How Persistent are Climate-Related Price Shocks?

Implications for Monetary Policy

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How Persistent are Climate-Related Price Shocks? Implications for Monetary Policy

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ABSTRACT: Climate change is likely to lead to more frequent and more severe supply and demand shocks that will present a challenge to monetary policy formulation. The main objective of the paper is to investigate how climate shocks affect consumer prices in a broad range of countries over a long period using local projection methods. It finds that the impact of climate shocks on inflation depends on the type and intensity of shocks, country income level, and monetary policy regime. Specifically, droughts tend to have the highest overall positive impact on inflation, reflecting rising food prices. Interestingly, floods tend to have a dampening impact on inflation, pointing to the predominance of demand shocks in this case. Over the long run, the dominant monetary policy paradigm of flexible inflation targeting faced with supply-induced climate shocks may become increasingly ineffective, especially in LIDCs. More research is needed to find viable alternative monetary policy frameworks.

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1. Introduction

Climate change is likely to lead to more frequent and more severe supply and demand shocks that will present a challenge to monetary policy formulation. On the supply side, extreme weather events, such as droughts, will likely increase food price volatility. While shocks may be two-sided, adverse supply shocks, in particular, create difficult trade-offs for monetary policy since they may push prices up and output down (Klomp 2020). Moreover, frequent supply shocks will make it more difficult to disentangle permanent from transitory shocks, complicating the analysis of price and output data, and creating communication and credibility challenges (NGFS 2020).

Policy uncertainty about climate-related transition policies could affect demand, investment, and inflation expectations. More frequent shocks and higher uncertainty may also contribute to depressing potential output and to the lowering of the equilibrium real interest rate (Bylund and Jonsson 2020), further hampering the conduct of monetary policy. In this case, the failure of monetary policy authorities to account for these effects would result in a poor forecast of the output gap, which in turn will lead to a suboptimal policy outcome. Monetary policy transmission may also be affected by a rise in stranded assets in intermediaries' balance sheets and increased credit risks (NGFS 2020). Medium-term effects on inflation expectations due to a changing energy mix, increased costs of carbon pricing, and lower coal, gas, and oil prices are also possible, but hard to ascertain at this point (Coeuré 2018, Osterloh 2020).

The main objective of the paper is to investigate how climate shocks affect consumer prices in a broad range of countries. To this end, this paper takes a holistic approach to examine the impact of different types of natural disasters as well as temperature and precipitation shocks on headline and food inflation, covering a wide variety of countries of differing income status and monetary regimes at national and subnational levels.

Unlike most studies that look at point estimates, we are more interested in assessing the persistence (duration) of impact on overall consumer price index (CPI) and some of its components, drawing on Fratzscher and others (2020) and Parker (2018), and their implications for monetary policy. In addition to advanced economies (AEs) and emerging markets (EMs) included in Fratzscher and others (2020), this paper includes a large set of low-income and developing countries (LIDCs) which are disproportionally affected by natural disaster shocks due mainly to inadequacy of infrastructure.

A key tenet of modern monetary policymaking, especially under flexible inflation-targeting (FIT) regimes is to "look through" temporary supply shocks. FIT implies that monetary policy aims at stabilizing both inflation around the inflation target and real output around its normal level. However, this policy yields suboptimal outcomes when countries face persistent supply shocks which can de-anchor inflation expectations. Therefore, understanding the duration and intensity of climate shocks is particularly important for effective monetary policymaking.

To investigate the impact of climate shocks on inflation, this paper uses the local projection methods of Jordà (2005) and Jordà and others (2020). We draw on two sets of climate shock data—natural disasters and deviations of certain climate indicators from their long-run average. The natural disaster dataset comprises of the EM-DAT database obtained from the Centre of Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain, while temperature and precipitation are from the Climate Research Unit of the University of East Anglia (CRU TS v. 4.03). This is the first analysis to exploit the two datasets comprising

of natural disaster events and climate change covering a representative set of countries. Our sample includes up to 183 countries over the period 1970-2018 on a quarterly basis.[1]

The main findings of the paper are the following. First, we confirm the well-documented evidence that the frequency and intensity of climate shocks have increased over time, but with some additional insights. This is particularly driven by storms and floods, which became far more prevalent than other climate shocks. There is also clear evidence of global warming, although we do not find much evidence of increased precipitation. In general, the increased frequency of natural disasters is far higher in developing countries than in advanced and emerging market economies. Second, we find that the impact of climate shocks on inflation depends on the type and intensity of shocks, country income level, and monetary policy regime. To be more specific, we find that droughts tend to have the highest overall positive impact on inflation, which becomes acute with severe droughts, mainly driven by supply shocks. The effects are more pronounced in terms of food inflation. Since food typically represents around 40 percent of the CPI basket in LIDCs, the impact on headline inflation is also high. Interestingly, floods tend to have a dampening impact on inflation, pointing to the preeminence of demand shocks (Cantelmo 2022). Third, we find that the monetary policy regime does affect the impact of climate shocks in line with Fratzscher and others (2020). In general, in IT countries climate shocks tend to have lower and less persistent impact on inflation. Our results are generally confirmed, with some nuances, if we look at less extreme cases of climate shocks—long-run deviations of climate indicators.

The heterogeneous results based on different types and intensity disasters indicate that impact of climate shocks on inflation has not been linear, particularly for LIDCs. So, what does this imply for monetary policymaking going forward? This finding suggests that monetary policymaking in LIDCs is challenging—apart from other well-known structural issues[2]—given that monetary authorities have to contend with shocks that may induce more significant and prolonged effects on inflation and output. In this context, "looking through" the shocks may not be a viable option. Consequently, they may have to act decisively, especially to avoid second-round effects.

Going forward, it is likely that all groups of countries will face increasing climate shocks, although the exact path—but not the direction—is highly uncertain. What this implies for monetary policy frameworks is not yet a settled debate. On the one hand, as argued by McKibbin and others (2020), FIT may not be up to the challenge. In their view, given that in reaction to climate change policymakers are taking actions that affect both supply and demand, e.g., carbon taxes, central banks should anticipate and respond to inflation increases and output declines, quite a challenging feat for the current generation of policy rules and models. They contend that nominal income targeting is an attractive policy rule especially because it does not require the central bank to understand the precise nature of the climate (policy) shock. An alternative view is held by Cantelmo and others (2022). They argue that, based on the simulation of a small open-economy new Keynesian model with disaster shocks, FIT is still a superior choice to alternatives (including nominal income targeting) as it is welfare maximizing in the presence of demand and supply shocks.

The remainder of the paper is organized as follows. The next section gives a brief overview of related literature. Section 3 discusses the data and transformations. In addition, it presents some stylized facts based on descriptive statistics of natural disasters, temperature, precipitation, and inflation dynamics. Section 4 outlines

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[1] Similar analysis by Fratzscher and others (2020) includes 76 countries, mostly AEs and EMs.
[2] See, for instance. Mishra and others (2012).

the local projection model and presents the empirical results. Section 5 concludes with some policy implications.

2. Related Literature

The study of the impact of climate change on monetary policy is relatively recent. Most of the economic literature on the impact of climate change has focused on growth (e.g., Dell, Jones, and Olken, 2012, 2014; Burke, Solomon, and Miguel, 2015; Carleton and Solomon, 2016; Loayza and others, 2012). More recent papers examine the price impact, which is particularly relevant for monetary policymaking. For instance, Cashin and others (2017) study the macroeconomic effects of a unique weather phenomenon—El Niño—whose frequency and impact has risen as a result of climate change. They employ a dynamic multi-country model to analyze the macroeconomic transmission of El Niño weather shocks on growth, inflation, and commodity prices.

The most important challenge of climate change to monetary policy is that it is likely to lead to more frequent and severe supply shocks. These in turn could induce higher and more volatile inflation as well as greater uncertainties about ensuing output gaps. A particularly challenging conundrum arises when an adverse weather event pushes prices up and output down. At the same time, as noted by NGFS (2021), more frequent supply shocks will make it more difficult to disentangle permanent from transitory shocks, thereby complicating the analysis of price and output data. In turn, this would create communication and credibility challenges for central banks. Similarly, a recent study covering 400 earthquakes for 85 countries over the period 1960 to 2015, concludes that the effects of natural disaster shocks are consistent with those of supply shocks (Klomp 2020). They lower output while at the same time generating upward pressure on inflation.

There are relatively fewer papers that have studied the impact of climate shocks on prices, and even fewer on what it means for monetary policy.[3] Perhaps one of the most comprehensive treatments of the issue is by Fratzscher and others (2020), even if their focus is not on climate, but the shock-absorbing powers of IT as a monetary framework in AEs and EMs. To overcome endogeneity issues, they use natural disasters as exogenous shocks. They find that IT improved overall economic outcomes by lowering inflation and its volatility, and raising output growth. Parker (2018) probably has the most comprehensive treatment of the impact of disasters on inflation covering over 220 countries and territories. Using a dynamic panel framework, he finds that there is relatively limited impact of disasters on consumer price inflation (and its components) in AEs, while for developing economies the impact is significant and can last several years.

The current generation of DSGE models used by central banks is not particularly well-adapted to deal with such climate-related shocks for several reasons, in part because the use of a representative firm or consumer may not be suitable for analyzing complex system-wide transitions (Batten and others, 2020). Indeed, in such a system the steady state itself is uncertain. Moreover, climate change renders past information progressively less useful, reducing its value for projecting future trajectories (Arndt and others, 2020). An early attempt to incorporate climate variables in a DSGE model to assess the appropriate monetary response in the aftermath of the Hurricane Katrina was estimated by Keen and Pakko (2011). The results suggest that contractionary monetary policy was needed to curb temporary inflationary pressure and output distortions associated with nominal rigidities.

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[3] Faccia, Parker, and Stracca (2021) is closely related to this paper, but it only covers 48 AEs and EMs.

There is no consensus on the appropriate monetary policy approach to deal with climate change, although some tools have been identified (Krogstrup and Oman, 2019). Some of the most vexing analytical issues pertain to how to modify current monetary frameworks to account for climate change. In terms of overall *policy strategy*, many central banks built their inflation credibility in a period of broadly benign macroeconomic conditions in the 1990s and early 2000s. The era of climate change may pose tougher challenges as they learn how to deal with such shifts, since rapid change could cause headaches, including for their core monetary policy models. Model-specific questions include how to model "green swan" events, i.e., unexpectedly rare climate events with far-reaching impacts; and how to incorporate tipping points in modeling, where the probability of catastrophic events suddenly rises.

On the operational front, central banks will have to decide how to account for climate-related risks in their collateral frameworks. Other issues relate to whether unconventional policy tools such as asset purchase programs can be structured to support climate-related financial objectives on everything from disclosure requirements to green lending. The NGFS (2021) proposes a menu of options to adjust operational functions of central banks in the areas of credit operations, collateral, and asset purchases, based of four guiding principles: (i) consequences for monetary policy effectiveness; (ii) contributions to mitigating climate change; (iii) effectiveness as risk protection measures; and (iv) operational feasibility.

A number of proposals have been made to "green" monetary policy. Schoenmaker (2019) is characteristic of this approach, and others include Coeuré (2018) and Papoutsi and others (2021). Schoenmaker (2019) proposes tilting the Eurosystem's asset and collateral framework toward low-carbon assets. He argues that although central banks have traditionally been in favor of market neutrality in their monetary operations, de facto the market is biased in favor of carbon-intensive companies. As a result, monetary policy is not carbon neutral. To avoid market disruptions, he proposes a slow tilting toward greener assets and expanding the range of eligible assets. He shows that such a modest tilting could reduce carbon emissions in the ECB's corporate bond portfolio by about 40 percent, although in terms of overall impact for the euro zone is likely to be very small. Similar results are obtained by Papoutsi and others (2021) who demonstrate that asset purchase with carbon tax would reduce financial frictions.

McKibbin and others (2020) offer perhaps the most comprehensive view of the major issues involved in modifying monetary policy to take into account climate change. They argue that IT as currently practiced would be an inferior framework in the face of climate change shocks. This is because in a typical IT framework central banks have to respond flexibly to the deviations of inflation from target and output from potential. Consequently, central banks must anticipate how the economy will adjust over future periods to change of policy today. Current DGSE models used by central banks face some challenges of analyzing climate shocks and their complex interactions with monetary policy because they are often not detailed enough. They lack, for instance, sectoral disaggregation of climate shock impacts and how different assets and relative prices are affected. They argue that in the face of high degrees of uncertainty, nominal income targeting is a superior choice to IT. This is because it avoids creating expectations of higher future inflation in the face of shocks and does not require the central bank to understand the precise nature of the climate shock, and unobservable variables, e.g., the output gap.

Most DSGE models with climate-related shocks are based on the model proposed by Barro (2006) who estimates disaster shocks as risks with substantial negative effects on output.[4] More recent work by Cantelmo and others (2022) has contested the views of McKibbin and others (2020). They try to overcome the lack of consensus in the literature by developing a small open-economy New Keynesian model with natural disaster shocks to evaluate welfare under different monetary policy regimes. They do this by extending standard models in several dimensions, including by (i) allowing the effects of disasters in productivity to have permanent and temporary components; and (ii) considering Taylor-type interest rate rules, appropriately modified (including by introducing exchange rates). Their simulations, with particular focus on emerging market and developing economies (EMDEs), show that it is optimal for the central bank to focus primarily on inflation stabilization by allowing departures from the inflation target in the aftermath of shocks. In particular, FIT has the best performance in terms of lower inflation variability and lower consumption-equivalent welfare loss. They argue that nominal income targeting is still an inferior option because it does not sufficiently account for exchange rate dynamics. Accounting for the latter would entail large shifts in the exchange rate and hence in inflation.

Most of the work on climate change and monetary policy has focused on AEs. A notable exception is Arndt and others (2020) which assesses the implications of climate change for central banks in EMDEs. They note that given structural characteristics of EMDEs such as greater vulnerability to climate shocks, lower fiscal space, less well-anchored inflation expectations and lower monetary policy credibility, their central banks will have bigger challenges in confronting climate change. They argue that in general low and stable inflation has many advantages including clear nominal anchors, lower inflation premia and better access to international capital markets. In their view, introducing innovations such as "green QE" proposed in AEs has the potential to destabilize economies and test the independence of central banks. This paper bridges the existing gap in the literature by including, in addition to AEs and EMs, a large panel of LIDCs.

3. Data and Stylized Facts

3.1 Data Sources and Transformations

The study uses two datasets to capture climate shocks. The first dataset is based on information recorded on natural disasters events and the second dataset comprises of information on historical changes in temperature and precipitation.

Disasters

We use the EM-DAT database obtained from the Centre of Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain. The database identifies disasters as events where 10 or more deaths are recorded, 100 or more people are affected, resulting in a call for state of emergency and need for international assistance. The database covers a large number of disasters going as far back as the 1900s in all five continents.

Disasters are classified into two broad categories, natural and technical disasters. Natural disasters are caused by nature and include droughts, earthquakes, floods, and storms, wildfires, whereas technical disasters, such

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[4] Similar models are used by Gabaix (2012), Gourio (2012), Isoré and Szczerbowicz (2017), Fernández-Villaverde and Levintal (2018).

as industrial and transport accidents, are triggered by humans.[5] Our analysis focuses on climate-related natural disasters with effects on headline inflation, particularly droughts, floods, and storms. The dataset reports, for each event, the number of fatalities, which includes people who are confirmed dead, missing, and presumed dead. For a subset of events, it also includes the number of injured, people seeking assistance, and those who are affected.

Natural disasters differ in their intensity, which might have a nonlinear impact on inflation. In this paper, we consider all natural disasters in the baseline, and then explore moderate and severe disasters using a measure of disaster intensity proposed by the IMF (2003) and Becker and Mauro (2006), expressed as follows:

$$intensity_{i,t'}^k \begin{cases} = 1, \; if \; \frac{fatalities_{i,t}^k + 0.3 \times affected_{i,t}^k}{population} > \bar{a} \\ = 0, \; otherwise \end{cases} \tag{1}$$

where $k = 1, 2, 3$ is the type of disaster, i represents the country, and the event occurs at time t'. This dummy variable takes the value 1 when the sum of the number of fatalities and 30 percent of the number of affected people is greater than the threshold $\bar{a}$ and 0 otherwise. We refer to the cases with value 1 as moderate or severe disasters. For moderate natural disasters, we choose $\bar{a} = 0.0001$, or 0.01 percent of the population, as in Fomby, Ikeda, and Loayza (2013). For severe natural disasters, $\bar{a} = 0.01$ or one percent of the population, as in Becker and Mauro (2006).

Natural disaster shocks at the quarterly frequency, denoted as $D_{i,t}^k$ of type k for country i in quarter t, are defined as follows:

$$D_{i,t}^k = \sum_{t' \in t} intensity_{i,t'}^k. \tag{2}$$

In other words, a natural disaster shock of type k in in quarter t is the total number of disasters of type k that occur within quarter t. Similarly, a moderate (severe) natural disaster shock is the total number of moderate (severe) disasters in that quarter. Note that this measure of natural disaster shocks is a combination of frequency and intensity.

