9948	115	0,03	0,21	0,00	5,00
Storm	9916	115	0,17	0,59	0,00	5,00
Wildfire	9948	115	0,02	0,18	0,00	4,00
			Death rates - Annual frequency			
Drought	4650	122	0,00	0,05	0,00	3,32
Earthquake	4633	122	0,03	0,33	0,00	9,50
Volcanic activity	4648	122	0,00	0,04	0,00	2,74
Flood	4649	122	0,06	0,32	0,00	8,46
Storm	4643	122	0,06	0,47	0,00	9,65
Landslide	4647	122	0,02	0,16	0,00	5,57
Extreme Temperature	4639	122	0,03	0,33	0,00	9,97

Source: Baker et al. (2020), EM-DAT, Our World in Data, Own elaboration. N: number of countries. S.D.: Standard deviation. We keep $\text{NNAT}_{it} < 6$, $\text{DR}_{it} < 10$.

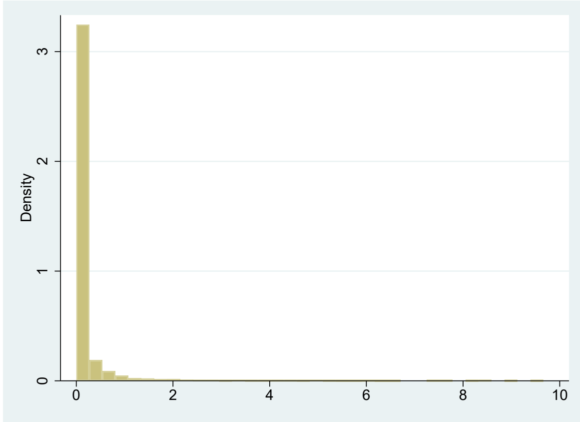
Table 12 and table 13 in Appendix A report the descriptive statistics of natural disasters by income level and by region. According to table 12, the number of disasters is more frequent in lower-middle-income countries. Similarly, on average the death rate is larger for lower-middle-income countries. Low-income countries have the smallest occurrence of disasters on average, and consequently one of the smaller death rates among the groups of countries. Interestingly, according to table 13 North America has on average the largest number of natural disasters followed by South Asia, but the smallest death rate. Regarding the death rates, MENA countries have the highest death rates originated by natural disasters, but on average the lowest occurrence of natural disasters.

Figure 2 shows the histogram of the number of natural disasters (a) and the death rates (b) at the country-quarter level and at the country-year level, respectively. The number of natural disasters is concentrated in 0, 1 and 2; while death rates are concentrated between 0 and 1. Also it reports the quarterly inflation and annual GDP growth at quarterly frequency. Notice that the inflation distribution is right-skewed, while the GDP growth distribution is more left-skewed. This suggests that undesired events (recessions and high-inflation periods) are relatively more severe than desired events.

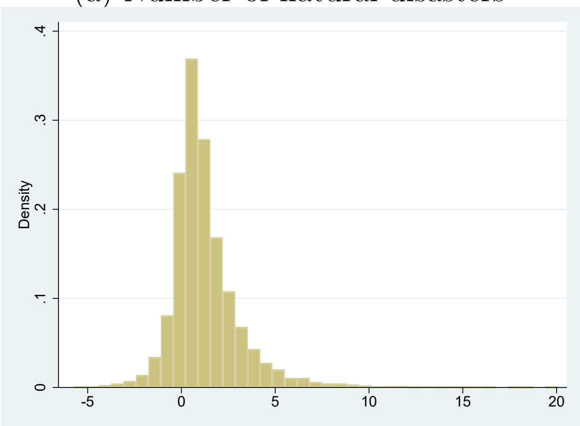
Figure 2: *Histograms of natural disasters*



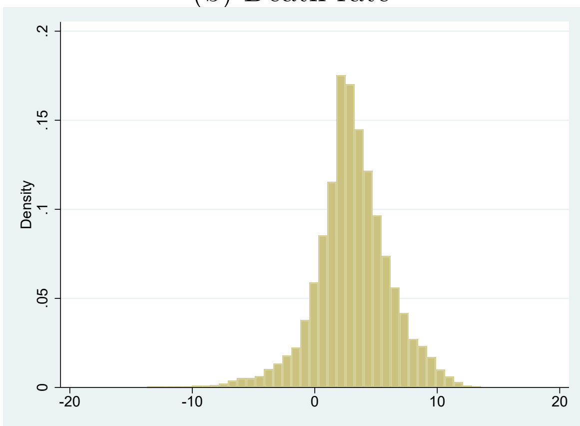
(a) Number of natural disasters



(b) Death rate



(c) Quarterly inflation



(d) Annual GDP growth

It reports the histograms of the number of natural disasters and the death rates for the 1970 - 2019 period at quarterly and annual frequency, respectively. Source: EM-DAT, Our World in Data.

