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Agricultural drought and food inflation: evidence on the role of monetary policy

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Abstract
While the impact of extreme weather events on food prices has been widely documented, much less is known about the effects of milder but more frequent weather disturbances—such as water shortages, or vegetation stress—that compromise agricultural production and can silently but persistently drive food inflation. Despite their cumulative relevance, there is still no comprehensive assessment of how such recurrent shocks and food price inflation interact with monetary policy, an essential instrument to preserve price stability. This study addresses this gap by examining how central banks respond to weather-induced food inflationary pressures, with a particular focus on low-income countries where food represents a large share of household expenditure. To this end, the interconnectedness between weather shocks, macroeconomic variables, and monetary policy is explored through a Panel Vector Autoregressive model estimated on quarterly data for 107 countries from 2000Q1 to 2019Q4, and separately for high- middle- and low-income economies. We introduce the Agricultural Stress Index, a satellite-based measure of agricultural land under water stress, as a novel proxy for less abrupt but more frequent weather disruptions. Results show that food prices are highly sensitive to such shocks, with stronger and more persistent effects in low-income countries. Moreover, central banks in these economies tend to lower policy rates, an expansionary response that may inadvertently amplify food inflationary pressures. These findings highlight the importance of prompt monetary policy responses to contrast the inflationary consequences of recurrent water stress.

Keywords Agricultural drought, ASI, Food inflation, Panel VAR, Monetary policy

JEL E31, E52, Q11, Q54

Introduction and background

Today more than ever, high food prices affect and destabilize the living standards of people living in developed and developing countries. There are clearly many different explanations for food inflation, such as global and domestic supply shocks, rising demand pressures, monetary shocks, or shocks to interest rates (Nguyen et al. 2017). Yet, food prices are, and will increasingly be, also influenced by the effects of weather shocks and climate change on agricultural production and yield (Batten et al. 2020). The effects of persistently high food prices can be particularly detrimental for households

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in developing countries, for whom food still plays a key role in consumption decisions (Cashin et al. 2017; Iddrisu and Alagidede 2020). These dynamics have important implications for food security, nutrition, and poverty (Erdogan et al. 2024; Escalante and Maisonnave 2022; Korale-Gedara et al. 2012). Even though some farmers may benefit from higher prices, the negative impact on poor rural and urban households usually outweighs such gains (Sam et al. 2021; Wodon and Zaman 2008), thereby increasing income inequality (Ivanic and Martin 2008; Marson and Saccone 2025). The consequences of sustained food price increases also affect households in developed economies. On one hand, they could lead individuals to revise their inflation expectations upwards (Anesti et al. 2025; Bonciani et al. 2024; Kikuchi and Nakazono 2023); on the other, they could exacerbate food insecurity among poorer families (Gregory and Coleman-Jensen 2013; Zhang et al. 2013).

A growing body of research examines the macroeconomic consequences of climate change, both through natural disasters and weather shocks related to rising temperatures. One line of research explores the consequences in terms of economic output. While Dell et al. (2012) find that rising temperatures harm economic growth in low-income countries, Burke et al. (2015) observe a similar, non-linear relation between temperatures and economic performance in both developed and developing countries. The impact that temperature anomalies and climate volatility can have in terms of reduced global economic activity has also been recently emphasized by Kahn et al. (2021) and Alessandri and Mumtaz (2022). Equally important is the strand of literature assessing the inflationary consequences that such events have in developed and developing countries alike. Inflation responds significantly to climate change, even though the effects vary across price aggregates such as core inflation (Cevik and Jalles 2023). In particular, weather shocks can have short-term price implications on energy and non-fuel commodity prices (Cashin et al. 2017) and can trigger price rises also in the electricity sector. Within this body of literature, there is broad consensus that the most sizeable impact of climate change is typically on food prices, an impact that stems from supply-side shocks occurring to the agricultural sector (De Winne and Peersman 2021; Suet al. 2025; Tigchelaar et al. 2018). Such evidence is quite overwhelming and is generally observed following different events or shocks, and in developing and developed countries alike. In the former set of countries, where a large share of the household budget is spent on food expenditure (Cashin et al. 2017; Iddrisu and Alagidede 2021), food prices are severely affected, more than other price categories, in the aftermath of hurricanes and floods in the Caribbean (Heinen et al. 2019). Brown and Kshirsagar (2015) capture weather disturbances using the Normalized Difference Vegetation Index (NDVI), a satellite-based indicator of cropland greenness. They observe that worsening vegetation conditions increase crop prices in local markets of developing countries, and that the local food price variation induced by such weather disturbance is greater than that induced by movements in international prices. Drier conditions are also associated with increased food prices in Latin America (Abril-Salcedo et al. 2020; Ouattara et al. 2025), especially for perishable food (Melo-Velandia et al. 2022; Salazar et al. 2023). In least developed countries such as sub-Saharan Africa, drier weather conditions also influence and exacerbate market price volatility and seasonality, as in Kakpo et al. (2022). Food inflationary effects following natural disasters have been observed also in developed countries such as the Euro area, where effects are more pronounced for food and beverage prices than for other categories (Beirne et al. 2021). Short-term inflationary effects of extreme temperatures have been observed also in Faccia et al. (2021) in both developed and emerging economies. Such effects exhibit a clear seasonal pattern, and shocks occurring in summer months are responsible for such effects.

This extensive strand of research provides a comprehensive assessment of the macroeconomic effects of weather shocks and natural disasters: the macroeconomic consequences can be both recessionary—i.e., reducing economic growth—and inflationary, in terms of increased prices and food prices (Batten et al. 2020; Fratzscher et al. 2020). Under such circumstances, central banks have an important role in mitigating and contrasting such effects. Yet, regardless of their mandates, central banks might face significant challenges. Central banks pursuing, at least theoretically, exclusively price stability, just like the European Central Bank, should implement a contractionary monetary policy to counter inflationary pressures, though higher interest rates might have adverse effects on economic growth and financial stability (Bouis et al. 2025). Other institutions, like the Federal Reserve Bank of the United States that target both output and price stability face a more nuanced trade-off. Monetary easing reduces interest rates to stimulate private investments and revitalize the economy. Yet, lower interest rates can in turn fuel further inflation (Bank of Canada 2023). Monetary policies can be even more problematic in low-income countries, where central banks must target a broader range of objectives, are less transparent and independent than central banks in advanced economies: it can be even harder for them to commit to low and stable prices (Ha et al. 2019).

Most of the literature adding a monetary policy twist to the impact of weather shocks on macroeconomic variables tends to focus on the short-term reaction of central banks following a natural disaster, disruptive and harmful, and their unpredictability surely requires a timely policy stance. Monetary responses have been studied for instance in the aftermath of the 2005 Katrina Hurricane (Keen and Pakko 2011) or of earthquakes (Klomp 2020). The general monetary policy recommendation emerging from these studies is to implement a contractionary monetary policy, i.e., by increasing the policy rate, to mitigate the short-term consequences of such shocks. A contractionary policy stance is recommended also by Fratzscher et al. (2020), and, even more recently, by Cantelmo et al. (2024) and Qi et al. (2025). The few exercises embracing such a wider perspective were carried out by Kunawotor et al. (2022) and Saou et al. (2025), using annual data to assess the impact of extreme weather events or weather shocks on African countries' annual inflation and food inflation, and monetary policy.

The present study

Even though the economic literature assessing the macroeconomic consequences of weather shocks is rapidly expanding, there is still no comprehensive assessment of how adverse weather conditions that increase water stress and drought in agriculture are simultaneously related to macroeconomic and monetary variables. The existing literature on the nexus between climate change and macroeconomic variables has typically focused on extreme weather events; nonetheless, persistent deteriorations in agricultural stress conditions, that are not necessarily caused by unanticipated natural disasters, are equally important and destabilizing (Alano and Lee 2016; Kamber et al. 2013; Montaud 2019).