Temperature and precipitation shocks

We also use high-resolution gridded datasets of monthly temperature and precipitation from the Climate Research Unit of the University of East Anglia (CRU TS v. 4.03). To obtain a country's quarterly temperature, we first calculate the area-weighted average of monthly temperature over all grids within each country, which yields country-level monthly temperature series. We then use the average of the monthly series within each quarter as the quarterly temperature. A similar computation is used to arrive at precipitation for each country at quarterly frequency. To get an idea of how climate change is impacting certain climate indicators, we compute climate shocks as deviations over long-term averages. Specifically, we construct country-specific z-score as

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[5] In the long term, human actions could be also responsible for the increased frequency and intensity of natural disasters. As the analysis in this paper focuses on the near- and medium-term impact of natural disasters on inflation, we abstract away from this channel. The classification in this paper follows closely the one that is usually used in literature, i.e,. the classification proposed by CRED.

deviations from the country's past averages. Let $T_{i,t}$ be the temperature for country i in quarter t; $T_{i,t}^{avg}$ the same quarter average temperature in the past 30 years preceding quarter t (Kahn and others, 2021; Vose and others, 2014; and Arguez and others, 2012); $\sigma_{i,t}^{T}$ the standard error of the same quarter temperature in the past 30 years preceding quarter t. The z-score is the temperature deviation from its long-run average scaled by its volatility. The z-score for country i in quarter t is expressed as follows:

$$T_{i,t}^{z} = \frac{T_{i,t} - T_{i,t}^{avg}}{\sigma_{i,t}^{T}}. \tag{3}$$

Precipitation z-scores are defined similarly. Z-scores are used as weather shocks in this paper. Given the difference in specification of natural disaster events (equation (1)) and precipitation z-scores (equation 3), we conduct the analysis separately.

The analysis uses monthly consumer price indices (CPI) for 183 countries over the period 1970 to 2018, obtained from the International Monetary Fund's (IMF) *International Financial Statistics* (IFS). From monthly CPI, we construct their quarterly counterparts with monthly averages and then calculate year-on-year inflation accordingly for each country. To ensure that each country has enough observations so that the dynamic impact of climate shocks can be estimated relatively accurately, we consider only countries with at least 10 years of observations. Incidences of hyperinflation experienced by some countries during the period covered are accounted for by restricting the inflation data within the range ±20 percent. Inflation data are then merged with climate information obtained from the EM-DAT and CRU-TS databases, into two sets of quarterly frequency data covering the period 1970-2018.

Country and monetary regime classifications

To capture heterogenous effects by country development countries are grouped following the classification proposed by *World Economic Outlook* of the IMF into: advanced economies (AE), emerging markets (EM), as well as low income and developing countries (LIDC). The effect of monetary policy is accounted for by dividing our sample into inflation-targeting (IT) and non-inflation-targeting (non-IT) countries using the information from Fratzscher and others (2020). The sample includes 33 AEs, 76 EMs, and 53 LIDCs for country classification, and monetary policy categories, 28 IT and 73 non-IT. The analysis of the effects of monetary policy is conducted on post-1990 data only as the IT regime was first adopted in New Zealand in 1990.

3.2 Stylized Facts

Figure 1 presents the frequency of natural disasters recorded in the EM-DAT database. The left graph splits the sample in two periods, which shows a sizable increase in the occurrences of almost all types of natural disasters from 1970-1995 to 1996-2018. For example, flood events averaged less than 50 each year between 1970-1995, but they more than tripled between 1996-2018.[6] The right graph shows a steady increase in the occurrence of climate-related natural disasters over the past five decades. Floods are by far the most common type of natural disaster with about 150 events every year on average in the past two decades, followed by

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[6] This increasing pattern could be partly driven by improved recording of events rather than by an increase in the frequency of occurrence (Cavallo and Noy, 2011), but this effect is relatively minor.

storms with about 100 occurrences. Droughts occur less frequently than floods and storms, ranked 7th between 1996 and 2018, but their frequency has been on a steady rise as well.

In addition, Figure 2 shows that the average number of natural disasters has increased over time across AEs, EMs, and LIDCs. The largest increase is registered for LIDCs, where natural disasters occurred once every two years between 1970-1995 and increased to twice every year between 1996-2018. In the most recent two decades, AEs, EMs, and LIDCs had a similar number of natural disasters, with an average of two events per year.

Table 1 presents the frequency of natural disasters by intensity, type, and the number of affected countries. Overall, about 31.9 percent of country-quarter observations are associated with at least one natural disaster. Considering each disaster, it is unsurprising that the statistics are consistent with the information depicted in Figure 1, with floods registering the highest portion of at least one event occurring (9 percent), followed by storms (5.2 percent), and droughts are last (1.6 percent). Some countries have experienced more than one flood or storm in a quarter. More intense disasters occur less frequently. For example, it is rare to observe a drought of moderate intensity (0.1 percent). And almost no countries experienced two severe floods in one quarter in the sample.

The most relevant type of natural disasters differs according to the development status of a country. While a larger fraction of AEs are affected by storms than EMs and LIDCs, a larger fraction of EMs and LIDCs are affected by droughts and floods than AEs. Notably, almost all LIDCs (53 out of 54 in the sample) have been affected by floods. As the intensity of natural disasters increases, the number of affected countries in the sample declines. It is worth noting that none of the AEs in the sample are affected by moderate or severe drought based on the definition in equations (1) and (3).

Table 2 presents summary statistics of the second set of data containing inflation, temperature, and precipitation by countries of different income status as well as monetary policy regimes. The results indicate that inflation across countries and over time has been 5.7 percent on average. However, the average masks interesting heterogeneity documented in the literature pointing to low inflation in AEs compared with EMs and LIDCs, and higher in LIDCs relative to EMs.[7] The classification based on monetary policy regime supports the finding in the literature that IT countries have on average lower inflation (3.3 percent) than non-IT countries (6.4 percent). This pattern is robust over different percentiles.

Positive z-scores for temperature for all types of countries support evidence of global warming. Specifically, the temperature in each quarter tends to be higher than the past 30-year average. Temperature z-scores are more elevated in EMs compared with AEs, and similar in LIDCs to EMs. Specifically, on average, temperature z-scores in EMs and LIDCs are more than 50 percent higher than that of AEs.

The difference across countries is more visible with the kernel density estimates of z-scores (Figure 3). The distribution of temperature z-scores has slightly thinner tails for LIDCs than for AEs and EMs. The results likely reflect geographical characteristics of countries. Most AEs and EMs are located outside of tropical regions, while LIDCs are located inside. Tropical areas tend to have more stable temperatures and thus the distribution of temperature z-scores is more concentrated at zero for LIDCs. In contrast to country differences, temperature

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[7] See Ha, Kose, and Ohnsorge (2019) and references therein on the difference in inflation dynamics across countries and monetary policy regimes.

distribution is indistinguishable across monetary policy regimes, i.e., the distribution of IT and non-IT overlaps. This is due to the fact that IT and non-IT countries are spread throughout the world, which implies that geographical location is weakly correlated with monetary policy regime.

The average precipitation z-scores are close to zero, implying that the average amount of precipitation has not changed much relative to the historical patterns. However, precipitation z-scores are skewed to the right, indicating more likelihood of positive precipitation shocks than negative ones. On average precipitation z-scores are higher for AEs than EMs and LIDCs. The distribution of precipitation z-scores shows that AEs tend to experience larger deviations from historical averages. Likewise, precipitation z-scores are the same for IT and non-IT. Here too, Igeographical ocation does not seem to play a role.
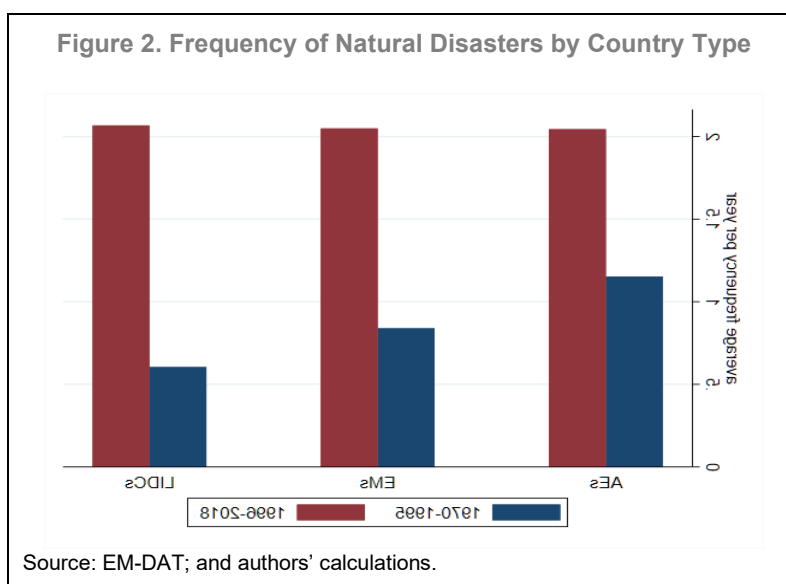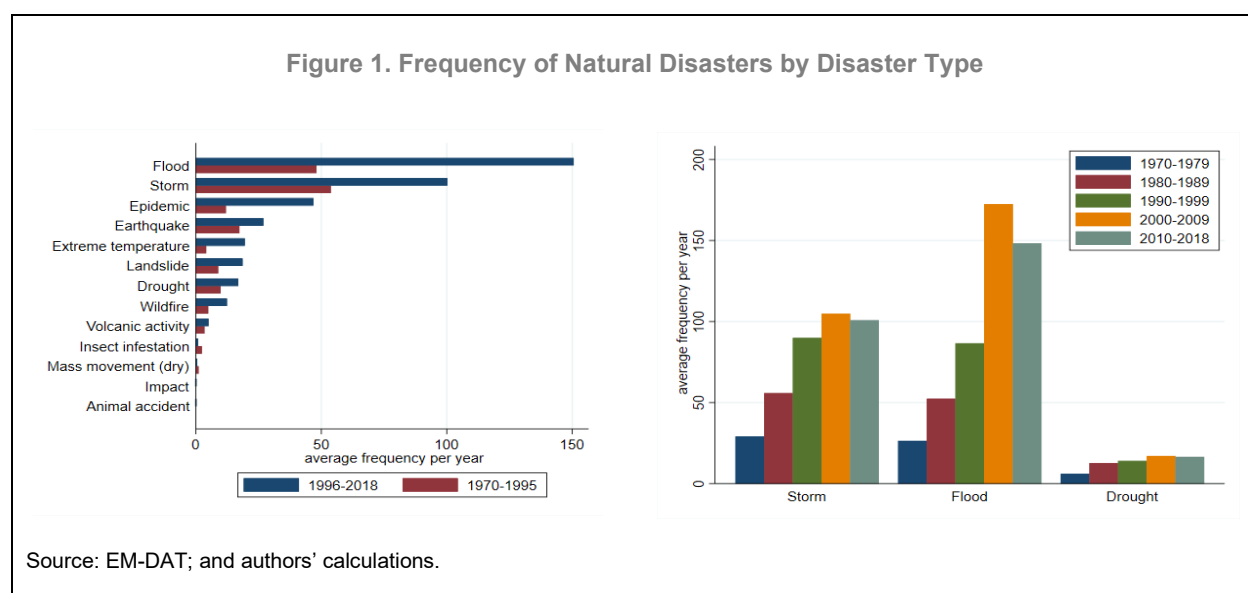

Figure 1. Frequency of Natural Disasters by Disaster Type

Source: EM-DAT; and authors' calculations.

Figure 2. Frequency of Natural Disasters by Country Type

Source: EM-DAT; and authors' calculations.

Table 1. Frequency Distributions of Natural Disaster by Type in Percentage of Total Observations

Frequency of Natural Disasters in Percent of Total Observations

All natural disasters

No. of events in a quarter	All	Droughts	Floods	Storms
	in percent of total			
0	68.1	98.4	88.6	92.6
1	18.1	1.6	9.0	5.2
2	6.4	0.0	1.7	1.1
3-5	5.3	0.0	0.7	0.9
>5	2.1	0.0	0.1	0.2
Total	100	100	100	100

Moderate natural disasters

No. of events in a quarter	All	Droughts	Floods	Storms
	in percent of total			
0	92.1	99.9	95.7	97.9
1	6.7	0.1	3.9	1.7
2	0.8	0.0	0.4	0.3
3-5	0.3	0.0	0.1	0.1
>5	0.0	0.0	0.0	0.0
Total	100	100	100	100

Severe natural disasters

No. of events in a quarter	All	Droughts	Floods	Storms
	in percent of total			
0	99.0	99.9	99.6	99.6
1	1.0	0.1	0.4	0.4
2	0.0	0.0	0.0	0.0
3-5	0.0	0.0	0.0	0.0
>5	0.0	0.0	0.0	0.0
Total	100	100	100	100

Number of Countries in the Sample and Affected by Natural Disasters

|	AEs	EMs	LIDCs
Total	37	92	54
Affected by drought	17	54	41
by moderate drought	0	7	9
by severe drought	0	3	7
Affected by flood	29	81	53
by moderate flood	22	63	53
by severe severe	3	27	17
Affected by strom	33	70	43
by moderate storm	17	47	26
by severe storm	5	23	10

Source: EM-DAT; and authors' calculations.

Table 2. Summary Statistics of Inflation, Temperature and Precipitation (1970-2018)

	Mean	p10	p25	p50	p75	p90
Total						
inflation	5.7	0.5	2.1	4.6	8.7	13.0
temperature z-score	0.5	-0.8	-0.1	0.5	1.2	1.9
precipitation z-score	0.03	-1.2	-0.7	-0.06	0.6	1.4
AEs						
inflation	4.5	0.5	1.6	3.0	6.3	10.6
temperature z-score	0.4	-1.0	-0.3	0.4	1.2	1.8
precipitation z-score	0.04	-1.2	-0.7	-0.03	0.7	1.4
EMs						
inflation	6.0	0.7	2.4	5.0	9.0	13.2
temperature z-score	0.6	-0.8	-0.09	0.6	1.3	1.9
precipitation z-score	0.04	-1.2	-0.7	-0.08	0.7	1.4
LIDCs						
inflation	6.3	-0.08	2.5	5.9	9.8	14.0
temperature z-score	0.6	-0.7	-0.06	0.6	1.2	1.9
precipitation z-score	-0.010	-1.2	-0.6	-0.04	0.5	1.2
Sub sample with information on IT/Non-IT (1990-2018)						
inflation	5.9	1.0	2.3	4.6	8.7	12.8
temperature z-score	0.5	-0.9	-0.2	0.5	1.3	1.9
precipitation z-score	0.04	-1.2	-0.7	-0.04	0.7	1.4
Non-Inflation Targeting						
inflation	6.4	1.1	2.6	5.3	9.3	13.5
temperature z-score	0.5	-1.0	-0.2	0.5	1.3	1.9
precipitation z-score	0.03	-1.2	-0.7	-0.05	0.7	1.4
Inflation Targeting						
inflation	3.3	0.7	1.6	2.8	4.4	6.7
temperature z-score	0.6	-0.7	-0.1	0.6	1.3	1.9
precipitation z-score	0.1	-1.1	-0.6	-0.04	0.8	1.6

Source: Authors' calculations.

Figure 3. Temperature and Precipitation z-Score Distribution

Source: Climate Research Unit, University of East Anglia; and authors' calculations.
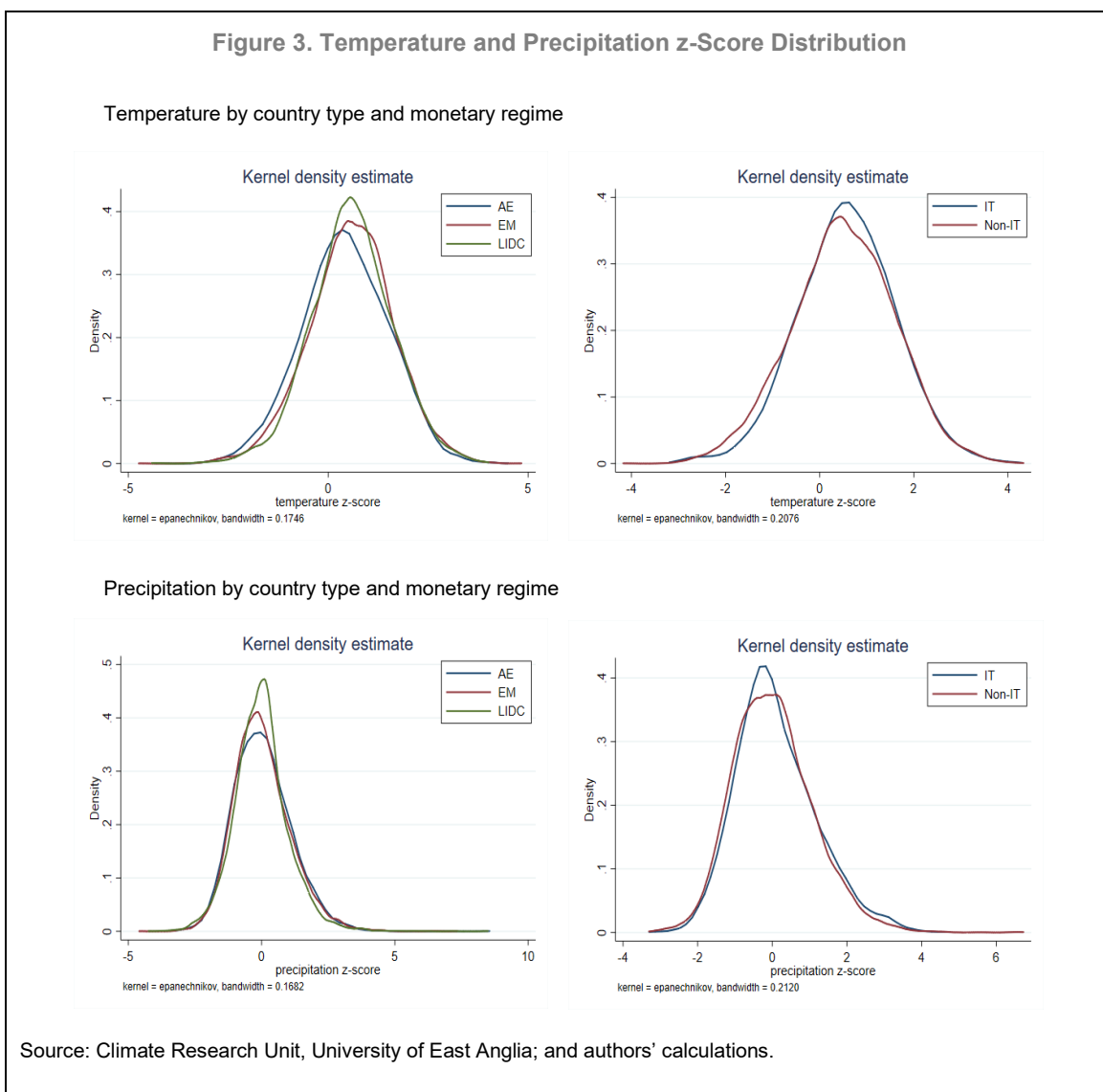
4. Empirical Strategy

4.1 Methodology

The main objective of our study is to assess the impact of climate shocks on inflation. The empirical approach uses the local projection (LP) method of Jordà (2005). The model is given by:

$$\pi_{i,t+h} = \alpha_{i,h} + \delta_{t,h} + \sum_{p=0}^{P} \beta_p^h D_{t-p} + \sum_{q=1}^{Q} \gamma_{q,h} \pi_{i,t-q} + \varepsilon_{i,t+h} \tag{3}$$

where $h = 0,1,2,\cdots$, is the horizon, $\alpha_{i,h}$ is country i fixed effects, $\delta_{t,h}$ is time fixed effects, and $\varepsilon_{i,t+h} \sim N(0, \sigma_\varepsilon^2)$ is an iid error term. The coefficient of interest β_0^h captures the dynamic multiplier effect (impulse response) of domestic inflation with respect to a climate shock at time t. The number of lags for natural disasters and inflation is denoted by p and q, respectively. We set $P = 1$ and $Q = 2$. In the baseline, we do not include other control variables because of limited data availability at quarterly frequency. In the appendix, we consider a set of controls, including the nighttime light-based measure of economic activity, exchange rate, and food weights in the consumption basket.