2.2 Empirical Model

To study our research question we propose the following linear model:

$$Y_{it} \quad = \quad \mu + \alpha_i + \omega_t + \beta_0 Y_{it-1} + \beta_1 X_{it} + CTRL_{it} + \epsilon_{it},$$

where the i subscript refers to a country, the t subscript refers to a sample quarter (or sample year) and ϵ_{it} is a random error that has a normal distribution,[7] Y_{it} is our endogenous variable. It could be annual or quarterly inflation or our measure of economic activity. For the former, we use annual real GDP growth (measured as the deviation of the log of the GDP) or real GDP cycle (measured as the log deviation of the real GDP from its long-term value). This latter is computed using the typical two-sided HP filter. Also Y_{it} could be the GDP or credit annual growth. X_{it} is our exogenous variable. It could be the the number of natural disasters, natural disaster shock, or the death rate (originated by the disasters). The occurrence of disasters is assumed to be exogenous, and independent of current or previous

[7]The normality assumption for the error is required to perform statistical tests. Otherwise, tests' results become inaccurate.

values of GDP or inflation. We might include an AR(1) term to control for mean reversion.

CTRL_{it} represents the control variables. In particular, we control by the monetary policy shock measure. We also might include country fixed effects (α_i) to control for unobservable country characteristics that do not vary across time or time fixed effects (ω_t). Notice that we do not include many control variables, since we believe that our exogenous variable (natural disaster) is exogenous enough. This also naturally alleviates the endogeneity concerns. Also, we follow the recommendation of Dell et al. (2014) and use a system of country and time fixed effects suffice to avoid the problem of overcontrolling. Adding many controls could result in underestimation, as the impact of disasters works precisely through these controls.

From a theoretical point of view, we expect that natural disasters hurt real activity. In particular, natural disasters produce capital, labor force and output losses. Further, through indirect effects, by reducing households' possibilities to generate income or via financial channels that constrain consumption and investment, natural disasters might deteriorate aggregate demand. Consistent with both these effects that jointly create a contraction of GDP, our hypothesis is that β_1 is negative when our endogenous variable is the real activity measure.

The impact of natural disasters on inflation depends on the dominance of the demand or supply channel. In particular, if indirect effects seriously deteriorate aggregate demand, we should expect negative effects on inflation, and β_1 would be negative when our endogenous variable is inflation. But, if natural disasters' effects on inflation through the supply channel are relatively stronger, attributable to damage of supply chains, inputs and/or production processes, it is expected increments on the production costs. Additionally, via a financial channel, natural disasters might elevate the marginal cost of funding. Together, these effects are anticipated to push inflation up and β_1 would be positive when our endogenous variable is inflation.

3 Regression Results

We first report regression results of the impact of natural disasters on inflation and later the impact on real activity.

Effects of natural disasters on Inflation

Table 3 reports the results when working with annual inflation and the annual measure of natural disasters (NAT) that goes from 1 to 4 of Baker et al. (2020) with different fixed effects, with an interaction term (columns 4-6 and 8), and with an AR(1) term (columns 7-8). In all cases we find on average a statistically significant and positive impact of a natural disaster shock on inflation, except in columns (6) and (8), while in columns (3)-(4), results are not statistically significant. Our preferred specifications are columns (6)-(8). If we do not consider any persistent component of inflation, as in columns (1) to (3), an increase of 1 (one additional quarter facing at least one natural disaster), in the disaster shock raises annual inflation by between 55 and 76 basis points. If we include the persistence of inflation, as in column (7), an increase of 1 in the natural disaster shock raises annual inflation by 308 basis points. These results suggest that the inflationary effects of natural disasters operate through supply-side forces that are relatively stronger than the demand-side forces.

In addition, column (8) shows evidence of a nonlinear impact of natural disasters. In general, the higher the previous year's inflation, the stronger the impact of the natural disaster shock. But, the non-linearity also points about one asymmetry. An increase of 1 in the natural disaster shock is inflationary when the initial level of inflation exceeds 6.1 per cent. However, when inflation is below this threshold or the disaster is more persistent, such a shock exerts a deflationary effect. This asymmetric and non-linear relationship indicates that natural disasters primarily operate through supply-side channels that dominate demand-side forces during periods of high inflation. In addition, given the AR(1) component is statistically significant, the inflationary effects last after one year, but its effects are expected to be reduced to one-fifth.

Table 3: *Inflation: Regression Results*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
π_{it-1}							0.223***	0.174***
							(0.0130)	(0.0141)
NAT_{it}	0.756*	0.763	0.549	-4.982***	-4.302***	-3.067**	3.077***	-2.646***
	(0.440)	(0.866)	(0.916)	(0.617)	(1.093)	(1.206)	(0.470)	(0.492)
π_{it-1} NAT_{it}				0.642***	0.568***	0.350***		0.265***
				(0.0511)	(0.115)	(0.117)		(0.0244)
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
F test (ρ-value)	0.0857	0.386	0.554	0	0.000149	0.0172	0	0
N	30	30	30	30	30	30	30	30
Country FE	No	No	Yes	No	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	Yes	Yes

Table reports regression results using the natural disaster shock (NAT_{it}) of Baker et al. (2020). It uses information at annual frequency for the 2004-2019 period. π_{it}: annual inflation. Clustered standard errors at country level are in parentheses. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method for columns 1-6: OLS. Estimation method for columns 7-8: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991).