This paper aims to fill these gaps by introducing a monetary policy perspective to analyse central banks' responses to food inflationary pressures induced by less extreme but more frequent weather shocks. To this purpose, the present study exploits the Agricultural Stress Index (ASI)—the share of agricultural land in water stress obtained from satellite and real-time data—which has rarely been used as a proxy for weather disturbances in economic studies (Kornher et al. 2024). By introducing ASI as a novel and exogenous measure of drought-related risk, this study contributes to broadening the scope of monetary policy analysis in the context of recurring and gradual weather disturbances.

In light of these considerations, the present study addresses the following research questions:

RQ1: How do food prices react to a worsening in ASI, i.e., to increased national water stress?

RQ2: What is the monetary policy response to the same shock in ASI?

RQ3: How does the monetary policy reaction to the same shock in ASI differ across high, middle, and low-income countries?

RQ4: What are the implications for food prices and monetary policy in inflation targeting countries?

From a methodological perspective, this paper is related to the literature employing reduced-form Panel Vector AutoRegressive (panel VAR) models to explore the relation among weather shocks and macroeconomic indicators. This panel approach has been proposed by Holtz-Eakin et al. (1988), and more recently by Abrigo and Love (2016) who assumed that the cross-sectional units share the same data generating process. Starting from this assumption, panel VAR models have been used to examine the transmission of monetary and financial shocks (Bhattacharya and Jain 2020; Jawadi et al. 2016). In the present study, we estimate a panel VAR model (Abrigo and Love 2016) on a sample of 107 countries from 2000Q1 to 2019Q4 to explore these interactions. This methodological framework allows us to add a monetary policy interpretation to the assessment of weather shocks on macroeconomic aggregates, and food prices in particular.

Building on these research questions, our analysis unfolds in several steps. First, we estimate the global macroeconomic consequences and monetary responses to a shock in ASI. Then, to account for potential heterogeneity across income groups and monetary policy regimes, we re-estimate our analysis on different sub-samples: first, among different income groups (high, middle, and low-income) and then on the subsamples of inflation targeting countries vs. non-inflation targeting countries. We further explore the specific case of low-income countries in sub-Saharan Africa, where both climatic vulnerability and monetary policy constraints are more pronounced. We also relaxed the assumption of homogeneity of the autoregressive coefficients across potentially heterogeneous countries and implemented a random-coefficients panel VAR approach, in which the autoregressive parameters are allowed to be partially country-specific (Jarociński 2010). This analysis, while methodologically appealing, requires a strongly balanced dataset, and was thus conducted on a smaller subsample of 37 high- and middle-income countries.

Finally, we conduct a series of robustness exercises to assess the stability of the model results to alternative lag structures, weather indicators (e.g., maximum ASI and the Standardized Precipitation Evapotranspiration Index, i.e., SPEI), and different country classifications (e.g., agricultural importers vs. exporters, and vulnerable vs. less vulnerable economies). This strategy enables us to detect heterogeneous transmission mechanisms of drought-related shocks into inflationary and monetary policy outcomes, providing a more nuanced interpretation.

The remainder of the paper is organized as follows. In Sect. "Data and methodological approach", we present the data used in the analysis and the methodological approach; Sect. "Results" presents the main findings and Sect. "Robustness analysis and alternative country aggregation" presents the results of several robustness checks conducted. Lastly, Sect. "Discussion and conclusions" discusses and concludes.

Data and methodological approach

Data and sources

Our analysis is based on a dataset of quarterly variables covering 107 countries from 2000Q1 to 2019Q4 (see Table A1.1 in Appendix). We include 25 advanced countries and 82 emerging and developing countries. Among the latter, 16 are classified as low-income countries. The set of variables used in this analysis consists of weather, macroeconomic and monetary policy indicators. In particular, we use the Agricultural Stress Index (ASI) as a proxy for extreme weather events, following the approach adopted in recent cross-country studies linking climate shocks and macroeconomic outcomes (Burke et al. 2015; Cashin et al. 2017; Cevik and Jalles 2023).

The ASI has been increasingly employed in empirical analyses to measure drought intensity and agricultural stress, as it combines both precipitation and temperature information into a spatially consistent indicator (Rojas 2020; Tigchelaar et al. 2018). Despite its limited application in economic studies (Kornher et al. 2024), it is a suitable variable to capture the macroeconomic effects of weather extremes, particularly in economies where agriculture plays a major role. ASI is collected by the Global Information and Early Warning System (GIEWS) of FAO and measures the share of crop land at high risk of drought, i.e., with a Health Vegetation Index lower than a critical threshold. ASI is measured in near-real time, i.e., every 10 days, and at the GAUL-1 level[1]. ASI has a high drought predictive power and its large-scale adoption is advocated by FAO timely monitor droughts at the global level and to take preventive actions (Rojas 2020). In our baseline analysis, we consider the quarterly country average.

Our set of macroeconomic variables includes the real gross domestic product (GDP) and two measures of consumer prices: the general consumer price index (CPI) and the Food CPI. GDP captures the overall output response to climatic shocks, while the inclusion of both general CPI and Food CPI allows us to disentangle the transmission of weather shocks to headline and food inflation, as emphasized in previous studies (Ha et al. 2019; Parker 2018). For approximately 40 countries, we obtained quarterly GDP series from the Federal Reserve Economic Data (FRED) portal. These data are in local currency units and seasonally adjusted. We deflated them using the seasonally adjusted GDP deflator of the corresponding quarter. For the remaining developing countries for which quarterly statistics were missing, we interpolated the annual GDP, in local currency units, obtained from the World Bank database, using the quarterly value of imports retrieved from the UN Comtrade database. Prior to this, import data were seasonally adjusted and deflated using

[1] GAUL is the Global Administrative Unit Layer developed by FAO-Geonetwork that allows global geo-spatial analysis by harmonizing boundaries and names of the administrative units at global level. GAUL 1 refers to the sub-national level.

the seasonally adjusted consumer price index. As for prices, we use the quarterly general CPI and the Food CPI, with 2015 as the base year, retrieved from FAOSTAT. Both indices were seasonally adjusted before being introduced in the analysis.

Finally, the short-term nominal interest rate is included as a proxy for monetary policy stance, allowing us to assess how central banks react to climate-induced supply shocks. This specification follows standard panel VAR approaches investigating the interaction between macroeconomic variables and policy responses (Bernanke and Blinder 1992; Gertler and Karadi 2015). Since the official policy rate was available for only a limited number of countries, we used the short-term interest rate as the monetary policy instrument. Depending on data availability, the short-term rate is defined as either the deposit rate or the discount rate (Mohaddes and Raissi 2018), and was obtained from the International Monetary Fund – International Financial Statistics (IMF-IFS) dataset.

Overall, this set of variables provides a coherent framework to assess the macroeconomic transmission of climate shocks, from weather anomalies to output, prices, and policy reactions, while ensuring comparability with existing empirical research.

We carry out our estimation on the entire sample and then on relevant and meaningful country aggregates (see Tables A1.2–A1.4 in the Appendix for further details on country group composition). The first is the World Bank income classification, to identify different response patterns depending on economic development (high-income, middle-income, and low-income countries). Then, we focus on low-income countries located in sub-Saharan Africa (SSA), not only because of their higher exposure to climate change and global warming (Ranger et al. 2025), but also for the multi-mandate role of SSA central banks, including "macroeconomic forecasting, monetary-fiscal policy, and sovereign debt management" (Ranger et al. 2025, p. 19.2).

Last but not least, we adopt a monetary policy lens to evaluate and compare responses between inflation and non-inflation targeting countries. To this end, we use the central bank objective score (Romelli 2022, 2024) which ranges from 0 (when central banks' objectives do not include price stability) to 1 (price stability as the only or primary objective of central banks). In the present study, we classify a country as inflation targeting when the 2000–2019 average score exceeds 0.9, and non-inflation targeting otherwise.[2] This distinction is grounded on the evidence that inflation targeting could act as an effective shock absorber (Fratzscher et al. 2020).

Methodological approach: the panel VAR model

To explore the interconnectedness between weather shocks, macroeconomic impact, and monetary response, we estimate a panel VAR following the methodology of Abrigo and Love (2016).