Impulse response functions (IRFs) are constructed separately using a sequence of estimates β_0^h for each horizon based on the least-squares technique. Heteroscedasticity and autocorrelation consistent (HAC) standard errors are used to correct for potential effects of heteroscedastic variances and autocorrelation in the error terms. In addition, Driscoll and Kraay (1998 henceforth DK) standard errors are used to address cross-sectional and serial correlation. Recently, Jordà, Singh, and Taylor (2020) have used a similar model in assessing the economic impact of pandemics over the long run.

There are several advantages of using the LP approach as highlighted by Jordà (2005). The increasing popularity of the LP method in empirical macroeconomic analysis is mainly due to its simplicity and flexibility. It yields outcomes that are similar to those of widely used structural vector autoregressive model (Montiel-Olea and Plagborg-Møller 2021; Plagborg-Møller and Wolf 2021). Jordà and Salyer 2003 demonstrate that LP estimation is robust to misspecification and nonlinearity, whereas a SVAR produces more efficient estimates. However, Plagborg-Møller and Wolf (2021) provide evidence that LP estimations can attain efficiency similar to that of the SVAR when the number of lags and observations are large enough. Finally, LP models are not subject to stringent identification schemes, such as the Cholesky zero restriction or similar restrictions used in SVARs.

To examine the impact of climate change on inflation, the paper focuses on natural disasters and climate shocks. Natural disasters, by their very nature, can be seen as extreme climate events. Climate shocks are comparatively more moderate as they do not necessarily lead to natural disasters, but they are all-encompassing since all countries in the world have experienced some deviations of temperature and precipitation from their historical averages. Note that the baseline model does not include control variables and lagged inflation. Overall, the results remain qualitatively unchanged when they are controlled for. Appendix A enriches the analysis by examining the effects of natural disasters at the subnational level beyond the national level analysis. Note that acute effects are often felt locally.

4.2 Impact of Natural Disasters on Inflation

Heterogeneity across different natural disasters

Figure 4 presents the heterogeneous response of inflation to droughts, floods, and storms with different intensity thresholds. Droughts tend to be inflationary, with more intense droughts exerting higher inflationary pressures in the short run. Upon impact of an average drought, inflation rises by 0.2 percentage point, exhibiting statistically significant response at the 95 percent level. The impact lingers at a similar level for the next four quarters but becomes statistically insignificant two quarters after the shock. By contrast, a moderate or severe drought raises inflation by 3 percentage points within four quarters. While the impact of a moderate drought peaks in the fourth quarter, that of a severe drought is more acute, peaking in the first quarter. Overall,

the impact of drought on inflation is temporary, lasting less than a year. These results are generally consistent with Parker (2018), except that he finds longer-lasting effects of droughts on inflation.

Surprisingly, floods exert a deflationary reaction, but the impact is statistically insignificant even at 68 percent level. The results are quite different with severe floods, which trigger a strong and statistically significant response (at 95 percent level), reaching 2 percentage points a year after shock. Using monthly data for a set of Caribbean islands, Heinen and others (2019) find that floods have only contemporaneous impact on consumer prices. Storms are initially inflationary, but the effects are short lived, significant for about two and three quarters for moderate and severe events, respectively. Subsequently, the response becomes negative and remained depressed for more than two years. Interestingly, both the magnitude and the duration of the impact as well as the significance level increase with the intensity of storms. The reaction of inflation to storms is consistent with Parker (2018) who finds evidence of short-term inflation impact for storms.

The differential impact of droughts, floods, and storms on inflation can be attributed to their differing impact on aggregate demand and aggregate supply. For example, if aggregate supply is reduced by more than aggregate demand, an inflationary impact can be expected. However, whether the change in aggregate supply dominates the change in aggregate demand is an empirical question. Unlike supply shocks, which cause considerable destruction of infrastructure, demand shocks operate through risk aversion by agents. The negative response of inflation to floods is consistent with the dominance of the demand shock over the supply shock as pointed out by Cantelmo (2022). The demand shock is induced by risk-aversion of agents following flood and storm shocks.[8] Risk-averse households and firms who have experienced floods, storms, and earthquakes tend to reduce consumption and investment even after fiscal support and reconstruction, which reduce output and dampen inflation. Figure 4 suggests that for floods, the subdued demand dominates the change in supply and the overall impact is deflationary empirically.

The role of food inflation is also important. With food taking up a large share of the consumption basket in EMs and LIDCs, the different impact on food inflation can dominate the impact on headline inflation. Appendix C provides some evidence that countries with a larger share of the consumption basket in food face higher inflationary pressures following droughts, floods, and storms. However, as shown in Appendix D, the production of major food items tends to increase following floods, which could lead to decreases in food prices. The lower food inflation following floods could therefore result in lower headline inflation in Figure 4.

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[8] Bourdeau-Brien and Kryzanowski (2020) provide evidence of a short-term jump in risk aversion for the US and by Burger (2009), Cameron and Shah (2015) and Cassar and others (2017) for EMDEs.

Figure 4. Response of Inflation to Natural Disaster Shock by Type and Intensity

All natural disasters

Moderate natural disasters

Severe natural disasters
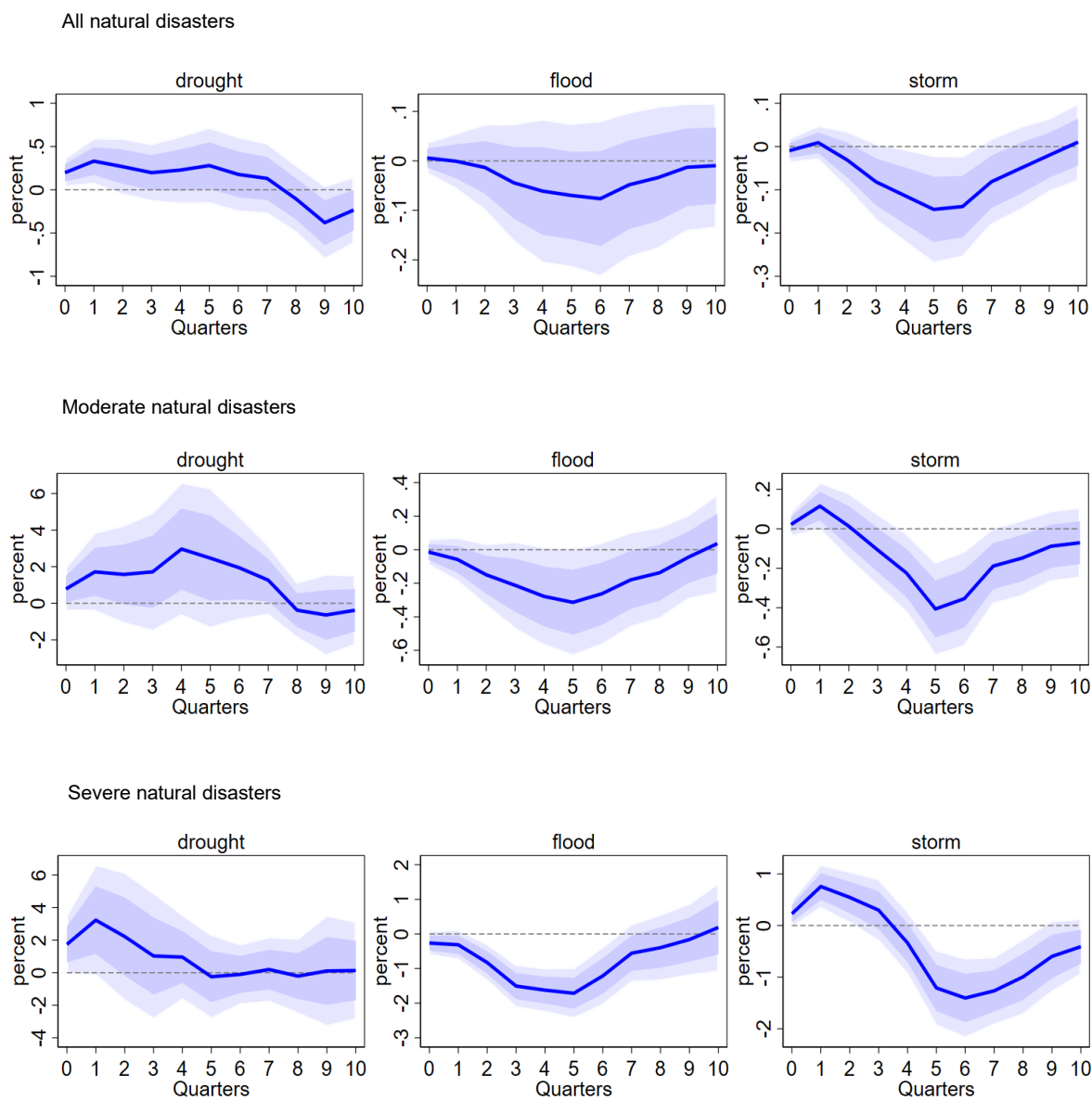
Source: EM-DAT, International Financial Statistics, and authors' calculations.

Finally, there is some evidence that temporal and spatial factors can influence the differential impact of floods and droughts (Baquie and Habtamu 2020). Floods generally tend to last for a short time and since they are mostly at the beginning or middle of the rainy season, farmers still harvest some replanted crops. On the the other hand, droughts tend to last longer. In terms of spatial coverage, floods usually cover a smaller land area (close to the major rivers or in lowlands) while droughts generally cover a larger area. Because of this the loss of crops tends to be more spatially concentrated for floods. Indeed, beyond the immediate flood zone, increased precipitation in the surrounding areas could lead to greater output and therefore induce a negative shock to inflation.

Heterogeneity across different country types

To highlight heterogeneity across countries, we assess separately the response of AEs, EMs, and LIDCs to droughts, floods, and storms with different intensities in Figure 5. Column (a) shows AEs IRFs for droughts, floods, and storms. They indicate that all these events are inflationary in AEs. The impact of drought is short-lived—inflation rises by 2 percentage points in the second quarter, stays elevated for about three quarters, and then declines. However, the estimates of the impact are not different from zero even at the 68 percent level. By contrast, upon the impact of a flood, inflation gradually increases by 0.2 percentage point within two years and is statistically significant at 68 percent level. Similarly, a storm raises inflation to above 0.2 percentage point within one year and its impact is statistically significant at the 95 percent level.

Columns (b) and (c) examine the impact of moderate and severe disasters on AEs. Moderate and severe drought are not represented due to limited observations reflecting relatively low frequency of these events. This implies that using equation (1) induces imperfect measurement of their impacts on affected population. The results for floods and storms show that more intense natural disasters might have different inflationary impact than less intense ones. Severe floods have a strong deflationary impact in the first six quarters, decreasing inflation to -5 percentage points within a year, then becomes inflationary and significant the next year. This is in stark contrast to the impact of moderate floods, whose impact remains inflationary. Unlike the average storm that triggers the inflationary effects, moderate and severe storms have a deflationary impact.

Figures 6 and 7 show that for EMs and LIDCs, respectively. Droughts tend to be inflationary, while floods and storms tend to be deflationary. As the intensity of natural disaster increases, the magnitude of its impact tends to be larger. For example, an average flood reduces inflation in EMs by less than 0.5 percentage point within a year, a moderate flood reduces it by 1 percentage point and a severe flood by almost 4 percentage points. The dynamics of the impact also depends on the intensity of natural disasters. For instance, an average drought is inflationary for EMs, but severe droughts could exert deflationary pressures after one year.

Figure 5. Response of Inflation to Droughts, Floods, and Storms in AEs

(a)   All natural disasters   (b) Moderate natural disasters   (c) Severe natural disasters
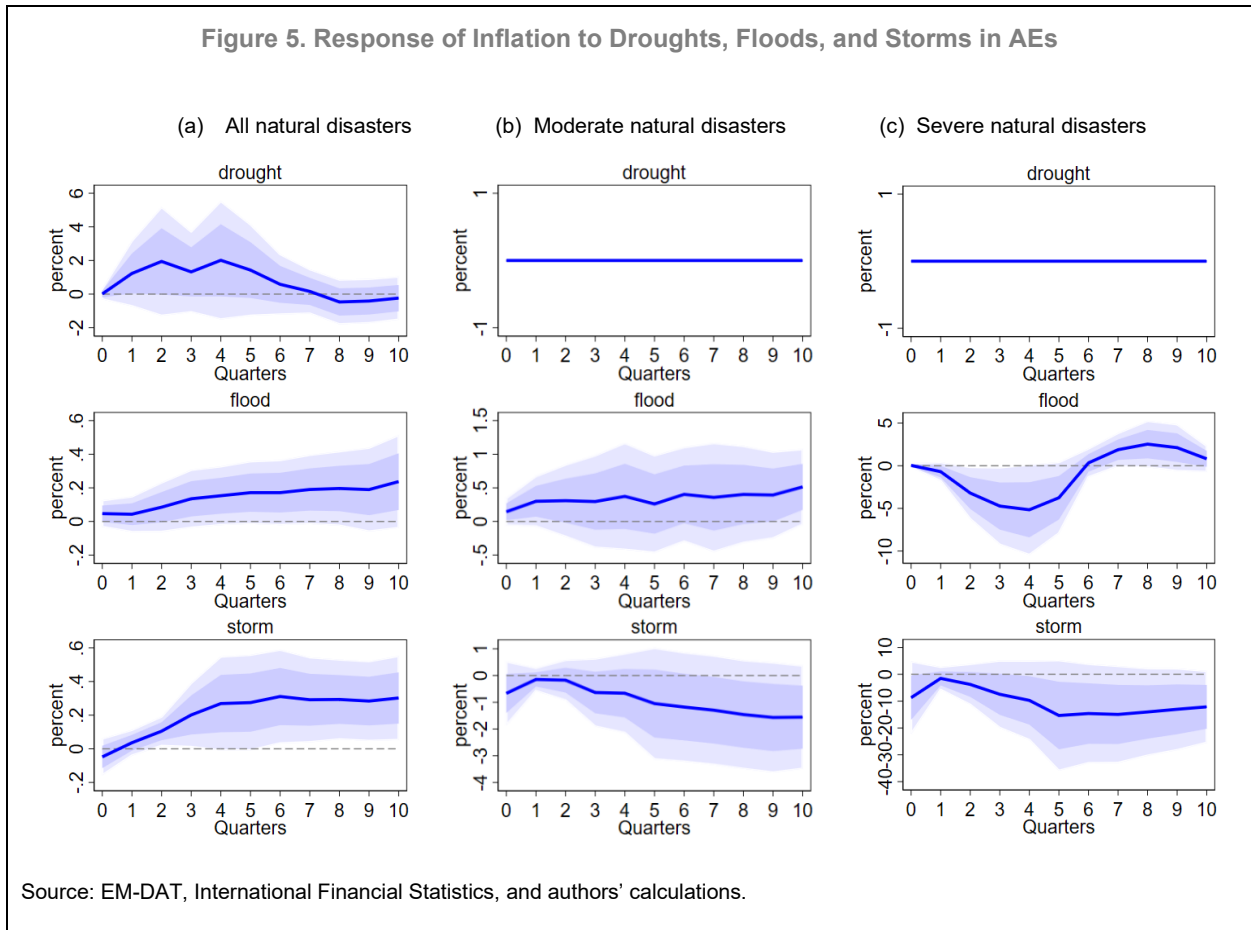
Source: EM-DAT, International Financial Statistics, and authors' calculations.