Table 4 reports the results when working with quarterly inflation and the number of natural disasters, NNAT, sourced from the EM-DAT database. This time we include as a control variable the monetary policy shock (MPS), to control for demand conditions induced by monetary policy, which could potentially counterbalance the supply-side effects of natural disasters. This time, our regression includes a larger number of countries. Qualitatively, the previous results hold. This is, on average, the number of natural disasters has a positive impact on inflation (columns 1-3 and 7-8), and this impact is quantitatively stronger for higher inflation levels (columns 4-6). For example, according to column 7, on average one natural disaster raises quarterly inflation in 7 basis points. Column 6 further indicates that when the initial inflation rate is 2 percent, the same shock generates an increase of about 17 basis points, more than double the baseline effect. When controlling for inflation lags (column 8), this estimated effect of one natural disaster decreases to 3.5 basis points. But, the cumulative impact remains meaningful: two natural disasters may increase quarterly inflation by roughly 7 basis points, while three disasters raise it by around 10 basis points.

Table 4: *Regression Results - Number of Natural Disasters*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
π_{it-1}							0.179***	0.184***
							(0.0108)	(0.0119)
NNAT_{it}	0.0744***	0.0775***	0.0893***	-0.196***	-0.156***	-0.0532**	0.0697***	0.0793***
	(0.0164)	(0.0156)	(0.0194)	(0.0189)	(0.0182)	(0.0216)	(0.0171)	(0.0190)
π_{it-1} NNAT_{it}				0.220***	0.191***	0.112***		-0.0223***
				(0.00841)	(0.00816)	(0.00775)		(0.00756)
MPS_{it}	1.489***	0.100	-0.103	1.143**	-0.0443	-0.182	0.952	0.982
	(0.536)	(0.582)	(0.515)	(0.519)	(0.566)	(0.509)	(0.679)	(0.678)
Observations	9,885	9,885	9,853	9,885	9,885	9,853	9,885	9,885
F test (ρ-value)	6.75e-07	4.54e-06	2.41e-05	0	0	0	0	0
N	115	115	115	115	115	115	115	115
Country FE	No	No	Yes	No	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	Yes	Yes

Table reports regression results using the number of natural disasters (NNAT_{it}) using EM-DAT. It uses information at quarterly frequency for the 1970:Q1-2019:Q4 period. π_{it}: quarterly inflation. Standard errors are in parentheses. MPS_{it}: monetary policy shock. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method for columns 1-6: OLS. Estimation method for columns 7-8: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991).

As an additional exercise, in the spirit of Ciccarelli and Marotta (2024), we use as a proxy for physical risk a variable that measure welfare costs of deaths: the death rate (DR) sourced from the third database (Our World in Data) which is at an annual frequency as our measure of the intensity of the natural disaster. Table 5 reports the results. In general, death rates originated from natural disasters have a positive impact on inflation (columns 1-3 and 7-8). As before, the impact is quantitatively stronger the higher the inflation rate (columns 4-6). When controlling for lagged inflation, the non-linear effect is no longer statistically significant (column 8), but the inflationary impact of disaster severity becomes more pronounced. It is worth noting that when using the ratio of deaths to the labor force instead, the results remain qualitatively similar, see table 14 in Appendix B.

Table 5: *Regression Results - Death rates*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
π_{it-1}							0.141***	0.142***
							(0.00874)	(0.00872)
DR_{it}	0.356*	0.330*	0.106	-2.081***	-1.561***	-0.901***	0.682*	1.225***
	(0.187)	(0.171)	(0.147)	(0.249)	(0.231)	(0.197)	(0.368)	(0.390)
π_{it-1} DR_{it}				0.292***	0.226***	0.122***		-0.0200
				(0.0203)	(0.0189)	(0.0160)		(0.0215)
Observations	4,607	4,607	4,607	4,607	4,607	4,607	4,607	4,607
R-squared	0.001	0.176	0.470	0.044	0.201	0.476		
N	122	122	122	122	122	122	122	122
Country FE	No	No	Yes	No	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	Yes	Yes

Table reports regression results using the death rates (DR_{it}) as our endogenous variable. It uses information at annual frequency for the 1970-2019 period. π_{it}: annual inflation. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method for columns 1-6: OLS. Estimation method for columns 7-8: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991).

Next, we report the results when splitting our full sample by type of natural disaster. Table 6 shows the results of the impact of the number of natural disasters by type (using EMD-DAT) on quarterly inflation. According to the table, some disaster types have a positive impact on inflation (droughts, earthquakes, extreme temperatures and floods), while others have a negative impact on inflation (storms). Regarding, those disasters that have a statistically significant positive effect, earthquakes, droughts and flood have an stronger effect on inflation, while extreme temperatures, have relatively smaller impacts. An explanation for the negative impact might be that these natural disasters have a relatively stronger impact through the demand channel, prevailing thus the indirect effects, while those with a positive impact have a relatively stronger impact through the supply channel.

Table 6: *Regression Results by type of natural disaster*

	Drought	Earthquake	Epidemic	Ext. temp.	Flood	Mass M.	Storm	Wildfire
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
π_{it-1}	0.253***	0.196***	0.177***	0.180***	0.178***	0.175***	0.170***	0.175***
	(0.0106)	(0.0108)	(0.0109)	(0.0109)	(0.0108)	(0.0109)	(0.0109)	(0.0109)
NNAT_{it}	0.208**	0.178***	0.110	0.128*	0.126***	0.0653	-0.0548*	0.0383
	(0.102)	(0.0635)	(0.0669)	(0.0774)	(0.0271)	(0.0749)	(0.0320)	(0.0892)
MPS_{it}	1.395***	1.085	0.528	0.921	1.179*	1.422*	0.519	0.439
	(0.344)	(0.730)	(0.752)	(0.651)	(0.661)	(0.734)	(0.678)	(0.657)
Observations	9,948	9,947	9,948	9,948	9,926	9,948	9,916	9,948
N	115	115	115	115	115	115	115	115
F test (ρ-value)	0	0	0	0	0	0	0	0

Table reports regression results using the number of each type of natural disasters (NNAT_{it}) using EM-DAT. It uses information at quarterly frequency for the 1970:Q1-2019:Q4 period. π_{it}: quarterly inflation. Standard errors are in parentheses. MPS_{it}: monetary policy shock. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). All regressions include both country and time fixed effects.