The panel structure of our data allows us to control for unobserved individual heterogeneity across countries. We consider five country-specific variables: the average ASI observed in the country, output (real GDP, in log deviations), prices (CPI, in log deviations), short-term nominal interest rates (in levels), and food prices (Food CPI, in log deviations). By stacking in vector $z_{i,t}$ the observations for country i in period t, we have the reduced form specification

[2] The score also considers the following intermediate values: 0.25 ("Price stability together with economic growth/development with no priority"), 0.5 ("Price stability plus other goals including financial stability of the financial system that may conflict with the former, without priority"), and 0.75 ("Price stability together with non-conflicting objectives but without priority") (Romelli 2022, 2024).

$$z_{i,t} = \sum_{l=1}^{p} A_l z_{i,t-l} + \upsilon_i + d_t + u_{i,t} \quad (1)$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, where A_l is a matrix containing the autoregressive parameters at lag l, υ_i are country-specific fixed effects, d_t are time effects, and $u_{i,t}$ is the vector of reduced form errors. These errors are serially uncorrelated, have zero mean, and variance equal to $E\left(u_{i,t}u'_{i,t}\right) = \Sigma$. Note that we are for the moment assuming that the autoregressive parameters in A_l and the error variance are common to all countries, but we let institutional differences across countries be captured by the fixed effects υ_i. In addition, we include the time effects d_t to control for global droughts or macroeconomic shocks that may affect all countries in the same way.

We estimate the panel VAR with the Stata package by Abrigo and Love (2016), which uses GMM with the lags of the endogenous variables as instruments. In all our estimations, we set the lag length of the autoregressive polynomial to two.

To associate an economic interpretation to our estimates, we can define $\varepsilon_{i,t}$ as the vector of structural shocks for country i. As these shocks are assumed to be orthogonal and to have unit variance, they are related with the reduced form shocks by $u_{it} = B\varepsilon_{i,t}$, where B satisfies $BB' = \Sigma$. As the last relation does not pin down B uniquely, we need a set of identification restrictions. Our approach is to adopt a simple recursive scheme and impose that B is lower triangular, so that the variables in vector z_{it} are ordered from the most exogenous to the most endogenous. In particular, our ordered vector of variables is given by:

$$\begin{bmatrix} ASI_{i,t} \\ \Delta GDP_{i,t} \\ \Delta CPI_{i,t} \\ Int\ rate_{i,t} \\ \Delta Food\ CPI_{i,t} \end{bmatrix} \quad (2)$$

In our ordering, the first variable is ASI, so we are able to interpret an increase in water stress in agriculture as an extreme weather shock: it is a purely exogenous variation in ASI, which can affect all other variables both simultaneously (i.e., within quarter) and with a lag. In other words, a weather shock can have an immediate impact on output, prices, the interest rate, and food prices. At the same time, our identification assumes that the macroeconomic variables cannot influence ASI simultaneously. This is a safe assumption, since economic activity may well modify the water stress sustained by crops, but this process will generally take some time and is unlikely to produce any effect in the short run.

In addition to understanding the transmission of weather shocks, we can exploit our recursive identification scheme to assess the effects of monetary policy. As interest rates are ordered fourth in $z_{i,t}$, we can interpret $\varepsilon_{4,it}$ as a monetary policy shock. Note that we are in fact assuming that:

(i) The interest rate is the policy instrument used by all the central banks in our sample.
(ii) Central banks respond to contemporaneous developments affecting ASI, domestic output, and overall inflation, while monetary policy changes start affecting those variables only after one quarter.
(iii) Central banks do not immediately react to changes in food prices, while food prices can be immediately affected by monetary policy shocks.

Therefore, under our structural representation we are letting monetary policy respond to fluctuations in the general level of prices, but not in food prices specifically. In other words, we are assuming that central banks in both advanced and developing countries target headline inflation (Anand et al. 2015). In addition, our scheme also differs from the traditional recursive approach for the identification of monetary policy shocks (see Christiano et al. (1999), among many others), as we let the central bank respond to a variable representing weather-driven water stress (ASI) and not just to output and prices.

Results

Descriptive statistics

The descriptive statistics of the variables used in the panel VAR analysis are reported in Table 1. These statistics are reported for the entire sample of 107 countries, and for the sub-samples of high- and low-income countries.

Figure 1 displays the trend of our two main variables of interest, namely ASI and Food CPI, in high-, middle-, and low-income countries. The trend in ASI is displayed in the left panel and shows that farmland stress reached very high levels in the early 2000s: low-income countries were hit in 2002 and high-income countries shortly after. Middle-income countries have not particularly been affected by such events. It is worth noting that ASI has a strong seasonal pattern in high-income countries, while in other countries water stress is not so clearly connected to the alternation of seasons and is instead related to other climatic factors. As for Food CPI, displayed in the right panel, low- and middle-income countries experienced similarly steep increases; in high-income countries, the increase has been instead smoother and more gradual.

Main results

The IRFs following a shock in ASI resulting from the panel VAR estimated following Abrigo and Love (2016) are displayed in Fig. 2. The left panel displays the IRFs when the panel VAR is estimated on the entire sample (107 countries), whereas the right panel shows and compares the IRFs obtained from the estimation of a panel VAR on the three income groups (high, middle, and low income). The remaining IRFs can be found in the Appendix (Figs. A2.1 – A2.6).

From the analysis of Fig. 2, we observe that a unit increase in ASI leads to an on-impact contraction in economic growth in the entire sample (left panel) and in the three income

Table 1 Descriptive statistics of the variables used in the panel structural VAR analysis

	Whole sample		**High-income**		**Middle - income**		**Low-income**	
	Mean	**St. dev.**	**Mean**	**St. dev.**	**Mean**	**St. dev.**	**Mean**	**St. dev.**
ASI	9.03	11.96	6.85	10.07	9.88	12.51	9.88	12.56
GDP (log)	122.10	123.80	271.20	46.22	72.26	99.50	26.28	2.79
GDP (log difference)	0.009	0.023	0.005	0.013	0.01	0.026	0.012	0.025
CPI	81.33	25.94	90.01	13.35	77.63	28.68	78.95	29.06
CPI (log)	4.33	0.39	4.49	0.17	4.27	0.42	4.29	0.43
CPI (log difference)	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.02
INTRATE (Interest rate)	6.19	5.36	2.95	4.14	7.00	4.23	9.29	3.74
Food CPI	84.16	25.92	89.26	14.44	81.43	29.54	82.77	29.74
Food CPI (log)	4.37	0.37	4.48	0.18	4.32	0.42	4.34	0.42
Food CPI (log difference)	0.01	0.02	0.01	0.01	0.01	0.02	0.02	0.03
N. obs.	8560		2400		4880		1280	

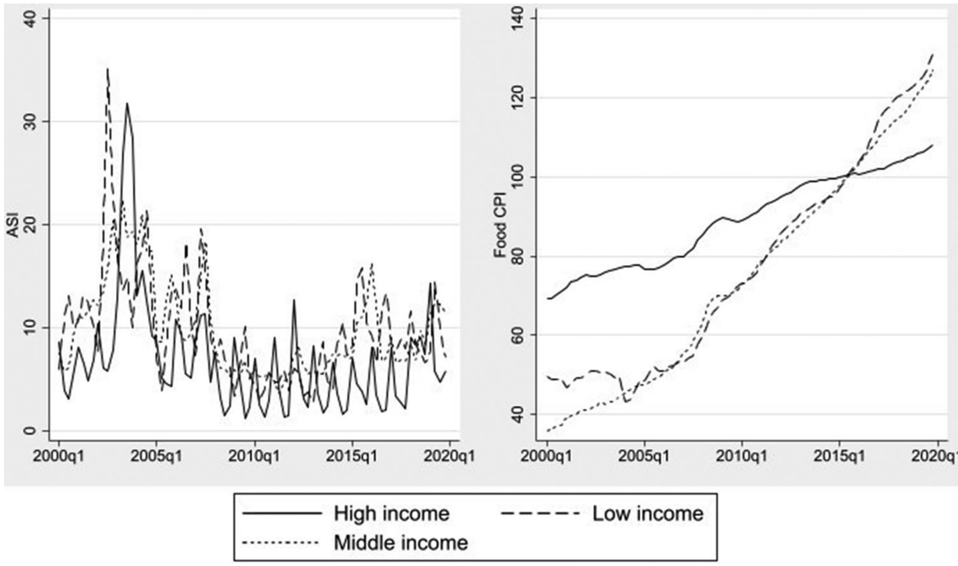

Fig. 1 ASI and Food CPI in high, middle and low-income countries. *Note: the left panel displays the average ASI by income group, ranging from 0 to 100. The right panel shows the average seasonally adjusted Food CPI by income group (2015 = 100)*