Figure 6. Response of Inflation to Droughts, Floods, and Storms in EMs

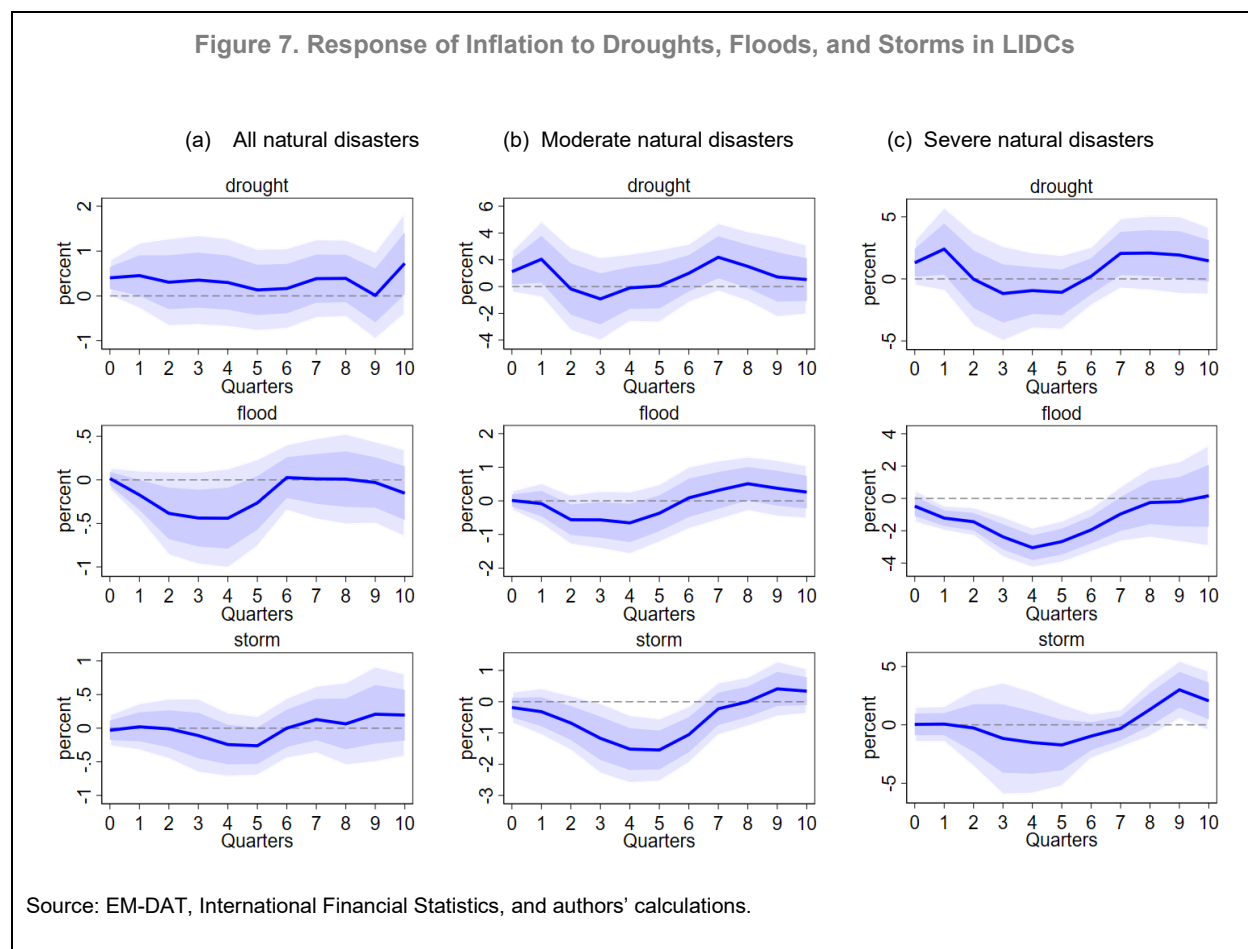(a) All natural disasters   (b) Moderate natural disasters   (c) Severe natural disasters

Source: EM-DAT, International Financial Statistics, and authors' calculations.

Figure 7. Response of Inflation to Droughts, Floods, and Storms in LIDCs
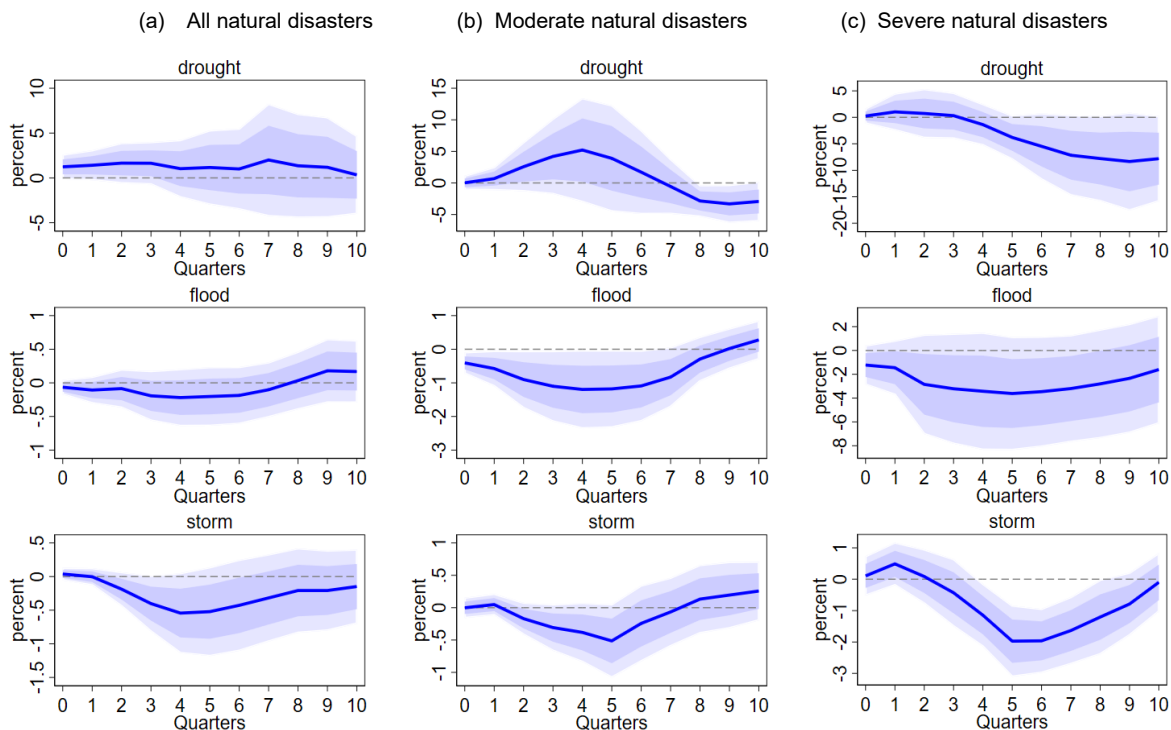
Source: EM-DAT, International Financial Statistics, and authors' calculations.

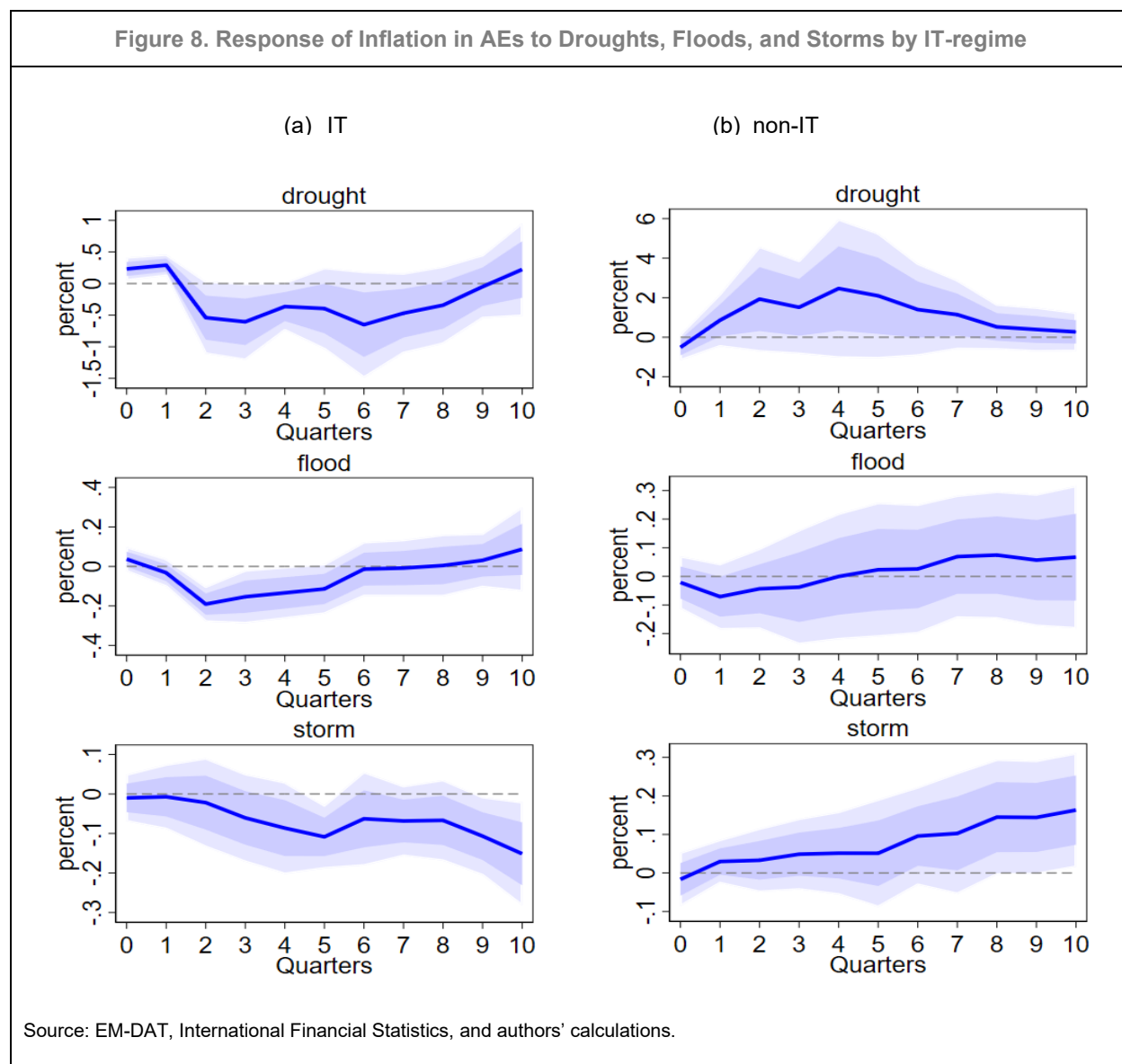### Heterogeneity across different monetary regimes

To account for the effect of monetary policy, we classify countries into 2 groups, namely: IT and non-IT. The results in Figures 8 and 9 provide some evidence that monetary policy contains inflationary pressures after natural disaster shocks in both AEs and EMs,[9] while it tends to accommodate the deflationary impact.
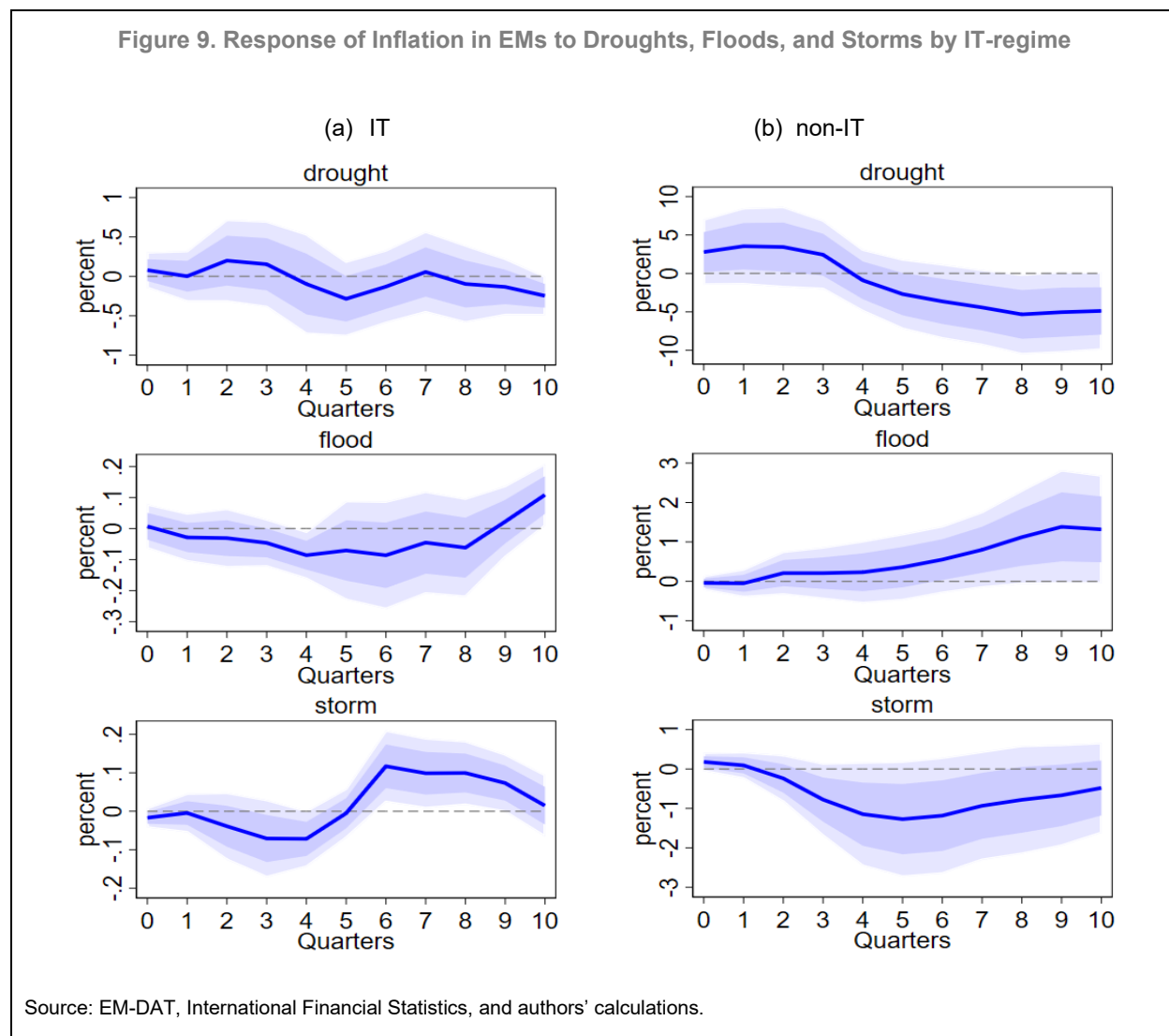
The left panel in Figures 8 and 9, presenting the results of IT countries, is in sharp contrast with those non-IT countries included in the right panel. Non-IT countries tend to have larger response of inflation to drought than IT countries. Figure 8 shows the initial inflation reaction of less than 0.5 percentage point for droughts in IT countries among AEs. In fact, the point estimates of the response are negative from the second quarter onward. The response in non-IT countries, however, is inflationary. Inflation rises and remains elevated at about 2 percentage points for about two years before decreasing to zero. Similarly, the impact of floods and storms in IT countries among AEs are slightly deflationary, while that for non-IT countries is inflationary. Such contrast highlights that monetary policy authorities have managed to contain inflationary pressures of natural disasters in IT countries.

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[9] Few LIDCs countries follow the IT framework with a flexible exchange rate regime.

The results for EMs (Figure 9) also suggest that IT countries are better insulated against the impact of natural disasters than non-IT countries. Specifically, inflation is anchored around zero in IT countries for droughts and floods. Storms' impact increases inflation in the second year remains by 0.1 percentage point, a marginal deviation from zero. For non-IT countries, the impact is quantitatively large: impact of drought generates inflationary pressure, with a 3 percentage points jump; inflation increases gradually after floods and reaches 1 percentage point in the second year, while it decreases with storms, down by 1 percentage point in the second year.

Appendix E provides additional evidence that countries with stronger monetary policy frameworks are better insulated against inflationary pressures following natural disasters.

Figure 8. Response of Inflation in AEs to Droughts, Floods, and Storms by IT-regime

Source: EM-DAT, International Financial Statistics, and authors' calculations.