Similarly, using the annual data for the death rate variable, in Table 15 in Appendix B, we present the results of the impact of annual inflation for each type of natural disaster. In contrast to the previous results, droughts have a negative impact on inflation, while storms have a positive impact on inflation. This divergence may be attributed to the fact that fatalities from droughts are more closely linked to demand-side forces, potentially mitigating the positive impact on inflation from supply side forces more linked to natural disaster intensity variables.

Effects of natural disasters on GDP growth and the business cycle

Now, we turn the analysis, to the effects of natural disasters on the economic real activity. In particular, we aim to measure the impact of the natural disaster shock (the measure of Baker et al. (2020)) on annual real GDP growth (RGDPG) and the output gap, for all and by type of natural disaster, controlled by the monetary policy shock. All regressions include both country and time fixed effects.

First, Table 7 reports that the number of natural disasters has a negative impact on real economic activity when considering all types of natural disasters. On average, an increment of 1 in the natural disaster intensity results in a drop of real GDP growth by around 9 basis points (column 1). This effect is persistent, and lasts for more than one year. The AR(1) component is high and statistically significant, around 0.89, with a half-life of around 6 quarters. This implies that following the occurrence of a disaster shock, its effects diminish by half only after 6 quarters.

When considering the impact of the different types of natural disasters, in general, we find a statistically negative effect of the number of natural disasters on GDP growth, except for some natural disasters (Epidemics, mass movements, storms and wildfires). Notice also that the impact on real activity is quantitatively stronger for earthquakes. On average an earthquake event reduces the annual real GDP growth by 195 basis points; while floods have on average the weakest impact (minus 65 basis points).

As an additional exercise, we evaluate the impact of the death rate variable (from Our World in Data), as another measure of natural disaster, on annual real GDP for all and by each type of natural disaster. Table 16 in Appendix B presents the results. For all types of natural disasters (column 1), we find a statistically significant negative impact of death rate on annual real GDP growth. In particular, one standard deviation of the death rate, reduces GDP growth by 173 basis points. By types of disasters, results are heterogeneous, death rates from volcanic activities and storms, are negatively related to GDP growth, while death rates from droughts and landslides are positively associated with GDP growth.

Table 7: *Regression Results - All and by natural disaster type*

	All	Drought	Earthquake	Epidemic	Ext. temp.	Flood	Mass M.	Storm	Wildfire
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$RGDPG_{it-1}$	0.896***	0.849***	0.856***	0.850***	0.850***	0.852***	0.851***	0.851***	0.850***
	(0.00514)	(0.00686)	(0.00799)	(0.00678)	(0.00695)	(0.00698)	(0.00684)	(0.00684)	(0.00678)
$NNAT_{it}$	-0.0863***	-0.819***	-1.954***	-0.197	-0.715***	-0.118***	0.545***	-0.0188	0.0129
	(0.0250)	(0.235)	(0.179)	(0.191)	(0.126)	(0.0449)	(0.153)	(0.0511)	(0.230)
MPS_{it}	0.656*	-0.0197	-0.0317	-0.122	-0.157	-0.208	-0.0839	-0.0457	-0.0865
	(0.357)	(0.406)	(0.472)	(0.401)	(0.411)	(0.410)	(0.404)	(0.403)	(0.400)
Observations	5,004	5,026	5,026	5,026	5,026	5,012	5,026	5,006	5,026
N	79	79	79	79	79	79	79	79	79
F test (ρ-value)	0	0	0	0	0	0	0	0	0

Table reports regression results using the number of natural disasters ($NNAT_{it}$) using EM-DAT. It uses information at quarterly frequency for the 1970:Q1-2019:Q4 period. $RGDP_{it}$: annual real GDP growth. Ext. temp: extreme temperatures. Mass M: mass movements. Standard errors are in parentheses. MPS_{it}: monetary policy shock. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). All regressions include both country and time fixed effects.

Finally, we perform an exercise using a different measure of real activity, the output gap, defined as the cyclical component of the real GDP. Table 8 reports the results. We find robust evidence of a negative impact of the number of natural disasters on the real GDP cycle, when considering all types of disasters; and also for each type of natural disaster, except for earthquakes. The latter could be because earthquakes' effects are mainly reflected in the estimated GDP trend, as they disrupt productive capacity and infrastructure. In contrast to the impact on real GDP growth, on average floods have a stronger negative impact on the real GDP cycle. Notice that this time we control for the level of financial deepening (credit to GDP ratio) and country openness (exports and imports to GDP ratio).