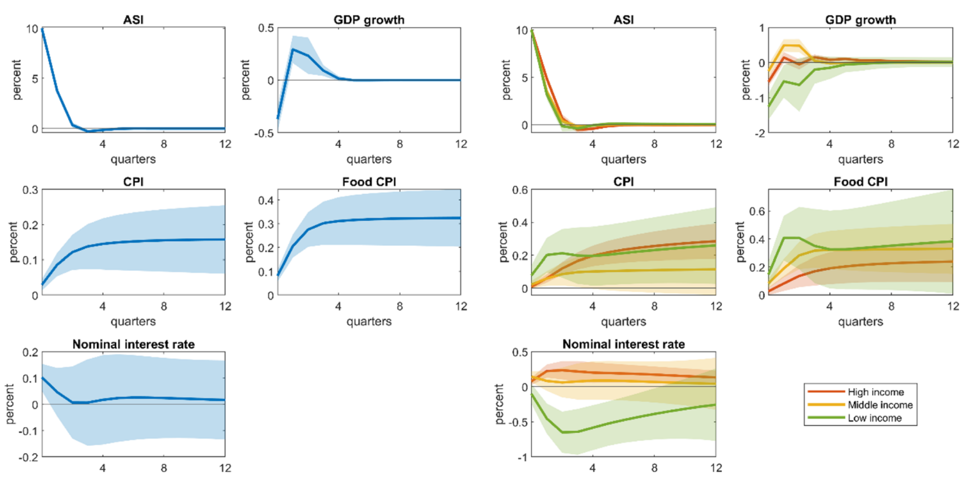

Fig. 2 Impulse-responses following a unit shock in ASI – entire sample and across income groups. *Note: the Figure above displays the IRFs and the 68% confidence bands based on 1000 Monte Carlo simulations. The IRFs obtained on the entire sample are displayed in the left panel. The IRFs pictured in the right panel are obtained from three different models estimated on the sub-samples of high, middle- and low-income countries. Both panels display the cumulated responses of CPI, and Food CPI*

groups considered (right panel). The initial contraction in output reaches almost −0.4% in the entire sample and is similar in high and middle-income countries. In both cases, output growth gradually recovers after approximately two quarters. In low-income countries, the impact on GDP growth is more pronounced: output falls to −1.2% on impact and stays negative for almost four quarters before the shock is absorbed. Hence, low-income countries are more severely affected by agricultural stress, in line with the results of Alessandri and Mumtaz (2022).

The effect that a shock in ASI has on overall and food prices is unquestionably positive and persistent over time. In the entire sample, the responses of CPI and Food CPI are similar, though the impact on Food CPI is larger: on impact, both prices increase (0.05% and almost 0.1% respectively) and gradually settle at persistently higher price levels (0.15% vs. almost 0.3%). A similar pattern characterizes price responses in low-income countries, where Food CPI is more sensitive than overall CPI: the impact is greater on impact (0.15% and 0.2% for overall and Food prices respectively) and at new permanent levels (0.25% and 0.4% respectively). Also, food prices peak at 1 quarter after the shock (almost 0.4%). Overall and food prices increase in high- and middle-income countries, too, yet the smooth increase in either price indicator suggests that the shock is less destabilizing, especially as far as high-income countries are concerned. Our findings are in line with previous works that detect inflationary pressures after weather events in general, and that food prices increase more than other commodity prices (Brown and Kshirsagar 2015; Faccia et al. 2021; Heinen et al. 2019).

The response of the nominal interest rate to a shock in ASI may provide some insight on central banks' behaviour. In the entire sample, the nominal interest rate increases on impact up to 0.1%, but the shock is soon absorbed. A similar response characterizes high- and middle-income countries, where the nominal interest rate increases on impact. Adjustment paths are slightly different: in high-income countries, the interest rate increases on impact and then stabilizes at a persistently greater level. In middle-income countries, the on-impact response exceeds that of high-income countries, but the response rapidly becomes non statistically significant. These patterns indicate that central banks in high and middle-income countries perceive the shock in ASI as a shock that triggers inflation and increase the interest rate accordingly, though with different intensities. Such evidence confirms the indication for a monetary policy tightening in the aftermath of a natural disaster reported in the literature (Fratzscher et al. 2020; Keen and Pakko 2011; Klomp 2020). In low-income countries, the nominal interest rate is reduced already on impact, and it keeps on decreasing to approximately −0.5%. Three quarters after the shock, the rate starts rising but the shock is never totally absorbed. We argue that such accommodative monetary policy, which reduces the nominal interest rate, is aimed at contrasting the negative effects on economic growth, which is the more pronounced across the three income groups (−1%). Even though our analysis examines central bank behavior to water stress and drought in agriculture rather than to natural disasters, we can nonetheless conclude that the observed reaction of monetary institutions in the least developed countries may further compromise their ability of maintaining prices at tolerable and stable levels.

A focus on sub-Saharan African countries

Figure 3 reports the panel VAR estimation results of the model estimated on the sample of sub-Saharan African low-income countries. As a baseline, the Figure also displays the IRFs of the entire sample of low-income countries. In the spirit of Ranger et al. (2025), this regional focus tries to explore whether central banks of SSA low-income countries can actually react to shocks in ASI that simultaneously affect economic output and prices. First, we observe that price responses are slightly different. Both overall and food prices are significantly impacted, but the effect seems to be similar in magnitude. Food prices increase abruptly on impact, peak at almost 0.4% after one quarter and generally stabilize. Overall prices in SSA low-income countries increase to more than 0.3% just two quarters after the shock and then stabilize. Relatively to the benchmark (entire