Figure 9. Response of Inflation in EMs to Droughts, Floods, and Storms by IT-regime

Source: EM-DAT, International Financial Statistics, and authors' calculations.
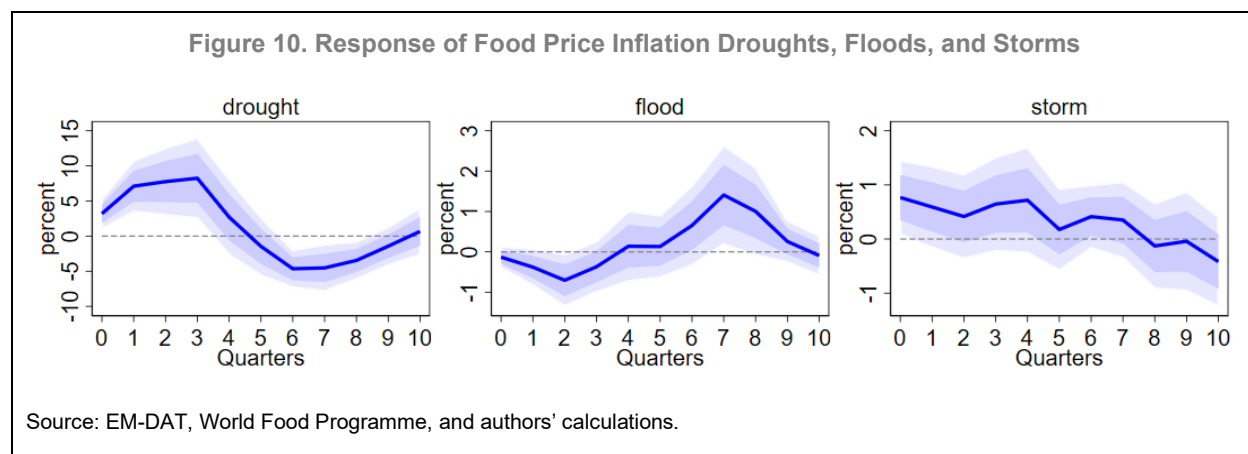
Food inflation

It is useful to dig deeper into the components of inflation induced by climate shocks. Arguably, climate shocks are more likely to exert stronger effects on agricultural products than on industrial products. At the same time, the weight of food products in the CPI is higher in LIDCs than in other countries. Thus, all things equal, climate shocks are likely to have a disproportionately higher impact on overall inflation in LIDCs. For example, Durevall, Leoning, and Birru (2013) and Kabundi (2012) provide evidence of the important role played by international food prices as a key driver of inflation dynamics in Ethiopia and Uganda, respectively. In particular, they highlight that inflation in these countries is elevated during drought periods.

Figure 10 shows that food inflation jumps sharply to over 5 percentage points upon the shock triggered by drought, then rises steadily, attaining the maximum of close to 10 percentage points in the third quarter after impact. Inflation stays elevated for the first year, then reverses into negative territory for about five quarters.

Such elevated inflation, though short-lived, is a big challenge to monetary policy implementation. The effect of floods is consistent with that observed for headline inflation, that is, mostly deflationary in the first year. Food prices rise with storms for four quarters. However, the effect is much smaller than in the case of droughts.[10] Appendix A provides a deeper analysis of natural disasters on food inflation and complements the main analysis. It does so by looking at natural disasters at the sub-national level and at different food products. This analysis has greater precision and provides interesting insights that may not be visible at the national level. For instance, droughts have a stronger impact on staples inflation in EMs than in LIDCs. Droughts show initial inflationary dynamics for some food items, such as staples, meat, and fish. However, initial deflationary responses are evident for other food items, such as eggs and milk.

Overall, the subnational analysis reveals a great deal of heterogeneity of the inflation response of individual food items to natural disasters. It shows that the inflation dynamics at the local level can be quite different from the pattern at the national level following natural disasters. At the local level, the extent and direction to which individual food items react to natural disasters also differ, depending on food categories, types of natural disasters and monetary policy regimes.

Figure 10. Response of Food Price Inflation Droughts, Floods, and Storms

Source: EM-DAT, World Food Programme, and authors' calculations.

4.3 Impact of Climate Shocks on Inflation

This sub-section supplements the analysis of natural disasters. The main premise here is that it is possible that by examining effects of temperature and precipitation shocks on inflation across countries some climate shocks that are not classified as natural disasters may nonetheless have noticeable effects on inflation. This subsection uses the same country groups (33 AEs, 76 EMs, and 53 LIDCs) and monetary policy categories (28 IT and 73 non-IT) used in the previous subsection.[11] As defined in Section 3, climate shocks are captured by deviations of temperature from country's average of the past 30 years, using z-scores as previously described. Shocks are expressed over a 10-quarter horizon.

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[10] Similar pattern emerges for EMDEs and LIDCs. The sample is small for AEs. These results are available upon request from the authors.

[11] Because the resolution of $0.5° \times 0.5°$ grided temperature and precipitation data is about 55km near the equator, a country of small geographic area may cover only one grid in the data whose centroid is not located within the country. We drop these countries in our analysis, which results in a smaller sample than that in our analysis of natural disasters.

Results

Figure 11 presents the results of the impact of climate shocks on headline inflation for countries of different income status. Figure 12 further decomposes weather shocks into positive and negative shocks to examine their asymmetric impact.[12] Panel (a) of Figure 11 depicts the response of inflation to temperature and precipitation shocks in AEs and shows that it is statistically insignificant in the first year. In the second year, however, inflation tends to decline. Figure 12 shows that this is a pattern across positive and negative temperature shocks, as well as negative precipitation shocks.[13]

Panel (b) of Figure 11 presents the results of responses of inflation in EMs. In contrast to AEs, temperature shocks do have a statistically significant impact on EMs. Specifically, following a temperature shock, inflation in EMs rises by 0.2 percentage points in the second quarter and becomes statistically significant at the 95 percent level, but the effect dies down soon afterwards. Figure 12 shows that this is mostly driven by positive temperature shocks, pointing to the asymmetric effects of temperature changes. While the impact of a positive temperature shock seems short-lived, a negative temperature shock has a persistent deflationary effect. Precipitation shocks have a negative and temporary impact on inflation in EMs. As shown in Figure 12, however, this largely reflects the inflationary impact of negative precipitation shocks, or drought-like conditions, highlighting the asymmetric nature of precipitation shocks.

Panel (c) of Figure 11 shows that unlike EMs, the impact of temperature shocks on LIDCs is muted, but much like in EMs, precipitation shocks have a negative and statistically significant impact on inflation. Figure 12 again shows that the impact of precipitation shocks reflects the inflationary pressures from negative precipitation shocks. Notably, one standard deviation lower precipitation than the historical average drives peak inflation twice as high in LIDCs as in EMs. In AEs, after a delayed reaction of about a year, inflation rises steadily and stays elevated at 0.2 percent. This result highlights the effectiveness of monetary policy in putting a lid on inflation in the short run. Lack of precipitation is associated with droughts and is likely an early indicator for poor harvests. This result is consistent with the previous findings of the inflationary impact of droughts on LIDCs and on food inflation.

Figure 13 shows the differential impact of climate shocks on inflation of different monetary policy regimes. With respect to temperature shocks, inflation seems better anchored in IT-countries than in non-IT countries. Throughout the 10-quarter horizon following a temperature shock, inflation in IT countries remains not statistically different from zero. By contrast, non-IT countries experience elevated inflation in the first year, peaking 0.1 percentage point in the second quarter, before it subsides.

There is, however, no strong evidence that inflation is better insulated against precipitation shocks in IT-countries than in non-IT countries. Precipitation shocks tend to have a negative impact on inflation, which shows up earlier in non-IT countries than in IT-countries.

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[12] Specifically, a positive shock is the positive component of the z-score, $T_{i,t}^{z+} = \max\left(T_{i,t}^{z}, 0\right)$, and a negative shock the negative component: $T_{i,t}^{z-} = \left|\min\left(T_{i,t}^{z}, 0\right)\right|$.

[13] For example, a positive temperature shock reduces inflation and a negative shock increases inflation in the 10th quarter for AEs in Figure 14.

Figure 11. Impact of Climate Shocks on Inflation
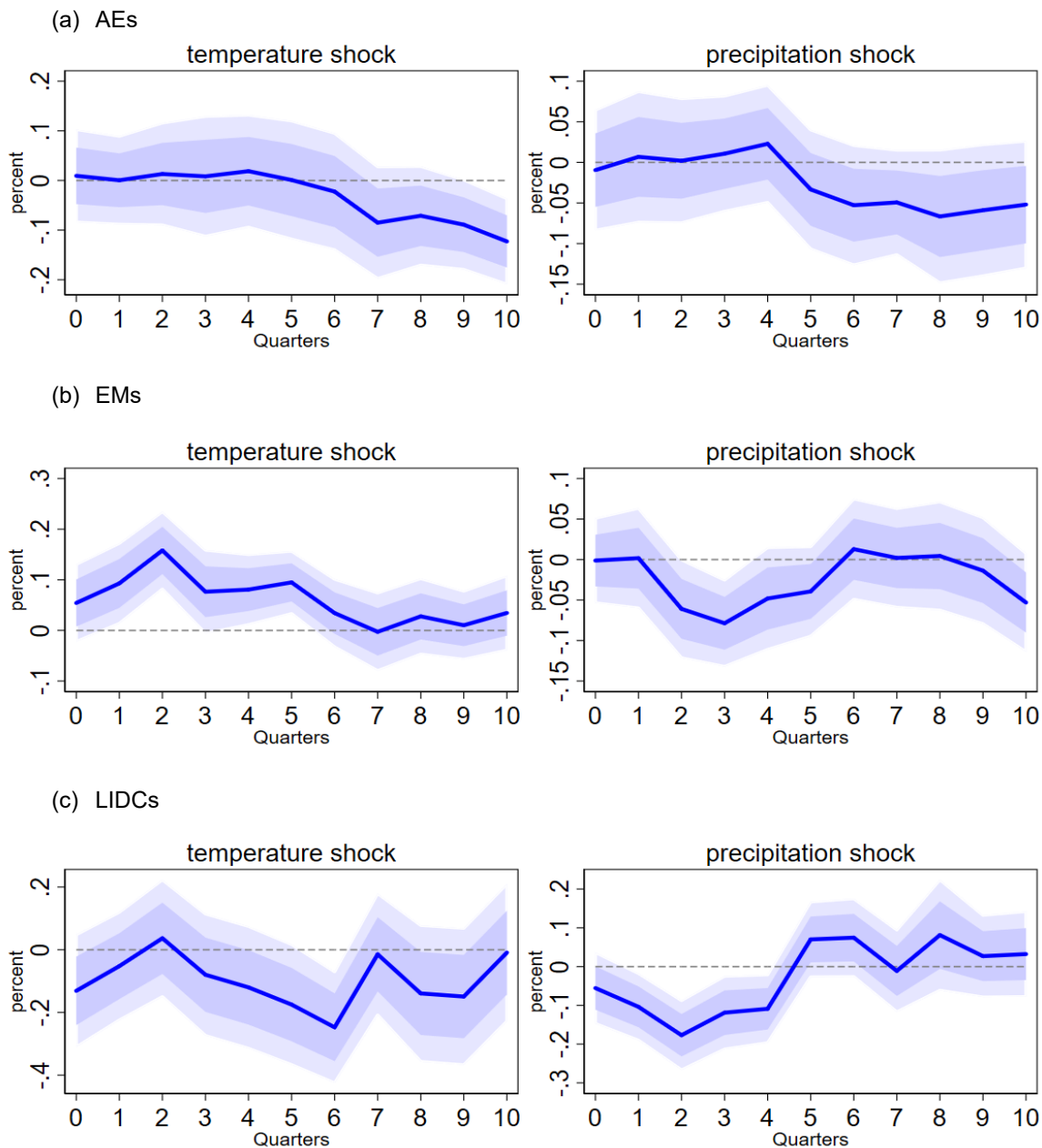
(a) AEs

(b) EMs

(c) LIDCs

Source: Climate Research Unit, University of East Anglia; International Financial Statistics; and authors' calculations.

Figure 12. Impact of Positive and Negative Climate Shocks on Inflation

Source: Climate Research Unit, University of East Anglia, International Financial Statistics, and authors' calculations
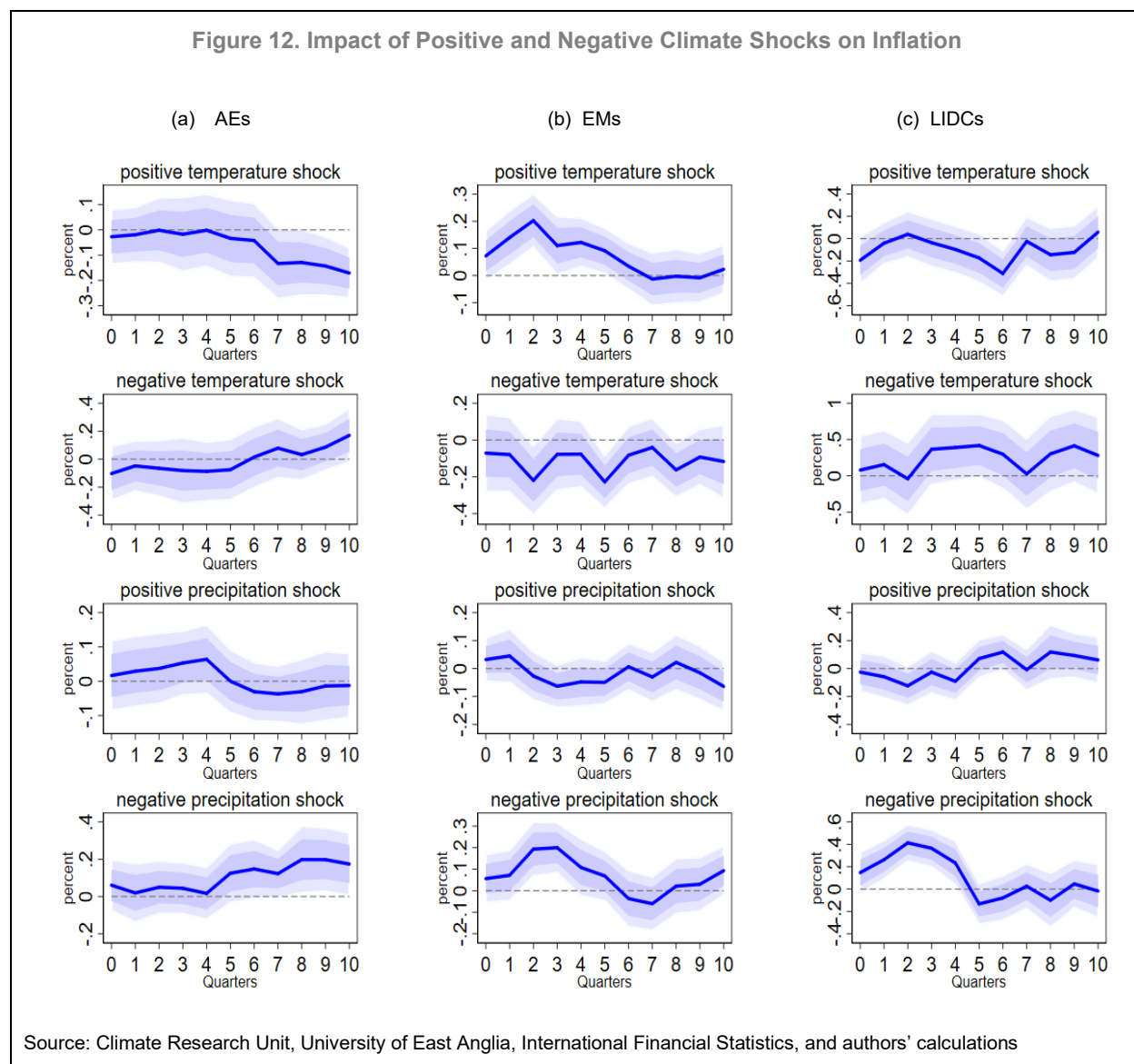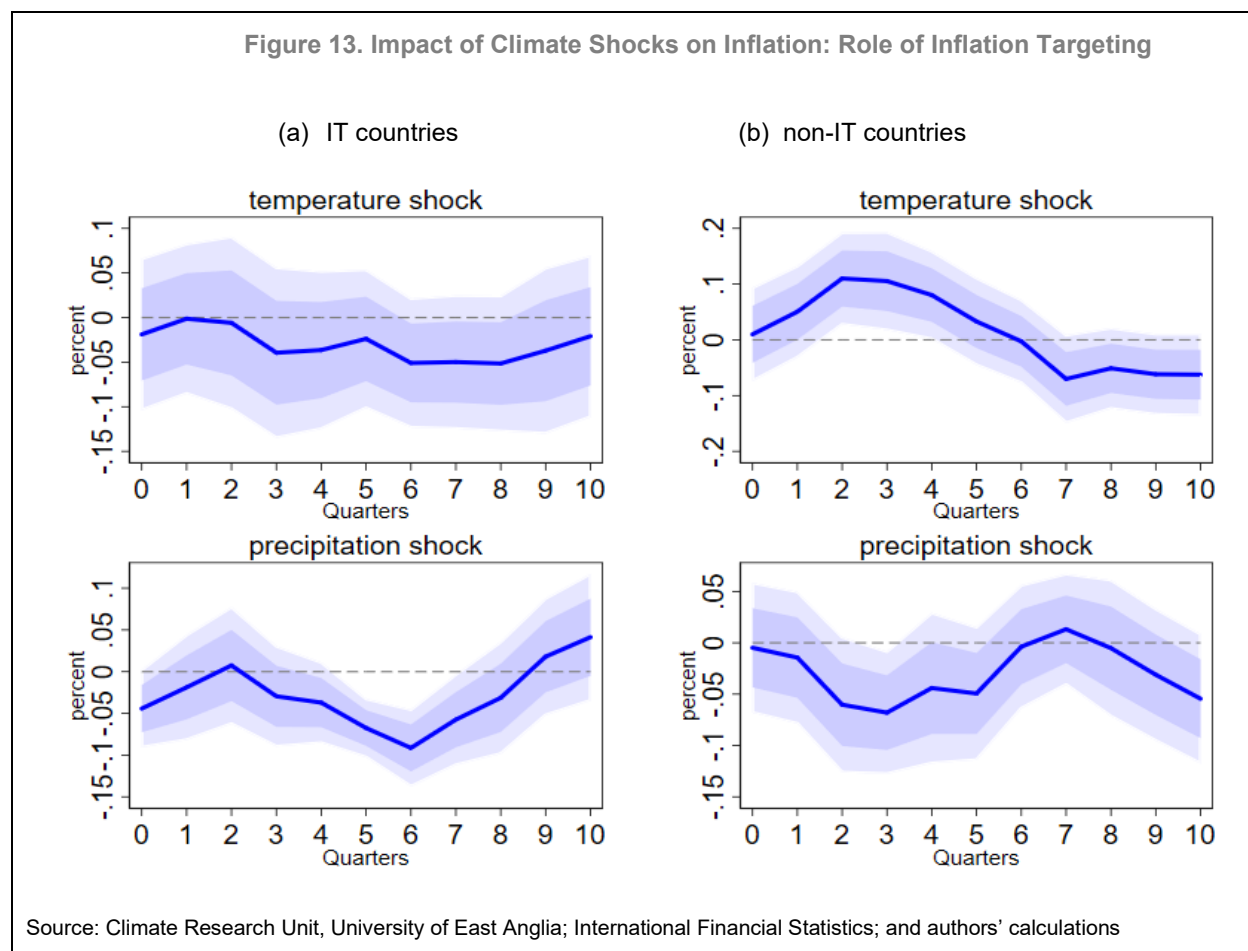
The above analysis shows that the impact of climate shocks on inflation depends on the types of climate shocks, countries' income status, as well as their monetary regimes. For AEs, inflation is generally well anchored for weather shocks in the short run.[14] For EMs, positive temperature shocks have a transitory inflationary impact while negative temperature shocks have a persistent deflationary impact. For both EMs and LIDCs, negative precipitation shocks play an important role in driving up inflation in the short term. While inflation seems better anchored in IT-countries than in non-IT countries with respect to temperature shocks, there is no strong evidence that it is better anchored in response to precipitation shocks.