On average, an increment of 1 in the natural disaster intensity results in a reduction of

GDP relative to its trend of around 3.5 percent (column 1). This effect is very persistent and lasts for more than 1 year. The AR(1) component is high and statistically significant, around 0.845. This implies that following the occurrence of a disaster shock, its effects diminish by half only after 4 quarters.

Table 8: *Regression Results - Real Business Cycle*

	All	Drought	Earthquake	Epidemic	Ext. temp.	Flood	Storm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$GDPC_{it-1}$	0.845***	0.855***	0.848***	0.853***	0.847***	0.848***	0.844***
	(0.00731)	(0.00740)	(0.00727)	(0.00727)	(0.00733)	(0.00732)	(0.00730)
$NNAT_{it}$	-0.0346***	-0.0433	0.0339	-0.0588	-0.0295	-0.0557***	-0.0303*
	(0.00946)	(0.0593)	(0.0343)	(0.0468)	(0.0396)	(0.0157)	(0.0171)
$CREGDP_{it}$	0.000391	0.000371	0.000465	0.000430	0.000469	0.000501	0.000481
	(0.000539)	(0.000542)	(0.000540)	(0.000542)	(0.000540)	(0.000540)	(0.000539)
$XMGDP_{it}$	0.00347***	0.00388***	0.00376***	0.00386***	0.00371***	0.00372***	0.00368***
	(0.000887)	(0.000890)	(0.000888)	(0.000891)	(0.000886)	(0.000887)	(0.000887)
MPS_{it}	0.199	0.136	0.113	0.121	0.189	0.177	0.236*
	(0.123)	(0.128)	(0.126)	(0.128)	(0.123)	(0.124)	(0.123)
Observations	2,320	2,326	2,326	2,326	2,326	2,322	2,318
N	46	46	46	46	46	46	46
F test (ρ-value)	0	0	0	0	0	0	0

Table reports regression results using quarterly information of real GDP cycle ($GDPC_{it}$) and the number of natural disasters ($NNAT_{it}$). $CREGDP_{it}$: credit to GDP ratio; $XMGDP_{it}$: exports and imports to GDP ratio. MPS_{it}: monetary policy shock. Standard errors are in parentheses. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). All regressions include both country and time fixed effects.

Discussion

These consistent results of the negative effects of natural disasters on GDP growth output gap and positive effects on inflation, indicate that natural disaster disseminates through the economy resembling characteristics akin to negative supply shocks or cost-push shocks.

As described in Clarida et al. (1999), in the presence of these types of shocks emerges a trade-off between inflation and output gap. Because inflation is driven by supply forces, the central bank can only engineer to reduce inflation in the near term by contracting the demand. This implies that, for an inflation-targeting central bank, natural disasters prompt a reassessment of how much additional lower economic activity needs to be generated to meet their inflation target. Also, the monetary policy stabilization strategy is under more uncertainty. Although the central bank can manage to reduce the gap between inflation and its target, it may not manage to affect the rate of convergence in the presence of natural disasters. Additionally, all these risks pose major difficulties in terms of monetary policy communication.

Also, the fact that disasters have nonlinear effects that depend on the state of the economy (as the initial state of inflation) may also introduce significant unpredictability in economic forecasts. This uncertainty can lead to inappropriate policy decisions, as central banks might either underestimate or overestimate the long-term impact of a disaster.

4 Robustness exercises

In this section, we perform some robustness exercises. We study the implications of natural disasters by country income level and by region. We evaluate the presence of nonlinear effects of natural disasters. And finally, we test the implications of natural disasters on the GDP cycle, as our measure of real activity.

4.1 Analysis by income group and by region

Table 9 reports previous regression results of the impact of the number of natural disasters on quarterly inflation (Panel A), and the impact of the death rate on annual inflation (Panel A), but by groups of countries segmented by income level. On average, the number of natural disasters has a stronger positive impact on inflation the lower the country's income. The dependence of natural disaster effects on the initial level of inflation is not statistically significant, except in high-income countries. In the latter economies, the significant statistically non-linearity effects suggest a small deflationary outcome of natural disasters (see column 8): an increment of 1 in the natural disaster intensity results in a reduction of inflation by around 7 basis points, for an initial level of inflation of 2 per cent.

However, the death rate has a stronger impact the higher the country's income, and the non-linear effects associated with the initial level of inflation become larger and statistically significant in these economies. In high income countries, the increment of 1 in the death rate results in an increase in inflation about 27 basis points, for a given initial level of inflation of 2 per cent. So natural disasters do not necessarily have a smaller impact on inflation in high-income countries. This result indicates that disasters with higher human costs may be particularly problematic for high-income countries, as they tend to trigger more severe supply-side disruptions, such as labor shortages, displacement, and breakdowns in local markets, which in turn generate upward pressure on prices.