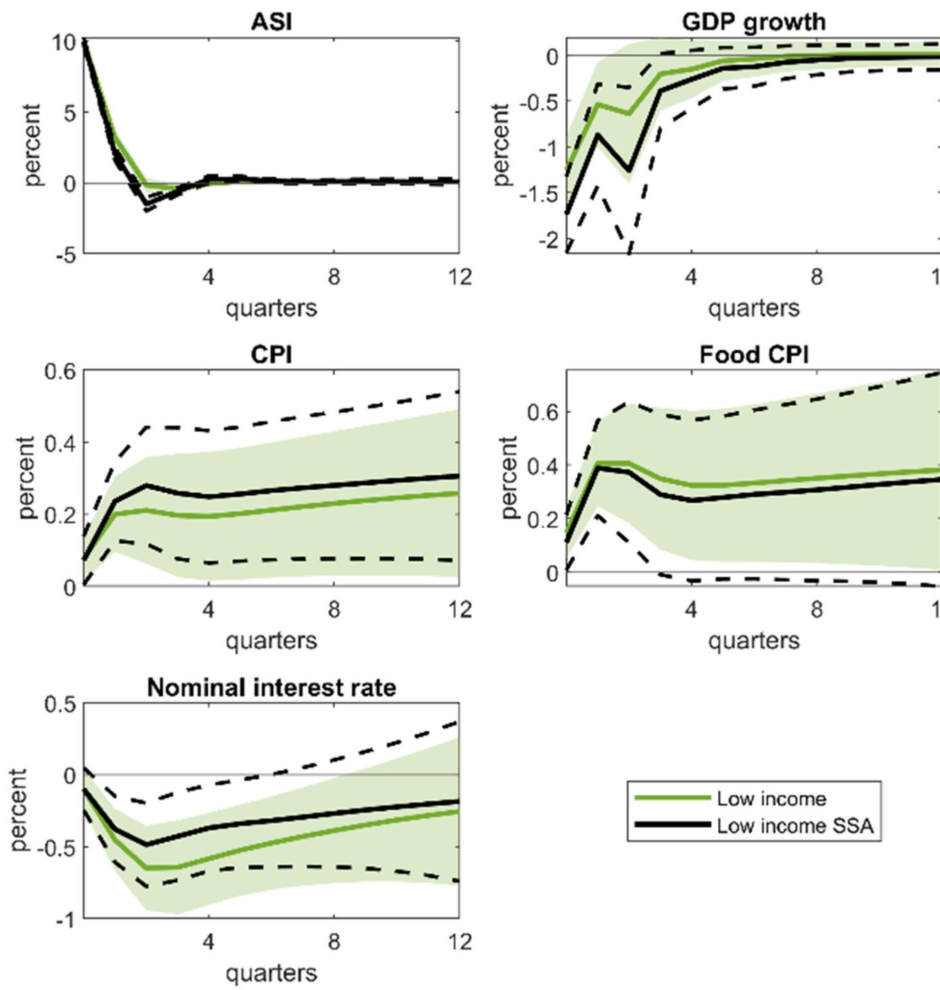

Fig. 3 Impulse-responses following a unit shock in ASI – sub-Saharan African (SSA) low-income countries. *Note: the Figure above displays the IRFs and the 68% confidence bands based on 1000 Monte Carlo simulations of the model estimated on the sample of sub-Saharan African low-income countries. As a baseline, the Figure also displays the IRFs of the entire sample of low-income countries. The panel displays the cumulated responses of CPI and food CPI*

sample of low-income countries), Fig. 3 indicates that the effect is similar for food prices but more pronounced for overall prices. The immediate reduction in economic activity is more pronounced in SSA low-income countries than in the benchmark sample (1.5% vs. –1% respectively) but convergence takes a similar amount of time before the shock is absorbed. Low-income countries in SSA reduce the nominal interest rate on impact but this reduction is smaller, in magnitude, relative to the entire sample of low-income countries.

Inflation vs. non-inflation targeting countries

In this section, we compare the impulse response function of inflation targeting countries with those of non-inflation targeting countries. In so doing, we can identify different inflationary dynamics and monetary policy stances between the two groups of countries. Even though food prices are, once again, more sensitive to a shock in ASI, Figure 4 indicates that the impact is greater in inflation targeting countries. Despite the difference in magnitude, food prices increase in both subsamples. Yet, only inflation

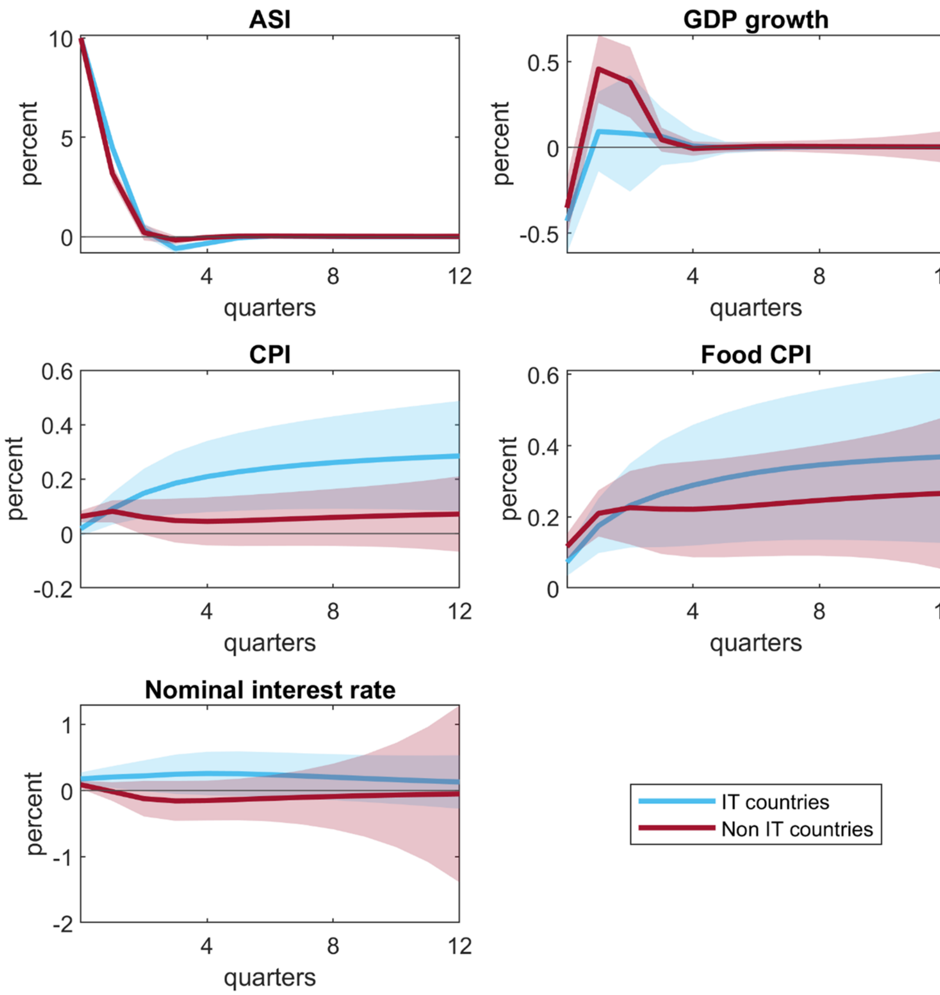

Fig. 4 Impulse-responses following a unit shock in ASI in inflation (IT) and non-inflation (non IT) targeting countries. *Note: the Figure above displays the IRFs and the 68% confidence bands based on 1000 Monte Carlo simulations and estimated on the subgroups of inflation and non-inflation targeting countries* (see Sect. "Data and sources" *for a description of the classification of monetary policy frameworks)*

targeting countries implement a restrictive monetary policy to contrast such price rises; the response of non-inflation targeting countries is in fact non-statistically different from 0.

A heterogeneous panel analysis

In the previous section, the analysis focused on describing average cross-country dynamics following a weather shock. While this pooled specification allowed us to highlight differences between broad country groups, data limitations - particularly the availability of food price series, which start only in 2000 - restrict the scope for country-level estimation. To move beyond the purely pooled approach, we rely on the notion that, although national economies differ, they are shaped by similar underlying economic forces. Hence, the parameters of the underlying VAR models are expected to be comparable across countries, but not necessarily identical. This reasoning motivates the use of a random-coefficients framework, which enables partial pooling of information across countries while still allowing for some degree of idiosyncratic dynamics. Specifically, we employ a Bayesian estimation strategy based on the hierarchical prior VAR model originally proposed by Jarociński (2010) and subsequently applied by Willems (2020), among others.

Formally, for each country i, we estimate a VAR model of the form:[3]

$$z_{i,t} = \sum_{l=1}^{p} A_{i,l} z_{i,t-l} + u_{i,t},$$

where $z_{i,t}$ is the vector of endogenous variables and the reduced-form shocks $u_{i,t}$ are normally distributed, $u_{i,t} \sim N(0, \sum_i)$ The autoregressive matrices $A_{i,l}$ are now specific to each country, allowing for heterogeneity in both the magnitude and persistence of responses. Stacking all time periods, this system can be expressed compactly as:[4]

$$z_i = x_i \beta_i + u_i.$$

The random-coefficients specification assumes that $\beta_i \sim N\left(\bar{\beta}\,\Sigma_\beta\right)$, so that the individual-country parameters are drawn from a common distribution centered around $\overline{\beta}$ with covariance Σ_β. This formulation allows for cross-country heterogeneity while maintaining statistical coherence through a hierarchical structure. The prior for $\overline{\beta}$ is flat, whereas Σ_β is modeled as the product of a scalar hyperparameter λ_1 and a diagonal matrix Ω_β, which mirrors the structure of the covariance matrix of the Minnesota prior. Namely, the diagonal elements of Ω_β are constructed as follows:

- For autoregressive coefficients: $\sigma^2_{jj,k} = \left(1/l^{\lambda_3}\right)^2$;
- For cross-variable lags: $\sigma^2_{jk,l} = \left(\sigma^2_j/\sigma^2_k\right)\left(\lambda_2/l^{\lambda_3}\right)^2$, where σ^2_j denotes the variance from a univariate AR(p) model for variable j;
- For exogenous regressors (including constants): $\sigma^2_{w_j} = \sigma^2_j(\lambda_4)^2$.