While temperature and precipitation are the most commonly used climate variables, Appendix F considers an alternative measure that takes evaporation into account. The results are qualitatively similar to those of precipitation.

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[14] These results are consistent with Cantelmo and others (forthcoming) and Fratzscher and others (2020).

Figure 13. Impact of Climate Shocks on Inflation: Role of Inflation Targeting

(a) IT countries   (b) non-IT countries

Source: Climate Research Unit, University of East Anglia; International Financial Statistics; and authors' calculations

5. Conclusion

The paper has investigated the impact of climate shocks on inflation and its implications for monetary policymaking. To do this, we looked at a large number of climate shocks in a wide variety of countries for a period of five decades. We have provided evidence that the frequency and intensity of climate shocks have increased, consistent with climate change. However, not all climate shocks have similar impacts on inflation. In general, droughts—although much less frequent than floods—tend to increase inflation. On the other hand, floods are more likely to dampen inflation. We also show that the impact of droughts on inflation underscores their effects on food prices. The underlying monetary policy regime has a material impact on how inflation dynamics evolve. In particular, as also shown by Fratzscher and others (2020), inflation-targeting countries (and more generally countries with stronger monetary policy frameworks) tend to withstand the inflationary impact better than others.

While the overall impact of climate shocks on inflation has generally been muted in the past, given the likely increase in the frequency and amplitude of climate shocks, the trend is for the impact to increase over time. This is likely to pose increasing challenges to monetary policy formulation. Currently, commonly used monetary policy frameworks and underlying models are generally ill-suited to address supply shocks, especially if the latter are increasing in frequency and amplitude. This is because it would not be appropriate to "look through"

such shocks if they are part of the landscape as it were. At the same time, tightening monetary policy could lead to output loss. Monetary policy in such circumstances would become less potent, especially given that, as argued by Bylund and Jonson (2020), the equilibrium real interest rate (r*) is likely to decline with climate change.

While it is not the objective of his paper to propose how to modify monetary policy frameworks in the face of climate change, some authors, e.g., McKibbin and others (2020) and Cantelmo and others (2022) have advanced potential alternatives. McKibbin and others (2020) propose nominal income targeting since it is much less demanding for policymakers as they do not need to have a precise understanding of the nature of climate shocks facing them. On the other hand, Cantelmo and others (2022) contend that the FIT paradigm is still a superior choice to all others they simulated. It is fair to say that the debate is not yet settled, and more research is needed to decide on the most appropriate frameworks. The research would also need to take into account the heterogenous impact (likely duration and intensity) by type of climate shock.

Appendix A. Natural Disasters and Food Inflation at the Subnational Level

The EM-DAT database used in the main text of the paper has all natural disasters coded at the country level, permitting studies of their aggregate impact on national headline inflation. The most acute impact of droughts, floods, and storms, however, are often felt at the local level in areas directly hit by the disasters. The inflation dynamics in those areas can provide additional insights into the overall impact of natural disasters.

This appendix complements the previous analysis at the country level by examining the relationship between natural disasters and inflation at the subnational level. We consider food inflation, as it is the only inflation data available at the subnational level for a large number of countries over an extended period. Since food accounts for a sizeable share of consumption basket for most LIDCs and EMs, food inflation is also a reasonable proxy for the trend in headline inflation.

Data

We construct a data panel of natural disasters and food inflation at monthly frequency and at the first administrative level, leveraging two datasets.

Geocoded Disasters (GDIS)

The GDIS dataset is a new open-source extension to EM-DAT that contains information on subnational locations of natural disasters between 1960 and 2018 (Rosvold and Buhaug, 2021). It provides centroid latitude and longitude coordinates for each administrative entity listed as a disaster location in the EM-DAT database. Natural disaster intensity is defined in a similar way to equation (1):

$$intesity_{i,j,t}^{k} \begin{cases} = 1, \ if \ \frac{fatalities_{i,t}^{k} + 0.3 \times affacted_{i,t}^{k}}{population_{i,j,t}} > \bar{a} \\ = 0, \ otherwise \end{cases} \tag{1A}$$

where k =1, 2, 3 is type of disaster, i represents country, j represents the first administrative region, and the event occurs at time t. Note that fatalities and affected population refer to the national level whereas population refers to the subnational level. On the one hand, fatalities and affected population at the first administrative level are not available; on the other, the impact of natural disasters should be concentrated in directly hit areas. Thus, the measure in equation (1A) is an appropriate approximation of the intensity of natural disasters.

Subnational Population

To obtain population at the first administrative level, we use the population count of Gridded Population of the World, Version 4, from Columbia University (CIESIN, 2018). The dataset consists of estimates of population at 30 arc-second (about 1 km at the equator) resolution for the years 2000, 2005, 2010, and 2015, with which we aggregate population to the first administrative level, using administrative boundaries in the Database of Global Administrative Areas (GADM 2.8). For years in which population data are not available, we interpolate and extrapolate population linearly for each administrative unit.

Food prices

World Food Programme (WFP) Vulnerability Analysis and Mapping provides data on global food prices, covering food items such as maize, rice, beans, fish, and sugar for 98 countries, 637 first administrative regions, and 2,475 markets since 1990. However, information on individual food items is not complete for all covered regions nor across all time periods.

To obtain food inflation, we first calculate the average price of individual food items each month and their implied year-on-year growth. We then group individual items into major food categories based on the WFP food basket, including staples, pulses, vegetables, fruit, meat and fish, eggs and milk, sugar, and oil. For each category, we use its median inflation as our measure of food inflation at the first administrative level. To merge with GDIS, we restrict the sample to the period between 1990 and 2018 and focus on regions with at least 5 years of data for each food category.

Summary Statistics

Table A1 presents our classification of eight food categories and their region coverage. The dataset has the best coverage for staples, covering 68 countries and 423 administrative units. For pulses and oil, the dataset's coverage is relatively good, while for other food categories it is limited.

Table A1. Food Categories and Region Coverage in World Food Programme Database			
Food category	Food items	Number of countries	Number of administrative regions
Staples	bread, cassava, maize, millet, potato, rice, sorghum, wheat, yam	68	423
Pulses	beans, lentils, peas, soybeans	29	154
Vegetables	cabbage, carrots, chili, cucumbers, eggplants, onions, peppers, spinach, tomatoes	5	33
Fruit	apples, bananas, mangoes, oranges, plantains, watermelons, rice	8	33
Meat and fish	meat, fish	17	68
Eggs and milk	eggs, milk	12	52
Sugar	sugar	15	80
Oil	oil	24	122

Source: World Food Programme; and authors' calculations.

Table A2 presents the distribution of inflation for different food categories during the sample period (1990-2018). The range of inflation is similar despite wide variation across different categories. Table A3 summarizes the frequency of natural disasters in regions where inflation of different food categories is available. Floods are the most prevalent type of natural disasters in the sample, consistent with the summary statistics in Figure 1.

Table A2. Distribution of Subnational Food Inflation by Category

	Mean	p10	p25	p50	p75	p90
Staples	9.5	-16.4	-4.7	3.7	18.5	42.5
Pulses	13.5	-19	-6.3	5.8	23.2	50.9
Vegetables	8.1	-25.2	-12.2	3.1	23.5	47.2
Fruit	15.8	-23.5	-7.3	6.7	26.9	64.5
Meat and fish	6.1	-5.7	-0.6	3	10.9	21.7
Eggs and milk	5.7	-8.4	-0.9	1.4	11.1	24.1
Sugar	8.7	-19.1	-8.7	0.7	18.9	45.8
Oil	7.1	-14.8	-4.7	1.7	13.5	35.6

Source: World Food Programme; and authors' calculations.

Table A3. Frequency of Natural Disasters in Regions with Food Inflation Data

	Droughts	Floods	Storms
	in percent		
Staples	0.28	0.96	0.16
Pulses	0.28	0.88	0.30
Vegetables	0.04	0.23	0.0
Fruit	0.03	0.50	0.07
Meat and fish	0.18	1.39	0.09
Eggs and milk	0.29	1.79	0.02
Sugar	0.27	1.84	0.11
Oil	0.34	1.05	0.41

Source: World Food Programme; Geocoded Disasters Dataset; and authors' calculations.
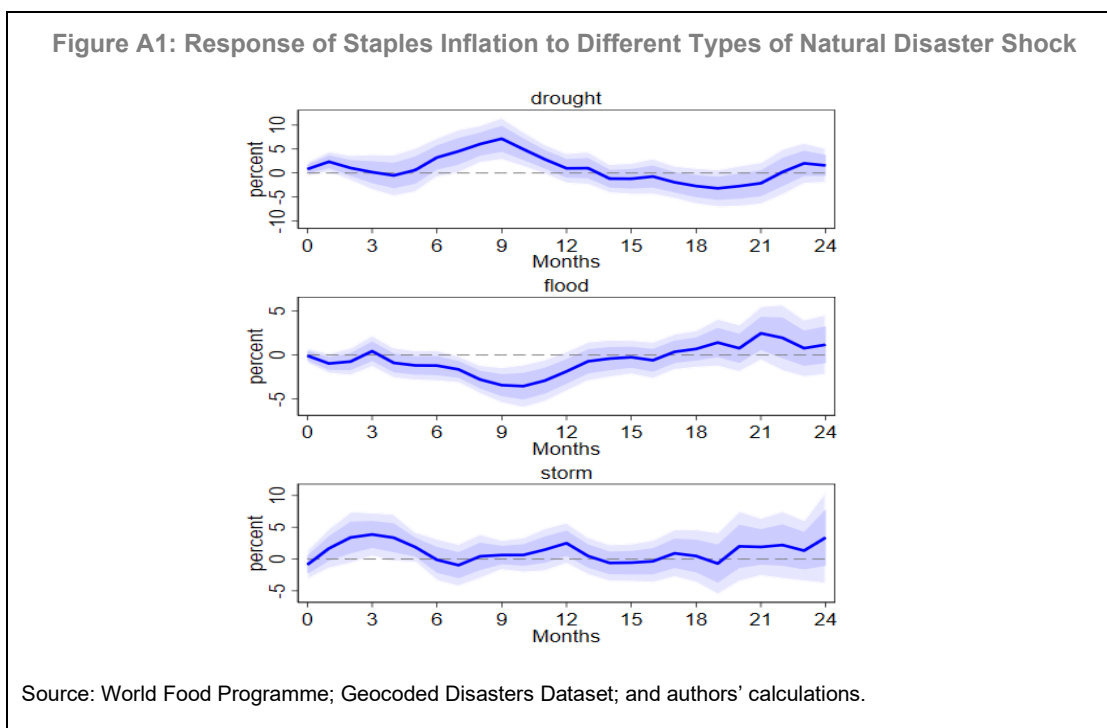
Results

Staples inflation

Figure A1 presents the results of the impact of natural disasters on staples inflation for all countries. Both time and region fixed effects are included in the local projection. Standard errors are clustered at the country level.

Upon impact of a drought, inflation gradually increases for 9 months before it subsides. The impact in the second year following the drought is slightly deflationary. Floods have a deflationary impact 6-12 months after their occurrence. The impact of storms is inflationary and seems to be persistent. Compared to Figure 11 that considers food inflation at the quarterly frequency at the national level, these patterns of inflation response are broadly similar, but the magnitude tends to be larger. With more variations across regions, the estimates are more precise.

Figure A2 presents the impact of natural disasters on staples inflation for EMs and LIDCs. Each type of natural disaster has qualitatively similar yet quantitively differing effects on EMs and LIDCs. Droughts drive staples inflation in EMs to well above 10 percentage points after muted reaction of about five months, but their impact on staples inflation in LIDCs is limited. Floods' deflationary impact in the 6-9 months is more visible for LIDCs than for EMs. Storms exert inflationary pressures on EMs in the first year while such pressures only manifest in the second year for LIDCs.

Figure A3 compares the impact of natural disasters on staples inflation between IT-countries and non-IT countries. Since IT regimes do not target the price of individual food items, one should not expect food inflation to be unchanged following natural disasters. In fact, the inflationary impact of droughts and storms on staples is stronger in IT-countries, raising staples' inflation by 10 percentage points in the first year of impact, more than double that for non-IT countries. This highlights the heterogeneous responses of different monetary regimes that can be masked when one looks at the overall response in Figure A1.

Figure A1: Response of Staples Inflation to Different Types of Natural Disaster Shock

Source: World Food Programme; Geocoded Disasters Dataset; and authors' calculations.

Inflation of other food categories

Figure A4 presents the impact of natural disasters on other food categories. To ensure that a nontrivial number of countries administrative regions are covered, we omit results for vegetables and fruits, which only have data for 5 and 8 countries, respectively.

It is clear in Figure A4 that the inflation response to natural disasters differs across different food categories. For example, droughts have an inflationary impact on meat and fish in the first 12 months, but its impact on eggs and milk is deflationary. Floods' deflationary impact is concentrated in sugar. Storms have a sizeable deflationary impact on eggs and milk.

Figure A2: Response of Staples Inflation to Different Types of Natural Disaster Shock by Country Income Status
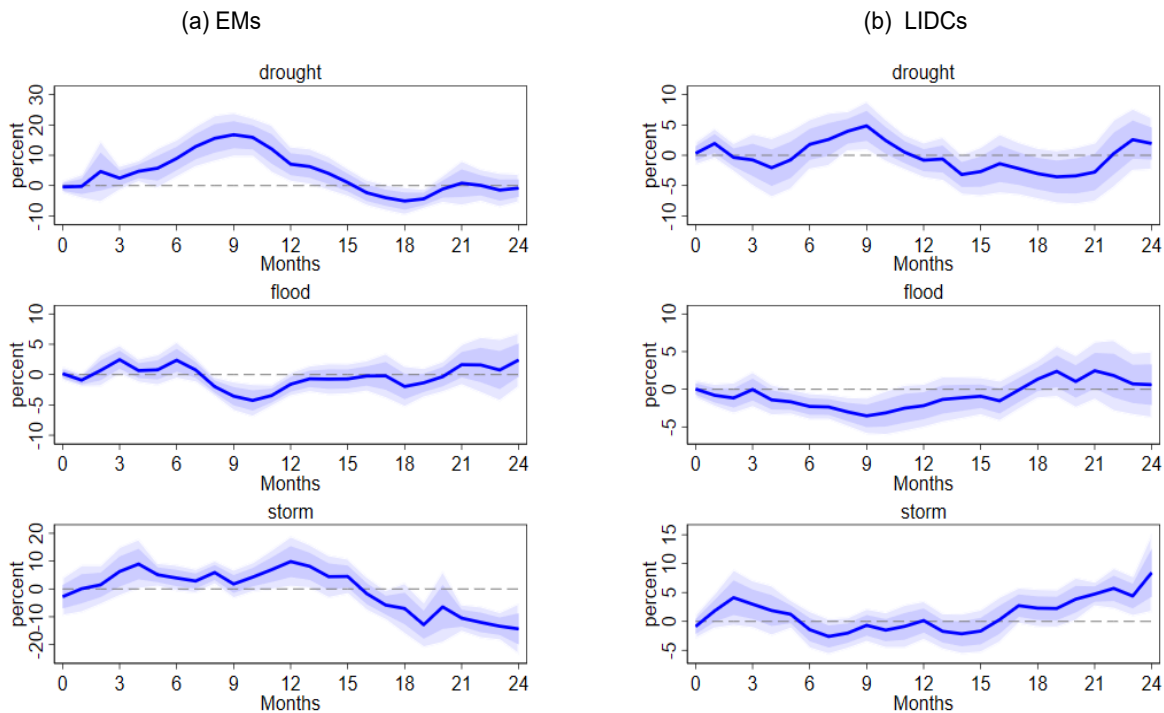
(a) EMs