Table 9: *Regression Results: By country income level*

	LI		LMI		UMI		HI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:								
π_{it-1}	0.140***	0.157***	0.179***	0.190***	0.253***	0.242***	0.117***	0.131***
	(0.0317)	(0.0394)	(0.0217)	(0.0249)	(0.0187)	(0.0199)	(0.0169)	(0.0174)
NNAT_{it}	0.233**	0.278**	0.181***	0.198***	-0.00579	-0.0447	0.0217	0.0650***
	(0.116)	(0.132)	(0.0364)	(0.0421)	(0.0371)	(0.0473)	(0.0206)	(0.0240)
π_{it-1} NNAT_{it}		-0.0337		-0.0281		0.0177		-0.0676***
		(0.0468)		(0.0171)		(0.0165)		(0.0181)
MPS_{it}	-3.311	-2.761	2.087*	1.950	1.743	1.682	0.428	0.511
	(3.624)	(3.596)	(1.268)	(1.264)	(1.307)	(1.307)	(0.355)	(0.355)
Observations	780	780	2,248	2,248	2,709	2,709	4,017	4,017
N	10	10	26	26	30	30	47	47
Panel B:								
π_{it-1}	0.247***	0.277***	0.234***	0.214***	-0.184***	0.118***	-0.106***	0.475***
	(0.0290)	(0.0301)	(0.0204)	(0.0212)	(0.0309)	(0.0105)	(0.0216)	(0.0103)
DR_{it}	2.005**	6.122***	3.678***	0.0931	5.968***	0.0139	-19.75***	-0.0599
	(0.950)	(1.131)	(0.415)	(0.421)	(0.842)	(0.421)	(1.731)	(0.333)
π_{it-1} DR_{it}		-0.406***		0.0215		0.0454**		0.106***
		(0.0949)		(0.0354)		(0.0209)		(0.0241)
Observations	363	363	992	992	1,218	1,218	1,989	1,989
N	11	11	27	27	35	35	48	48

Table reports regression results by country income level at quarterly frequency (Panel A) and annual frequency (Panel B) for the 1970-2019 period. NNAT_{it}: number of natural disasters. DR_{it}: death rate. MPS_{it}: monetary policy shock. LI: Low Income (no shown since there are zero observations); LMI: Lower Middle Income; UMI: Upper Middle Income; HI: High Income. Standard errors are in parentheses. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). All regressions include both country and time fixed effects.

Similarly, table 10 reports the regression results, but for countries grouped by regions. We find evidence that the number of natural disasters has a positive impact on inflation for MENA, SA and SSA countries. However, when using the death rate, which serves as a proxy for the welfare costs of disasters, we find a positive impact on inflation for EAP, ECA and LAC countries, with a relatively stronger impact for ECA countries. In all cases, there is no evidence of any statistically significant negative impact on inflation from natural disasters.

Table 10: *Regression Results: By geographical regions*

	EAP (1)	ECA (2)	LAC (3)	MENA (4)	NA (5)	SA (6)	SSA (7)
Panel A:							
π_{it-1}	0.206***	0.134***	0.339***	0.406***	0.228	0.263***	0.150***
	(0.0278)	(0.0184)	(0.0201)	(0.0332)	(0.168)	(0.0674)	(0.0220)
NNAT_{it}	-0.00717	-0.0201	0.0615	0.376***	-0.0143	0.182***	0.226***
	(0.0282)	(0.0381)	(0.0418)	(0.100)	(0.0211)	(0.0679)	(0.0734)
MPS_{it}	0.426	-0.525	1.153	0.551	0.120	1.505	1.198
	(1.029)	(0.654)	(0.849)	(0.997)	(0.349)	(4.653)	(1.357)
Observations	1,273	3,353	1,952	854	212	330	1,780
N	14	43	19	9	2	4	22
Panel B:							
π_{it-1}	-0.0294	0.291***	0.156***	0.559***	0.282	0.226***	0.227***
	(0.0232)	(0.00762)	(0.0134)	(0.0319)		(0.0475)	(0.0224)
DR_{it}	0.559***	2.526***	1.650***	0.305	0.691	-0.165	1.365
	(0.0990)	(0.344)	(0.341)	(0.289)		(0.232)	(1.289)
Observations	657	1,534	809	368	96	179	919
N	16	46	19	10	2	5	23

Table reports regression results by region at quarterly frequency (Panel A) and annual frequency (Panel B) for the 1970-2019 period. NNAT_{it}: number of natural disasters. DR_{it}: death rate. MPS_{it}: monetary policy shock. EAP: East Asia & Pacific; ECA: Europe & Central Asia; LAC: Latin America & Caribbean; MENA: Middle East & North Africa; NA: North America; SA: South Asia; SSA: Sub-Saharan Africa. Standard errors in parentheses. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). All regressions include both country and time fixed effects.

Similarly, table 17 and 18 in Appendix B presents the results associated with the impact of natural disasters on annual real GDP growth by country income level and by region, respectively. Table 17 reports that there is not evidence of some relationship between the number of natural disasters and GDP growth, when grouping countries by income levels. Finally, table 18 reports the results by geographical region, the negative impact of the number of natural disasters is observed in LAC and MENA countries.

4.2 Non-linear effects of natural disasters

Using the information of the death rate as our exogenous variable, as a proxy for the severity of disasters, according to table 11 we find evidence of second-order effects of the death rate on inflation, when considering all the types of disasters and also for each one of them.

When considering all types of disasters, we find a positive first-order effect and a negative second-order effect. This suggests that for relatively lower levels of the death rate, the impact on inflation is positive , suggesting a dominance of the supply channel; while as the death rate levels become higher, the impact on inflation turns negative , suggesting that, after a point of severity of the disaster, the demand channel dominates. This inverted U-shaped relationship between inflation and death rate also holds for death rates originated by earthquakes, volcanic activities, storms and landslides. For others droughts, we observe a U-shaped relationship, which means that the impact through the supply channel dominates for higher levels of death rates.