The hyperparameters λ_2, λ_3, and λ_4 have an interpretation that is similar to the Minnesota prior, while λ_1 controls the overall tightness of the prior. When $\lambda_1 = 0$, the variance of β_i is zero and the obtained estimate is simply the pooled estimator, whereas as $\lambda_1 \to \infty$, the estimates become fully country-specific. To find the appropriate intermediate value of heterogeneity across countries, the model assumes that λ_1 follows an inverse-gamma distribution with shape parameter s and scale parameter ν. The calibration of hyperparameters follows a standard practice:$\lambda_2 = \lambda_3 = \lambda_4 = 1$ and s = ν = 0.0005, consistent with the guidance in Dieppe et al. (2016).[5]

The main limitation of the random-coefficients approach is that it requires a strongly balanced panel. This constraint forces us to conduct the estimation on a subset of 37 countries over the period 2000Q1–2019Q4. Unfortunately, this sample includes only high- and middle-income economies, as time series for low-income countries are often incomplete. Nonetheless, it remains worthwhile to investigate the presence of heterogeneity in the transmission mechanism of weather shocks within this highly relevant group of more advanced economies.

[3] Our brief description of the hierarchical panel VAR approach follows that of Dieppe et al. (2016) and Willems (2020).

[4] To do so, first define $x_{i,t} = [z_{i,t-1}, \ldots, z_{i,t-l}]$ and stack $z'_{i,t}$ and $x'_{i,t}$ vertically for all time periods, to get
$z_i = x_i A_i + u_i,$
where z_i and u_i are of dimension $T \times n$, x_i is of dimension $T \times m$, and A_i has dimension $m \times n$, where n is the number of endogenous variables and $m \equiv np$. Second, use the vectorization operator to obtain
$z_i = x_i \beta_i + u_i,$
with $z_i \equiv vec(z_i)$, $x_i \equiv (I_n \otimes x_i)$, $\beta_i \equiv vec(A_i)$ and $u_i \equiv vec(u_i)$.

[5] The estimation was performed using the BEAR toolbox.

The main results of our analysis are presented in Fig. 5, which reports, for each country, the median response of food prices and interest rates four periods after an adverse weather shock—namely, a surprise one-standard deviation increase in ASI, which is once again ordered first in the vector of endogenous variables.

Several observations can be made. First, in 24 out of 37 countries the estimated response of the policy rate is positive, indicating that central banks tend to raise interest rates following an adverse weather shock. This behavior is consistent with an endogenous monetary policy reaction aimed at offsetting the inflationary pressures induced by the shock. On average, the general price level increases by about 0.3%, while GDP records a modest rise of 0.1% (not shown in the figure). Such a configuration is in line with the predictions of a Taylor-type rule, according to which central banks respond to inflationary pressures by tightening monetary policy.

Second, in the majority of countries (again 24 out of 37), an adverse ASI shock leads to an increase in food prices. This highlights a strong co-movement between food and general price dynamics in response to weather disturbances. In fact, the correlation between the two variables conditional on an ASI shock amounts to 0.92, underscoring the tight link between sectoral and aggregate inflationary pressures induced by the weather changes.

Third, the magnitude of the monetary policy response appears to be positively associated with the increase in food prices, as indicated by the upward slope of the fitted line in Fig. 5. This relationship provides further evidence of an endogenous policy reaction: central banks tend to raise interest rates more aggressively in those economies where general and food prices rise more markedly following an adverse weather shock.

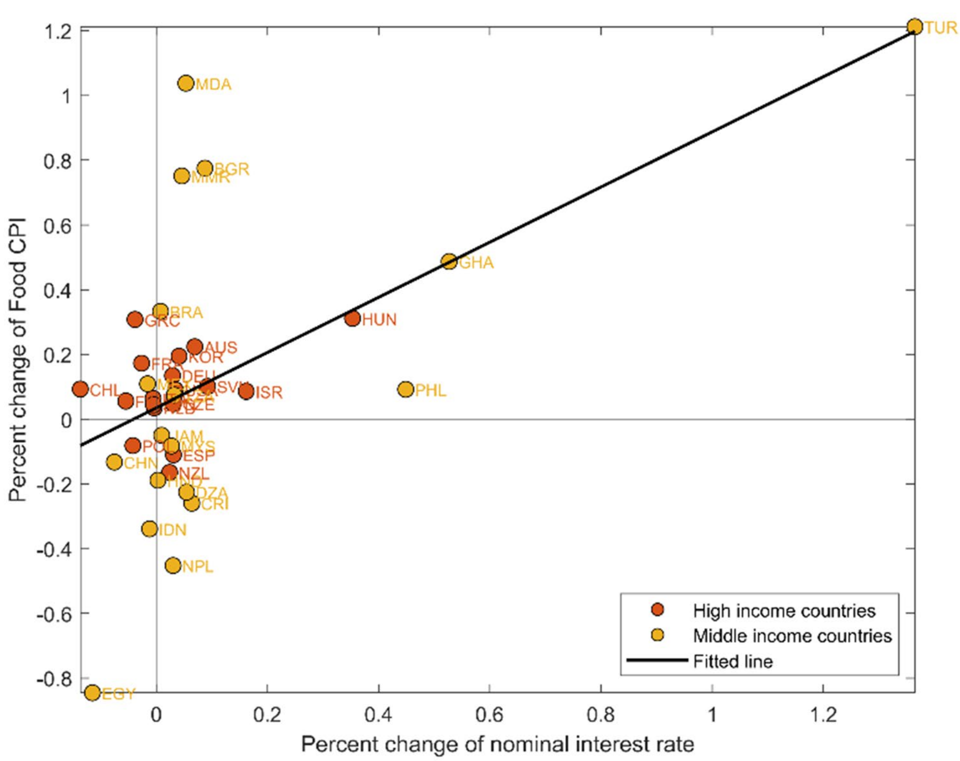

Fig. 5 Responses of the interest rate and food CPI in the heterogeneous panel VAR model. *Note: the Figure above displays the median responses of interest rates and food prices four periods after a weather shock, based on 5000 posterior draws for the heterogeneous panel VAR model*

In summary, this heterogeneous panel analysis appears to support our previous results concerning high- and middle-income countries, obtained in Sect. "Main results" using the group-wise homogeneous panel estimator.

Robustness analysis and alternative country aggregation

Overview

In this section, we present the results of a set of exercises conducted to assess the robustness of our identification strategy. First, we employed alternative lag specifications in the baseline model to see how shorter (1 lag) or longer (4 lags) sets of instruments affect the validity of our identification strategy.

As a second exercise, we considered shocks to different weather variables: the highest level of ASI in a given quarter and the Standardised Precipitation-Evapotranspiration Index (SPEI), a valid alternative measure to detect drought conditions (Vicente-Serrano et al. 2010). SPEI is based on a 0.5° resolution; we used the 4-month SPEI (i.e., computed from precipitation and evapotranspiration over the preceding four months) and weighted it by area. We then used the country-quarter average to match the time frequency of our main dataset.

Finally, we considered alternative country groups to explore how model dynamics are influenced by country characteristics beyond income. To this end, we first compared the responses of net agricultural importers and exporters (Willems 2020). Increased water stresses in agricultural exporting countries could affect agricultural output, reduce food availability for the domestic market, and increase domestic food prices: under such circumstances, exporting countries could reduce their exports, and global food prices could surge (Khalfaoui et al. 2024; Schenker and Osberghaus 2025). Rising global food prices are clearly transmitted to agricultural importing countries. Yet, food prices in importing countries could be affected by local weather shocks or natural disasters, too, that reduce domestic agricultural production and could disturb trade flows (Dallmann 2019; Oh and Reuveny 2010). To distinguish net agricultural importing from exporting countries, we exploit FAOSTAT trade balance data: in particular, we consider import and export values at base prices, expressed in USD thousands, for agricultural commodities excluding beverages, tobacco, and textiles. A country is then classified as importer (exporter) whenever the 2000–2019 average trade balance is negative (positive). The second country segmentation used as a robustness exercise relies on the concept of vulnerability, as defined by the Notre Dame Global Adaptation Initiatives (NDGAIN), i.e., "*The propensity or predisposition of human societies to be negatively impacted by climate hazards*" (Chen et al. 2015), which captures a country's exposure to climate change, its sensitivity to its consequences and its initiatives to reduce potential damage. Such a perspective complements the income segmentation discussed in Sect. "Results" with the given physical and climatic risks faced by each country.