(b) LIDCs

Source: World Food Programme; Geocoded Disasters Dataset; and authors' calculations.
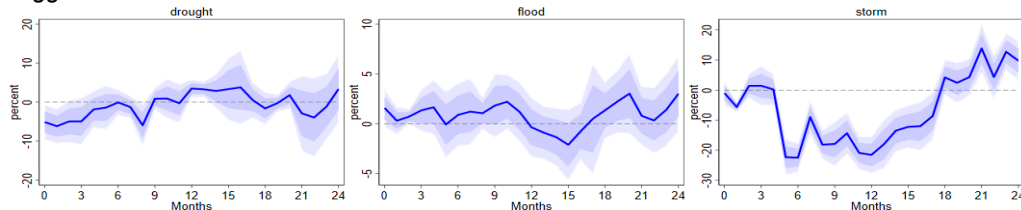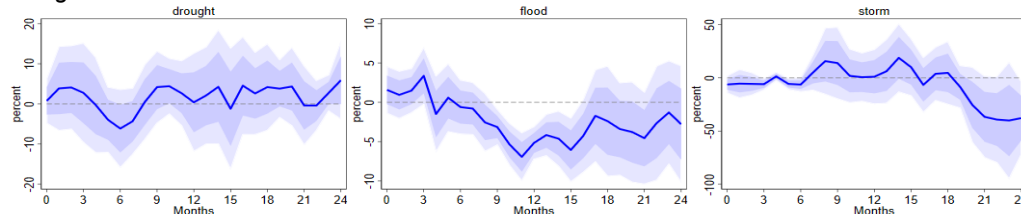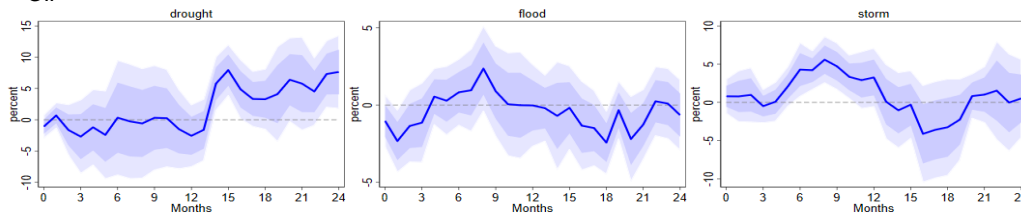
Figure A3: Response of Staples Inflation to Different Types of Natural Disaster Shock by Country Monetary Regime

(a) IT

(b) non-IT
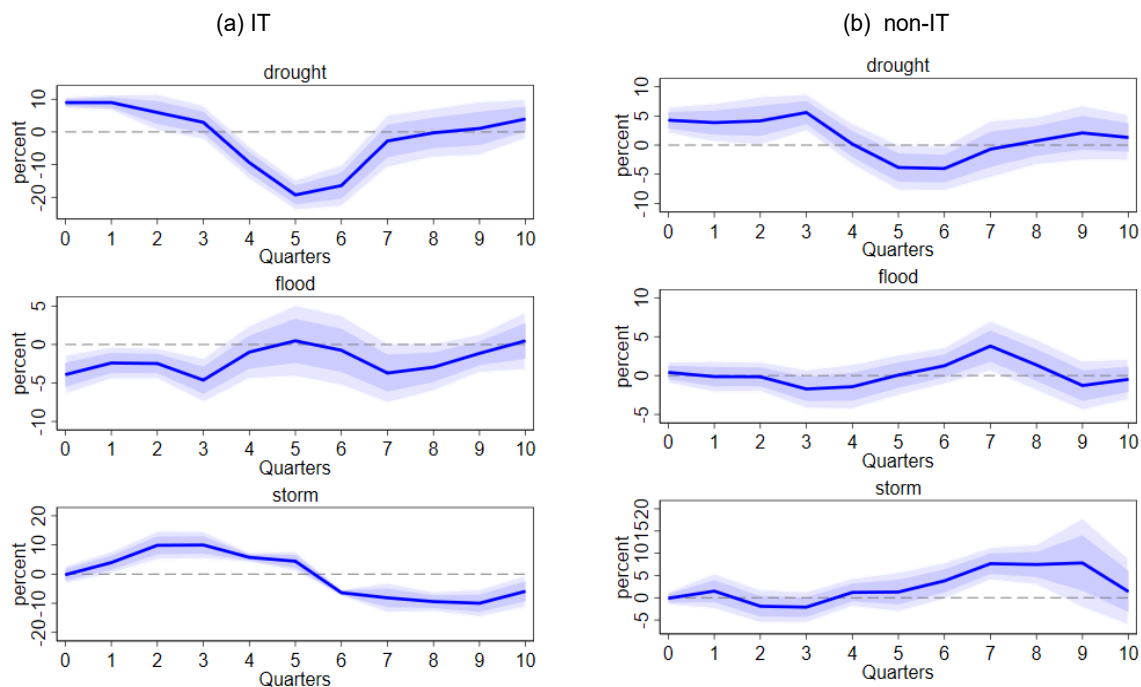
Source: World Food Programme; Geocoded Disasters Dataset; and authors' calculations.

As alluded before, the overall food inflation response to natural disasters therefore masks heterogeneity among various food categories. The contribution of each food category to overall food inflation depends on their relative weight in the consumption basket as well as the magnitude of their response to natural disasters, which may vary across regions.

Figure A4: Response of Food Inflation to Different Types of Natural Disaster Shock

Pulses
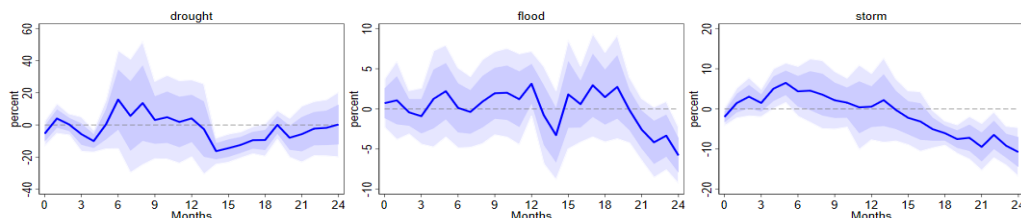
Meat and fish
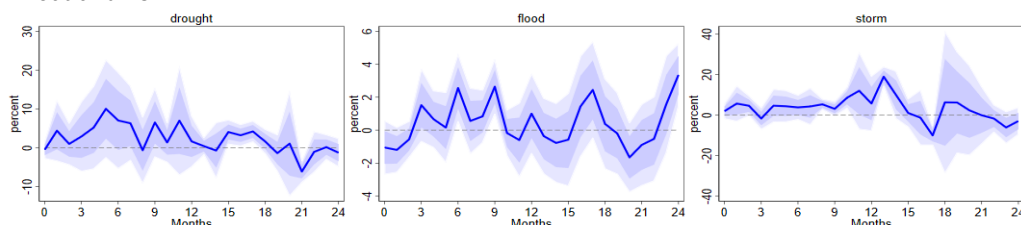
Eggs and milk

Sugar

Oil

Source: World Food Programme; Geocoded Disasters Dataset; and authors' calculations.

The results at subnational level reveal considerable heterogeneity of the inflation response of individual food items to natural disasters, although we do not have systematic explanations for the differentiated impacts by food item. They show that inflation dynamics at the local level can be quite different from that at the national level following natural disasters. At the local level, the extent and direction to which individual food items react to natural disasters also differ, depends on food categories, types of natural disasters and monetary regimes.

Appendix B. Results with Additional Control Variables

This appendix extends the baseline model by including additional controls:

$$\pi_{i,t+h} = \alpha_{i,h} + \delta_{t,h} + \sum_{p=0}^{P} \beta_p^h D_{t-p} + \sum_{q=1}^{Q} \gamma_{q,h} \pi_{i,t-q} + \delta_h' X_{i,t} + \varepsilon_{i,t+h}$$

where $X_{i,t}$ includes exchange rate growth, average night lights, and food weight in the CPI basket. Exchange rates are obtained from the *International Financial Statistics* database. Average night lights are computed from the monthly DMSP-OLS series and VIIRS series from the Earth Observation Group in the Colorado School of Mines. Food weight is based on the component of food and non-alcoholic beverages in the CPI basket from IMF data.

These variables are meant to account for the impact of exchange rate changes, economic growth (captured by night light) and the weight of food in the CPI basket, which mechanically biases CPI inflation upwards. Figures B1-B3 show that the results are broadly similar to those in Figures 5-7. However, with additional controls, the sample becomes smaller and several disaggregated results are missing. Notable differences are observed when considering the reaction of inflation to natural disasters in LIDCs. Natural disaster shocks induce inflationary responses in almost all cases with the marked exception of storms for the average moderate cases. Severe storms are inflationary for just about more than a year.
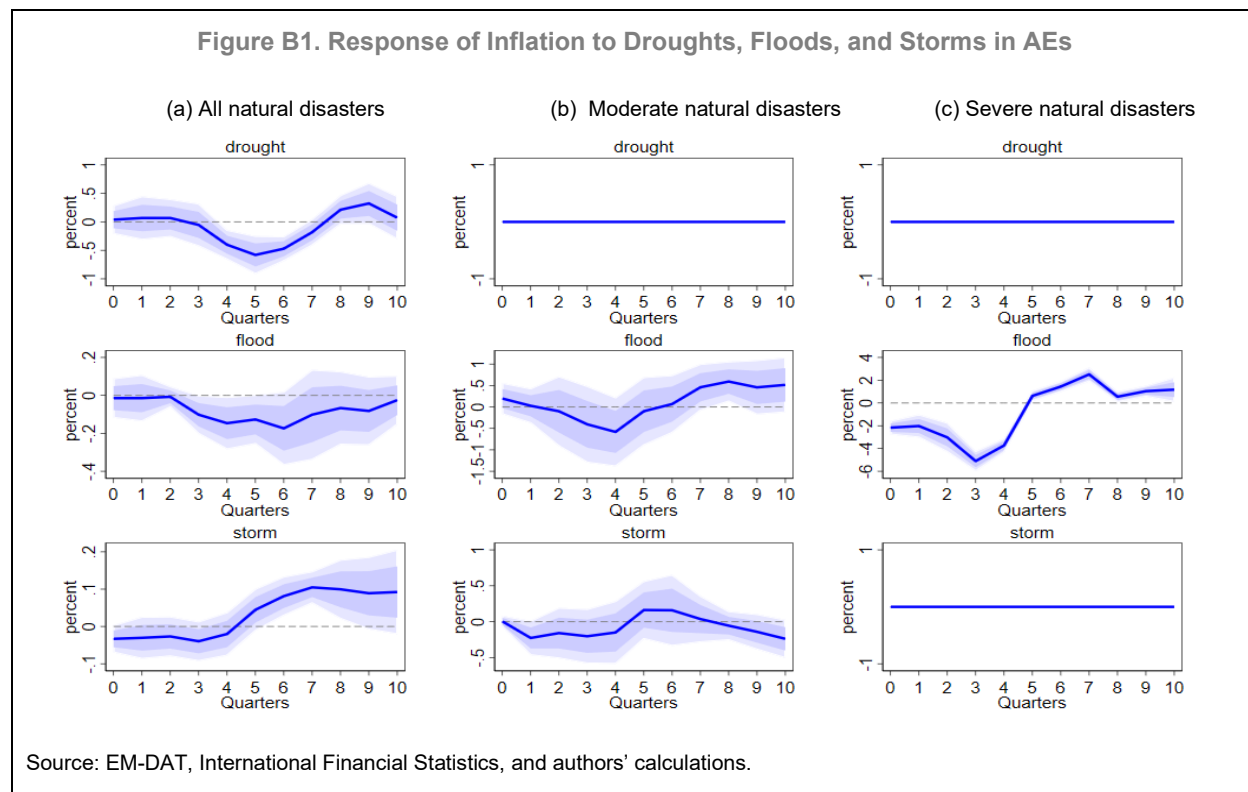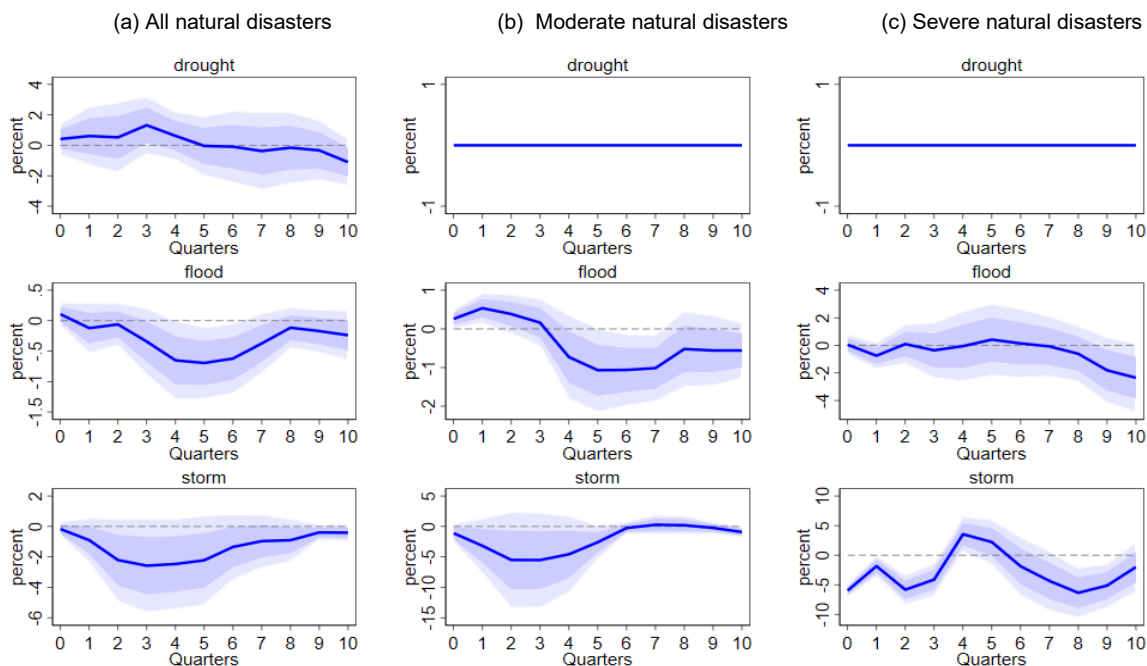

Figure B1. Response of Inflation to Droughts, Floods, and Storms in AEs

Source: EM-DAT, International Financial Statistics, and authors' calculations.

Figure B2. Response of Inflation to Droughts, Floods, and Storms in EMs

(a) All natural disasters   (b) Moderate natural disasters   (c) Severe natural disasters

Source: EM-DAT, International Financial Statistics, and authors' calculations.

Figure B3. Response of Inflation to Droughts, Floods, and Storms in LIDCs

(a) All natural disasters   (b) Moderate natural disasters   (c) Severe natural disasters
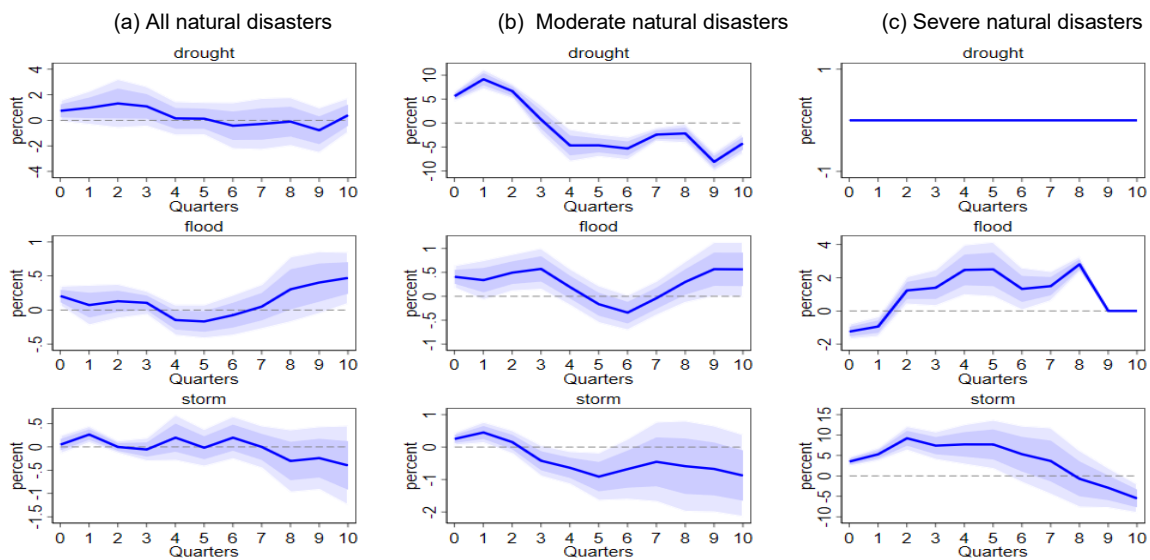
Source: EM-DAT, International Financial Statistics, and authors' calculations.
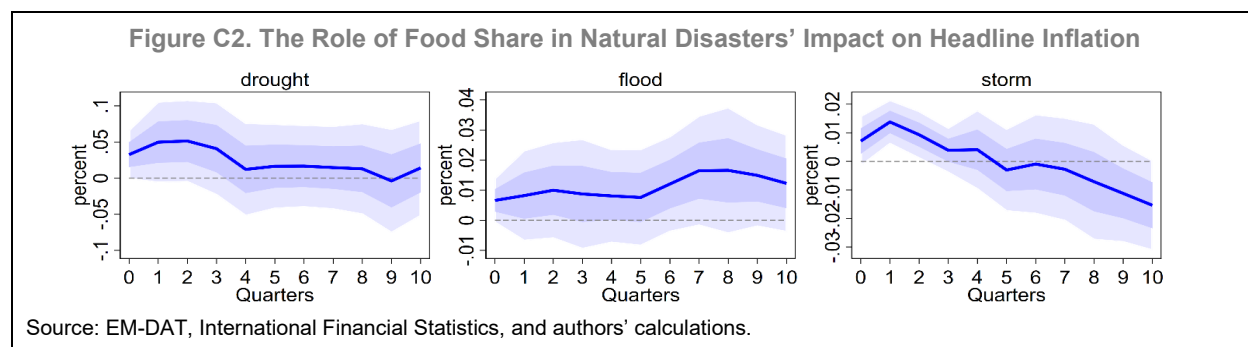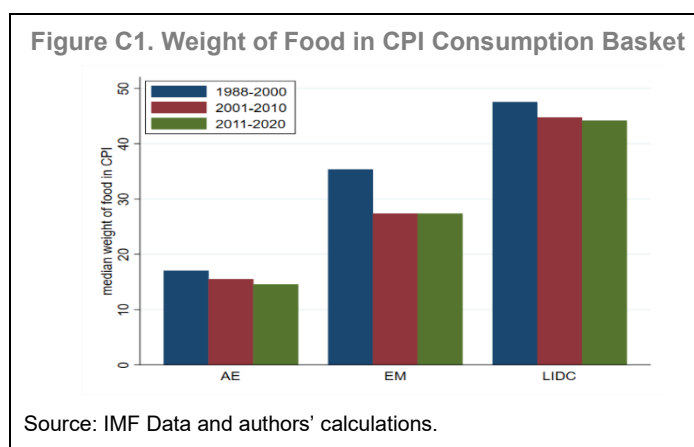
Appendix C. The Role of Food Inflation

Food accounts for a non-negligible share of the consumption basket in the consumer price index. Figure C1 shows that the median weight of food in CPI is around 15% for advanced economies, 25% for emerging markets, and 45% for low-income countries.