These negative secondary effects suggest that more severe events could lead to a lasting decrease in aggregate demand, potentially outweighing the supply-side impacts of natural disasters. This could reduce the trade-off faced by central banks when such large events occur.

Table 11: *Regression Results - second order effects*

	All	Drought	Earthquake	Volcanic act.	Floods	Storms	Landslide	Ext. temp.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7)
π_{it-1}	0.134***	0.139***	0.137***	0.132***	0.137***	0.139***	0.139***	0.138***
	(0.00870)	(0.00874)	(0.00871)	(0.00876)	(0.00875)	(0.00871)	(0.00875)	(0.00879)
DR_{it}	13.31***	-379.7***	15.67***	306.3***	-0.181	21.28***	11.62***	-3.099
	(1.000)	(32.28)	(1.651)	(36.82)	(1.646)	(1.497)	(3.432)	(2.798)
DR_{it}^2	-1.904***	117.4***	-2.195***	-117.0***	0.0568	-2.842***	-2.279***	0.459
	(0.143)	(10.06)	(0.223)	(14.07)	(0.246)	(0.201)	(0.737)	(0.374)
Observations	4,607	4,650	4,633	4,648	4,649	4,643	4,647	4,639
N	122	122	122	122	122	122	122	122
F test (ρ-value)	0	0	0	0	0	0	0	0

Table reports regression results using the death rates (DR_{it}) as our endogenous variable by different natural disasters type. It uses information at annual frequency for the 1970-2019 period. π_{it}: annual inflation. MPS_{it}: monetary policy shock. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). This estimation includes country and time fixed effects.

5 Conclusion

Our paper contributes to the literature on natural disasters and their macroeconomic effects, by providing evidence that physical risks act as negative supply shocks that are inflationary and contract GDP growth and output gap. In addition, we present some evidence of the compounding and the non-linear effects of natural disaster shocks. We use a simple econometric approach, and exploit cross-country variation observed in developed and developing economies after the occurrence of a natural disaster. We source variables related to the intensity of disasters from three different datasets to ensure robustness.

Our results provide evidence about the significant role of physical risk in perturbing business cycles and amplifying the trade-off dilemma between inflation management and economic activity for central banks. Our results have implications for the need for a different approach that may combine traditional monetary policy framework with disaster preparedness, risk management strategies, and fiscal policies. Acknowledging the limitations of monetary policy in a new era of climate risk and higher uncertainty opens up the need for further normative research to build a more resilient policy framework.

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Appendices

A Additional tables

Table 12: *Descriptive statistics of natural disaster by Income level*

Variables	Obs	N	Mean	S.D.	Minimum	Maximum
Number of natural disasters - Quarterly frequency						
Low Income	780	10	0,40	0,66	0,00	4,00
Lower middle income	2248	26	0,79	1,35	0,00	8,00
Upper middle income	2709	30	0,61	1,07	0,00	8,00
High income	4017	47	0,44	1,03	0,00	8,00
Death rates - Annual frequency						
Low Income	363	11	0,12	0,43	0,00	4,98
Lower middle income	992	27	0,29	0,81	0,00	8,07
Upper middle income	1218	35	0,26	0,87	0,00	8,54
High income	1989	48	0,12	0,59	0,00	8,88

Source: EM-DAT, Our World in Data, Own elaboration. N: number of countries. S.D.: Standard deviation. We follow the income classification of the IMF.

Table 13: *Descriptive statistics of natural disaster by Region*

Variables	Obs	N	Mean	S.D.	Minimum	Maximum
Number of natural disasters - Quarterly frequency						
East Asia & Pacific	1273	14	1,10	1,63	0,00	8,00
Europe & Central Asia	3353	43	0,32	0,66	0,00	8,00
Latin America & Caribbean	1952	19	0,50	0,85	0,00	6,00
Middle East & North Africa	854	9	0,28	0,66	0,00	5,00
North America	212	2	2,44	2,55	0,00	8,00
South Asia	330	4	1,85	1,90	0,00	8,00
Sub-Saharan Africa	1780	22	0,39	0,71	0,00	5,00
Death rates - Annual frequency						
East Asia & Pacific	363	11	0,12	0,43	0,00	4,98
Europe & Central Asia	992	27	0,29	0,81	0,00	8,07
Latin America & Caribbean	1218	35	0,26	0,87	0,00	8,54
Middle East & North Africa	1989	48	0,12	0,59	0,00	8,88
North America	96	2	0,08	0,11	0,00	0,66
South Asia	179	5	0,60	0,95	0,00	5,20
Sub-Saharan Africa	919	23	0,08	0,34	0,00	6,53

Source: EM-DAT, Our World in Data, Own elaboration. N: number of countries. S.D.: Standard deviation. We follow the region classification of the IMF.