Results

First, we re-estimated the panel VAR on the entire sample considering alternative lag specifications (Fig. 6). In particular, we used 1 lag as recommended by the informative Modified Bayesian Information Criterion (MBIC) (see Table A2.1 in Appendix) and also considered a four-lag structure to control for potentially longer autocorrelation. Results are robust to either lag specification: food prices are more sensitive to a shock in ASI,

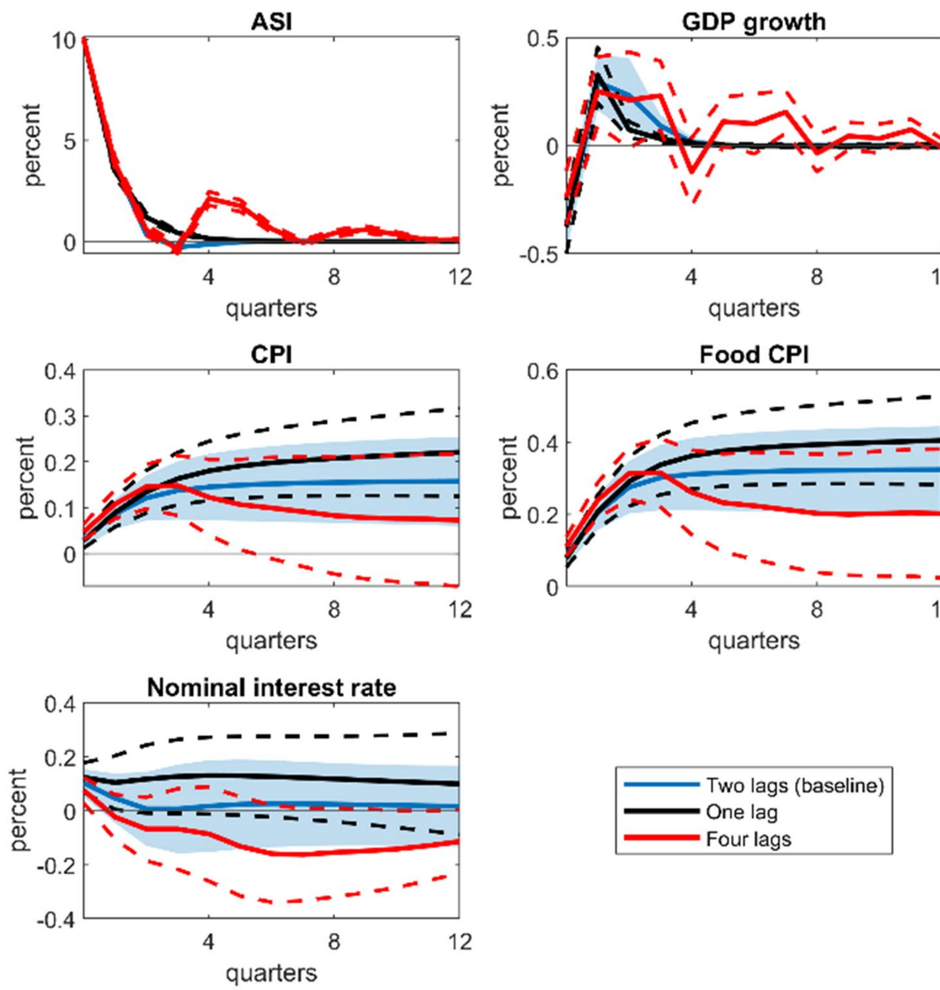

Fig. 6 Impulse-responses following a unit shock in ASI – alternative lag specifications. *Note: the Figure above displays the IRFs and the 68% confidence bands based on 1000 Monte Carlo simulations of the model estimated on the sample of sub-Saharan African low-income countries. The panel displays the cumulated responses of CPI, and food CPI*

but the effects are smaller in the long run when longer lags are used. Similar patterns characterize the response of overall prices. Economic output initially declines in either case, but the shock is absorbed after approximately four quarters. Lastly, the response of central banks is similar to the main analysis: on impact, central banks increase the interest rate, presumably to contrast the inflationary pressures triggered by the shock. In both specifications, the shock is rapidly absorbed.

Figure 7 plots the IRFs obtained when alternative weather variables are used as exogenous shocks. The right panel refers to an increase in the maximum ASI, while the left panel shows the responses to drier conditions as measured by the SPEI.[6]

Although the responses to maximum ASI shocks are smaller than in the baseline model with average ASI, food prices remain more affected than overall prices, both on impact and in the long run, thus confirming the main panel VAR results. The monetary policy response to a maximum ASI shock is not statistically significant, despite the inflationary pressure observed.

[6] Recalling that the index ranges from −2 to +2, with negative (positive) values indicating drier (wetter) conditions, we considered the opposite of the original SPEI. In doing so, a shock in SPEI is equivalent to an increase in drier conditions, making it closer to a shock in ASI in terms of interpretation.

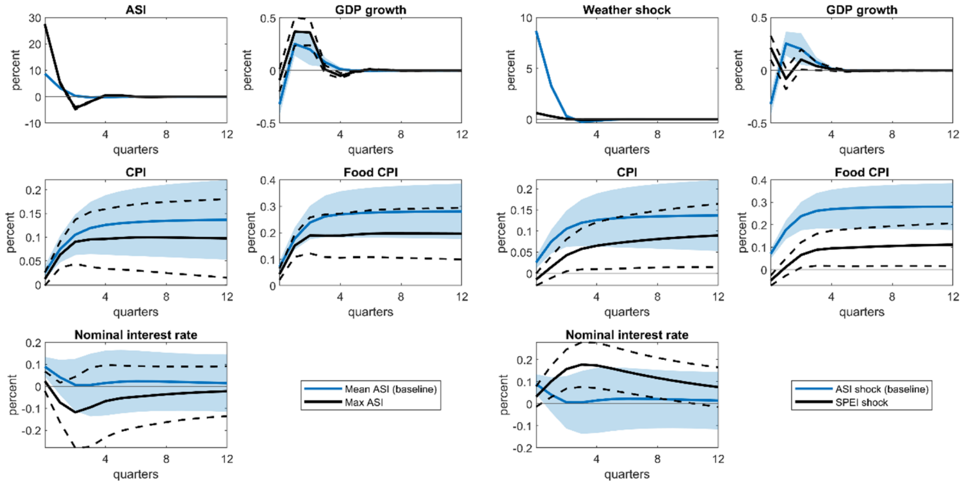

Fig. 7 Impulse-responses following a unit shock in maximum ASI (left panel) and SPEI (right panel). *Note: the Figure above displays the IRFs and the 68% confidence bands based on 1000 Monte Carlo simulations. Both panels display the cumulated responses of CPI, and food CPI*