However, food inflation data is not available for most countries. We explore the extent to which the share of food in the CPI consumption basket affects natural disasters' impact on headline inflation through the following regression equation:

$$\pi_{i,t+h} = \alpha_{i,h} + \delta_{t,h} + \sum_{p=0}^{P} \beta_p^h D_{t-p} + \sum_{p=0}^{P} \kappa_p^h F_{t-p} D_{t-p} + \sum_{q=1}^{Q} \gamma_{q,h} \pi_{i,t-q} + \varepsilon_{i,t+h}$$

where F_t is the weight of food in the CPI consumption basket in period t. The coefficient κ_0^h before the interaction term captures the effect of a marginal increase in food share on natural disasters' impact on headline inflation.

Figure C2 displays the results for $\kappa_0^h, h = 0,1,2, ...$ Overall, a higher share of food in the consumption basket leads to more inflationary pressures following natural disaster shocks, especially in the short term. With the growing share of food in the basket, droughts exert more inflationary pressures than floods and storms when the share of food increases.

Figure C1. Weight of Food in CPI Consumption Basket

Source: IMF Data and authors' calculations.

Figure C2. The Role of Food Share in Natural Disasters' Impact on Headline Inflation

Source: EM-DAT, International Financial Statistics, and authors' calculations.

Appendix D. The Impact of Floods on Food Production

To better understand the impact of floods on inflation, this section explores the response of agricultural production to floods. To this end, we use data from the Food and Agriculture Organization of the United Nations on individual food item production. It is worth noting that this data is only available at an annual frequency. To explore the dynamic response of food production to flood we aggregate natural disasters data to the annual frequency and use the same local projection method as in the main text .

Figure D1 shows the results for three major food items: rice, maize, and meat. For all floods on average, food production increases in the ensuing years after the impact. Moderate floods tend to be beneficial for food production, while severe floods' impact tend to be negative in the initial years.

Figure D1. Selected Food Production After Floods

Source: EM-DAT, FAOSTAT, and authors' calculations.
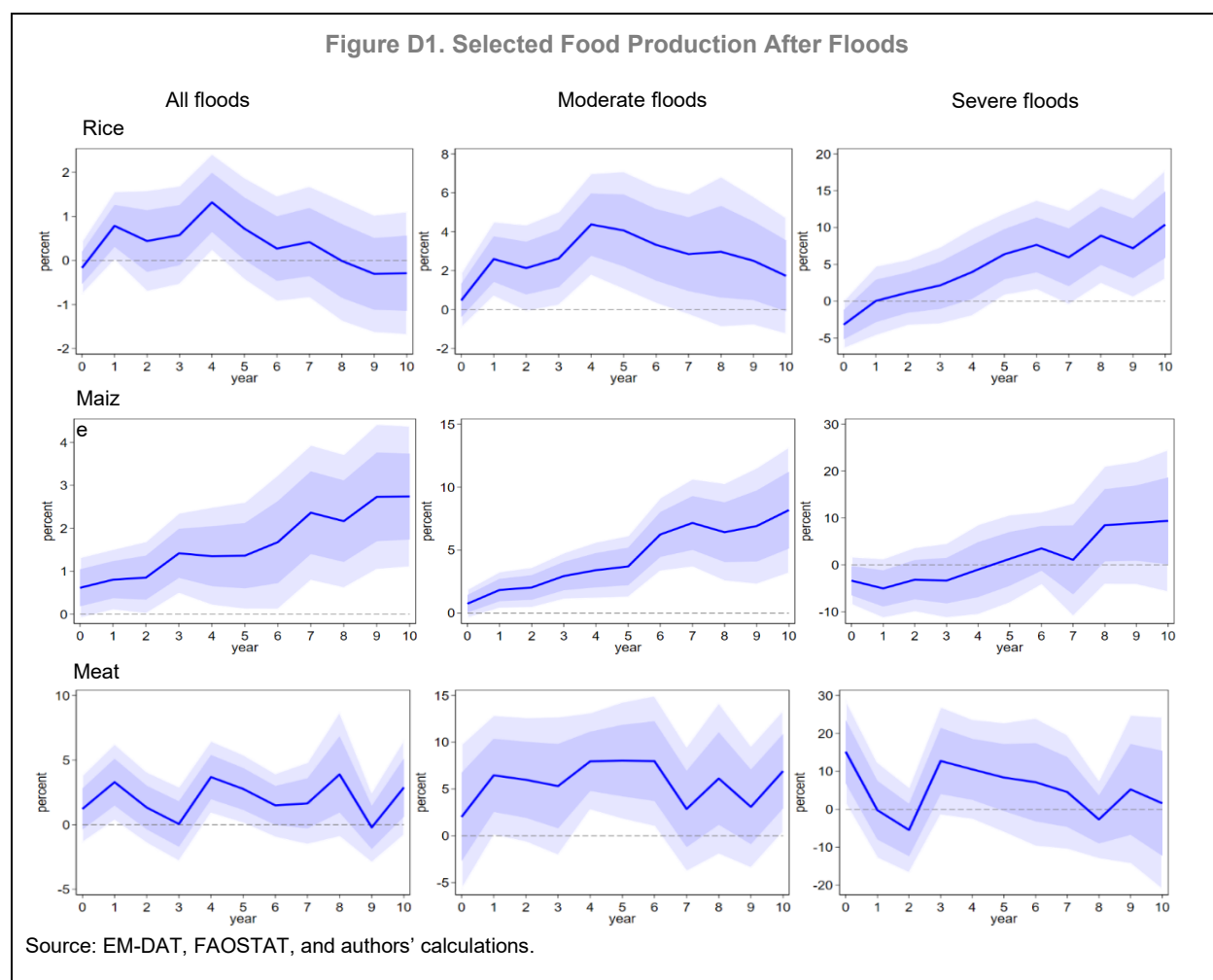
Appendix E. Alternative Measure of Monetary Autonomy

The measure of monetary regimes in the main text uses data from Fratzscher and others (2020), which is a binary variable that distinguishes between inflation targeting and non-inflation targeting regimes. In this section, we explore an alternative measure from Unsal and others (2022), which provides a more holistic view of monetary policy frameworks, including independence and accountability, policy and operational strategy, and communications (IAPOC).

The IAPOC ranges from 0 to 1. It is an annual measure from 2007 to 2018, which we expand to a quarterly measure by simply assigning the same value to all quarters in the same year. We use the same specification as in Appendix C by replacing κ_p^h with the IAPOC.

Figure E1 shows that an improvement in the IAPOC does not imply any particular direction change in the inflation response to different types of natural disasters. Stronger monetary policy frameworks are not associated with lower or higher inflationary impact of drought, but they seem to be associated with lower inflationary impact of floods and higher inflationary impact of storms.

Figure E2 shows separate results for countries depending on whether a country exhibits the IAPOC above or below the median. Although the response of inflation in each group is mostly not significant, the confidence intervals for countries with weaker monetary policy frameworks are mostly wider than those of countries with stronger monetary policy frameworks.

Taken together, Figures E1 and E2 provide some evidence, albeit weak, that countries with stronger monetary policy frameworks are better insulated against natural disasters' impact on inflation than those with weaker monetary policy frameworks.
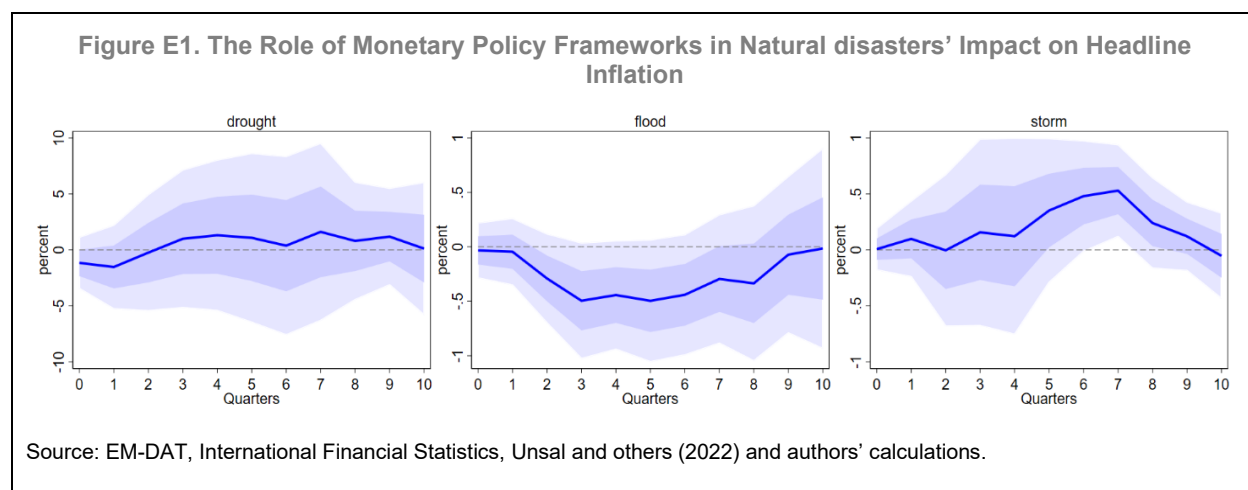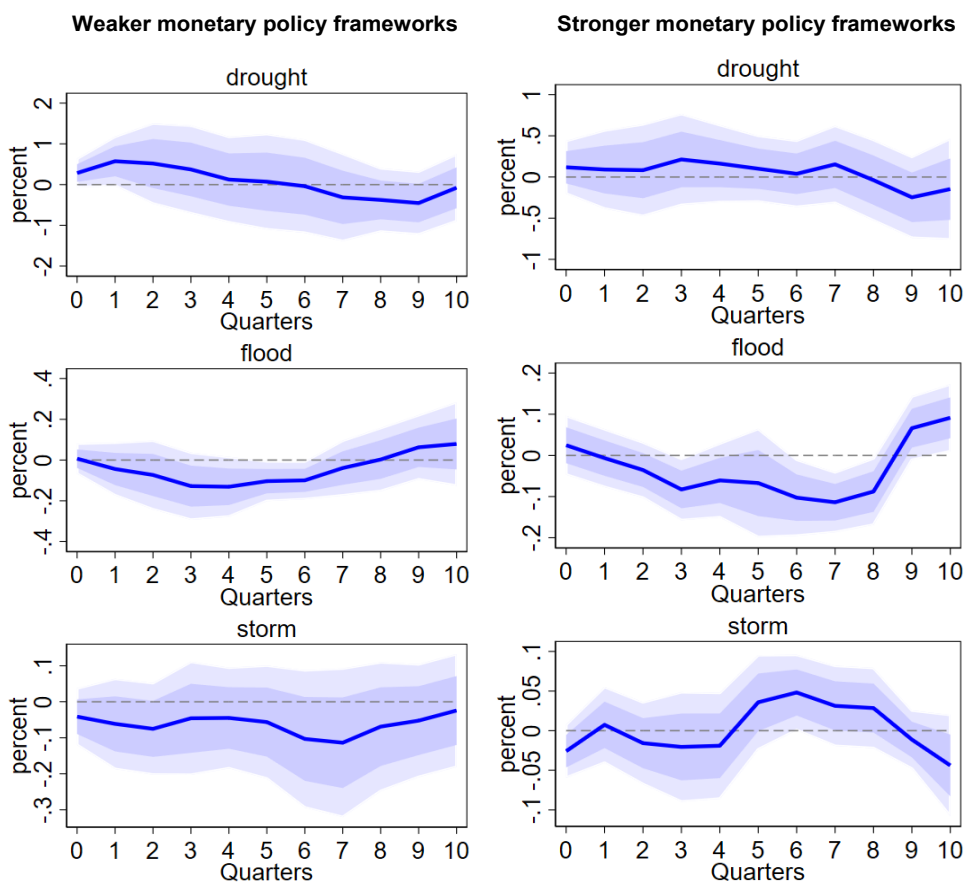

Figure E1. The Role of Monetary Policy Frameworks in Natural disasters' Impact on Headline Inflation

Source: EM-DAT, International Financial Statistics, Unsal and others (2022) and authors' calculations.

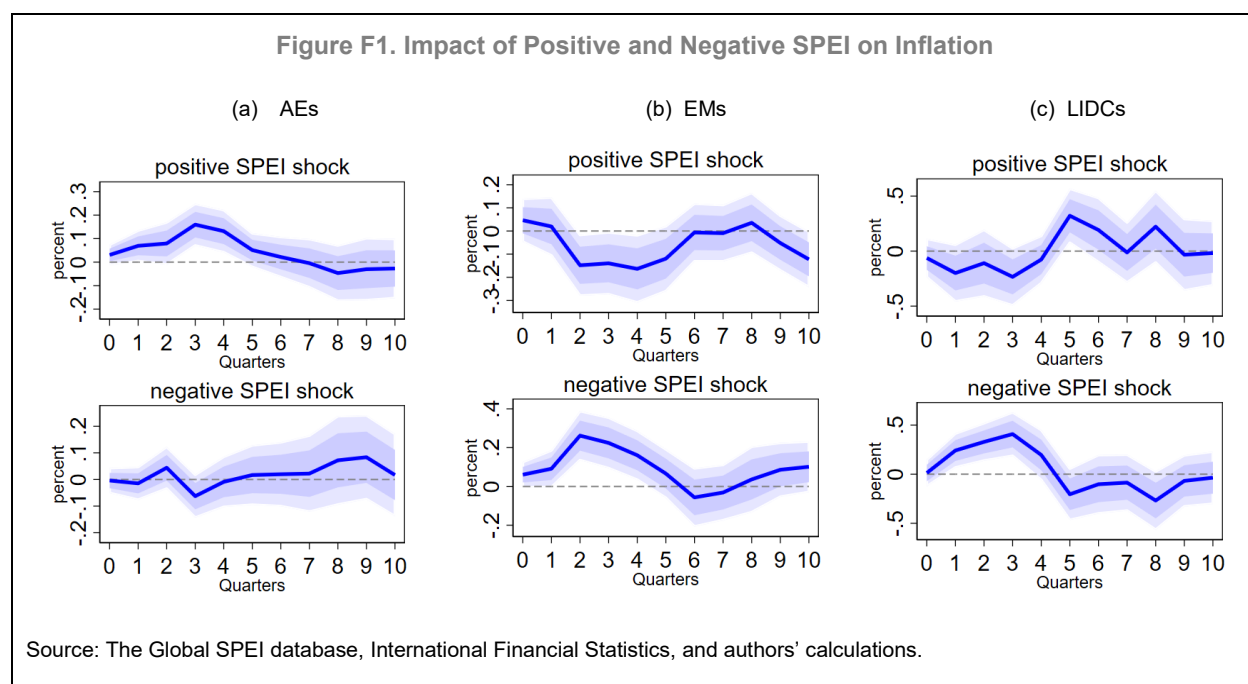**Figure E2. Natural disasters' Impact on Headline Inflation: Less vs. More Central Bank Autonomy**

Source: EM-DAT, International Financial Statistics, Unsal and others (2022) and authors' calculations.

Appendix F. Alternative Measure of Temperature and Precipitation

This section explores alternative measures of climate shocks and their impact on inflation. In particular, we consider the 3-month Standardized Precipitation Evapotranspiration Index (SPEI) from the Global SPEI database, which is based on monthly precipitation and potential evapotranspiration from the Climatic Research Unit of the University of East Anglia. This index combines both temperature and precipitation into a single measure to capture persistent climate shocks. For example, droughts are brought about by higher temperature and lower precipitation, making the SPEI a suitable aggregate measure to consider.

Figure F1 presents the impact of positive and negative SPEI on Inflation for countries with different income status. The results are qualitatively similar to those for precipitation shocks in Figure 12. In particular, negative SPEI shocks are inflationary for emerging markets and low-income and developing countries.

Figure F1. Impact of Positive and Negative SPEI on Inflation

Source: The Global SPEI database, International Financial Statistics, and authors' calculations.

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PUBLICATIONS

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