B Additional Regressions

Table 14: *Regression Results - Deaths to labor force ratio*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
π_{it-1}							0.520***	0.592***
							(0.0139)	(0.0187)
DTP_{it}	2,442***	2,122***	486.3	-4,771***	-4,524***	-3,415***	-20.30	1,895***
	(486.5)	(481.4)	(415.4)	(540.0)	(534.6)	(477.2)	(248.9)	(320.9)
π_{it-1} DTP_{it}				1,136***	1,071***	645.6***		-107.3***
				(52.34)	(52.25)	(45.78)		(29.72)
Observations	1,538	1,535	1,538	1,538	1,535	1,538	1,538	1,538
F test (ρ-value)	5.79e-07	0.00368	1.12e-05	0	0	0	0	0
N	90	90	90	90	90	90	90	90
Country FE	No	No	Yes	No	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	Yes	Yes

Table reports regression results using the ratio of number of deaths to number of labor force (in thousands) (DTP_{it}) as our endogenous variable. It uses information at annual frequency for the 1970-2019 period. π_{it}: annual inflation. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method for columns 1-6: OLS. Estimation method for columns 7-8: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991).

Table 15: *Regression Results by type of natural disaster*

	Drought	Earthquake	Volcanic act.	Floods	Storms	Landslide	Ext. temp.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
π_{it-1}	0.142***	0.138***	0.137***	0.137***	0.142***	0.133***	0.140***
	(0.00876)	(0.00871)	(0.00876)	(0.00872)	(0.00874)	(0.00873)	(0.00880)
DR_{it}	-128.2***	1.341	86.39***	0.0318	4.046***	-7.850***	-1.440
	(13.10)	(0.840)	(21.82)	(0.700)	(0.550)	(1.761)	(1.003)
Observations	4,650	4,633	4,648	4,649	4,643	4,647	4,639
N	122	122	122	122	122	122	122
F test (ρ-value)	0	0	0	0	0	0	0

Table reports regression results using the death rates by each natural disaster type (DR_{it}) as our exogenous variable. It uses annual information for the 1970-2019 period. π_{it}: the annual inflation is our endogenous variable. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). All regressions include both country and time fixed effects.

Table 16: *Regression Results for all and by type of natural disaster*

	All	Drought	Earthquake	Volcanic act.	Floods	Storms	Landslide	Ext. temp.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$RGDPG_{it-1}$	0.242***	0.261***	0.251***	0.258***	0.252***	0.247***	0.250***	0.251***
	(0.0177)	(0.0181)	(0.0179)	(0.0180)	(0.0177)	(0.0177)	(0.0178)	(0.0179)
DR_{it}	-2.338***	311.7***	-0.0777	-5.187***	0.720	-1.456***	19.99***	-0.00873
	(0.155)	(48.46)	(0.561)	(0.992)	(0.482)	(0.0986)	(2.068)	(0.507)
Observations	1,607	1,621	1,620	1,621	1,621	1,620	1,621	1,610
N	86	86	86	86	86	86	86	86
F test (ρ-value)	0	0	0	0	0	0	0	0

Table reports regression results using the death rates for all and by each natural disaster type (DR_{it}) as our exogenous variable. It uses annual information for the 1970-2019 period. $RGDPG_{it}$: the annual real GDP growth is our endogenous variable. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). All regressions include both country and time fixed effects.

Table 17: *Regression Results: By country income level*

	LMI	UMI	HI
	(1)	(2)	(3)
$RGDPG_{it-1}$	0.499***	0.861***	0.949***
	(0.0203)	(0.0121)	(0.00728)
$NNAT_{it}$	-0.0194	0.00772	-0.0523
	(0.0360)	(0.0474)	(0.0359)
MPS_{it}	-0.302	1.058	0.408
	(0.617)	(0.925)	(0.308)
Observations	394	1,423	3,070
N	10	24	42
F test (ρ-value)	0	0	0

Table reports regression results by country income level at quarterly frequency the 1970:Q1-2019:Q4 period. $NNAT_{it}$: number of natural disasters. MPS_{it}: monetary policy shock. LI: Low Income (no shown since there are zero observations); LMI: Lower Middle Income; UMI: Upper Middle Income; HI: High Income. Standard errors are in parentheses. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). All regressions include both country and time fixed effects. Results for LI countries are not reported since N=1.

Table 18: *Regression Results: By geographical regions*

	EAP (1)	ECA (2)	LAC (3)	MENA (4)	SSA (5)
$RGDPG_{it-1}$	0.907***	0.875***	0.672***	0.912***	0.854***
	(0.0129)	(0.00721)	(0.0164)	(0.0182)	(0.0434)
$NNAT_{it}$	-0.00340	0.137**	-0.233***	-0.309**	-0.111
	(0.0200)	(0.0535)	(0.0514)	(0.130)	(0.115)
MPS_{it}	0.323	0.619	1.190*	-0.0750	-0.721
	(0.531)	(0.390)	(0.664)	(0.496)	(0.765)
Observations	729	2,690	876	287	222
N	10	38	15	5	6
F test (ρ-value)	0	0	0	0	0

Table reports regression results by region at quarterly frequency the 1970:Q1-2019:Q4 period. $NNAT_{it}$: number of natural disasters. MPS_{it}: monetary policy shock. EAP: East Asia & Pacific; ECA: Europe & Central Asia; LAC: Latin America & Caribbean; MENA: Middle East & North Africa; NA: North America; SA: South Asia; SSA: Sub-Saharan Africa. Standard errors in parentheses. N: number of countries. *** Statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%. Estimation method: Generalized Method of Moments (GMM) estimator of Arellano and Bond (1991). All regressions include both country and time fixed effects. Results for NA & SA countries are not reported since N=1 and N=2, respectively.