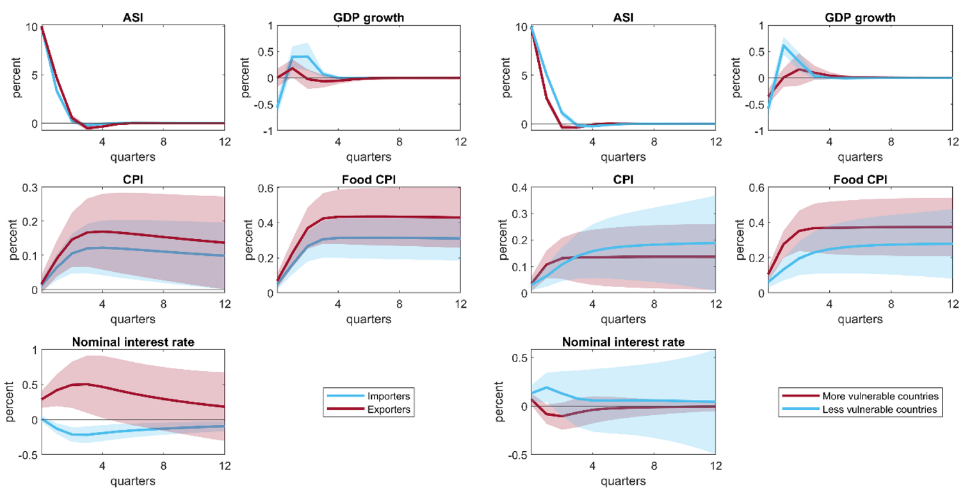

Fig. 8 Impulse-responses following a unit shock in ASI – net agricultural importers and exporters (left panel), and more and less vulnerable countries (right panel). *Note: the Figure above displays the IRFs and the 68% confidence bands based on 1000 monte carlo simulations using alternative country aggregation. The left panel compares the IRFs of agricultural importers and exporters, whereas the right panel compares the IRFs of more and less vulnerable countries. Both panels display the cumulated responses of CPI, and food CPI*

When considering the SPEI, food prices initially decline but gradually converge to higher levels in the long run, while the policy rate reacts only temporarily and weakly. Overall, these findings confirm the robustness of the model, especially when the maximum ASI is used, and highlight that different climatic indicators capture distinct dimensions of weather stress, resulting in heterogeneous transmission dynamics.

Lastly, we evaluate the dynamics across alternative country aggregates (Fig. 8): net agricultural importers vs. exporters (left panel), and vulnerable vs. non-vulnerable countries (right panel). Because our cumulative IRFs reflect local rather than global shocks, food price responses are milder in net importers. In these countries, local droughts affect only part of food supply, while most food inflation depends on international prices that lie beyond domestic control. In exporters, by contrast, local shocks directly reduce supply and may trigger export restrictions, amplifying domestic price pressures (Mamun and Laborde 2025). Moreover, in exporter countries, local agricultural shocks tend to raise inflation through supply and trade channels, prompting monetary tightening to curb price pressures (Cantelmo et al. 2024; Cevik and Jalles 2023). In importing countries, where food inflation is driven mainly by external prices, the same shocks are less inflationary and more recessionary, leading central banks to adopt a more accommodative monetary stance (Ha et al. 2019; Ranger et al. 2025).

Dynamics between vulnerable and non-vulnerable countries (Fig. 7, right panel) do not only confirm the increased incidence of shocks on food prices, but also indicate that central banks in less vulnerable, and generally more developed, countries react to such a shock with an increase in the nominal interest rate. In more vulnerable countries, central banks do not react to shocks in ASI, despite these being simultaneously inflationary and recessionary.

Discussion and conclusions

The macroeconomic effects of weather events are clear and well documented in the literature: extreme weather events tend to reduce economic growth and increase prices (Batten et al. 2020; Cashin et al. 2017; Dell et al. 2012). Since these recessionary and inflationary weather shocks will become increasingly frequent in the near future, central banks can play a fundamental role in mitigating the macroeconomic consequences and inflationary pressures already in the short run. In order to provide a broader interpretation of macroeconomic and monetary policy reactions to weather shocks, which is currently missing or only partially addressed in economic literature, the present study explores the simultaneous relations among weather shocks, food inflation, and monetary policy providing both a global assessment and a perspective that accounts for country heterogeneity.

Building on this motivation, the present analysis offers a novel, agri-food-oriented insight on how water stress and drought in agricultural land are linked to macroeconomic variables and monetary policy. In the present study, exogenous weather variations are not captured through extreme weather events or natural disasters, but rather by an indicator of stress in agricultural land. This measure is the Agricultural Stress Index (ASI), a near real-time remote-sensing technology with a strong drought-predictive power, which has rarely been used in economic studies (Kornher et al. 2024). Increased water stress can in fact be a silent and relentless early warning of droughts, and can in turn compromise agricultural yield, economic growth and price stability especially in low-income countries. To this purpose, we construct a global sample of 107 countries using quarterly data, from 2000Q1 up to 2019Q4, and estimate a panel VAR model (Abrigo and Love 2016) to explore how macroeconomic and monetary policy variables respond to an exogenous variation in ASI, i.e., to an increase in water stress in agricultural land.

Within this framework, the present study initially assesses the macroeconomic impact (on GDP as well as on general and food prices) of an increase in ASI. This assessment is conducted first on a global sample of 107 countries and then on different country aggregates to explore how responses to weather shocks are affected by different structural characteristics (for instance, the income level, and the monetary policy regime). In so doing, we observe that, in line with previous studies and in response to our first Research

Question (RQ1), food prices tend to be more seriously affected by weather shocks than general prices (Abril-Salcedo et al. 2020; Brown and Kshirsagar 2015; Heinen et al. 2019), but differently from previous findings (Faccia et al. 2021), the effects persist also in the long run. Apart from this, our analysis also reveals that the impact of an increase in ASI is more detrimental to the food prices of low-income countries, presumably because of their higher reliance on agriculture, limited adaptive capacity, and weaker infrastructure (Açci et al. 2024; Bayo et al. 2025; Qi et al. 2025). By contrast, high-income countries, nonetheless impacted by an increase in ASI, have greater economic resilience and adaptive capacity (Eichengreen et al. 2024; Fankhauser and McDermott 2014) to better internalize the shock and avoid excessive repercussions on long term food prices. Overall, these findings are in line with the consensus on the negative consequences that extreme weather events, temperature anomalies can have on economic growth (Burke et al. 2015; Dell et al. 2012; Kahn et al. 2021) and price stability (Faccia et al. 2021; Kim et al. 2021; Mukherjee and Ouattara 2021).

The second, and perhaps more relevant contribution of the present study is related to the analysis of central banks' responses to a shock in ASI. The interpretation of monetary policy addresses the second and third Research Questions (RQ2 and RQ3). The panel VAR model estimated on the entire global sample and on different country clusters generally indicates that central banks in high and middle-income countries tend to contrast the inflationary pressures triggered by the climatic shock by increasing the interest rate, in line with monetary policy recommendations observed in the literature (Cantelmo et al. 2024; Keen and Pakko 2011; Parker 2018). Central banks in high-income countries strictly pursue inflation targeting strategies (Fratzscher et al. 2020), and such a response is the natural reaction to contrast inflation. In low-income countries, central banks find it more difficult to anchor inflation expectations, let it be for their weak institutional capacity, for the broader set of monetary policy objectives faced, or for the higher exposure to foreign prices (Ha et al. 2019; Ranger et al. 2025). Our findings indicate in fact that central banks in low-income countries tend to accommodate the shock by reducing the interest rate rather than contrasting inflation. This evidence is confirmed when focusing only on sub-Saharan Africa low-income countries, where central banks reduce the interest rate, though to a lesser extent than when all low-income countries are considered. The patterns characterizing central banks' responses in low-income countries may reflect also structural and institutional features of monetary policy in low-income economies, where limited policy credibility, shallow financial markets, and political constraints often weaken the transmission of interest rate changes (Carare et al. 2023; Mishra et al. 2012). In principle, central banks in low-income countries should conduct a restrictive monetary policy to prevent overall and food prices from remaining at excessively high levels. In practice, this is harder as contractionary monetary policy can further destabilize food prices, an event also known as the "price-puzzle" (Tas 2011), especially in emerging countries (Ha et al. 2024; Iddrisu and Alagidede 2021). The contractionary effects that a monetary policy tightening might have on prices in least developed countries suggest that monetary interventions following a worsening in agricultural conditions should be complemented with expansionary fiscal measures (for instance, food subsidies or agricultural investment subsidies) to offset the negative effects on output (Akber et al. 2022; Ginn and Pourroy 2019; Iddrisu and Alagidede 2020).

Beyond income heterogeneity, we also explore how different monetary policy frameworks shape monetary responses to a shock in ASI; in so doing we address the fourth Research Question (RQ4). In this regard, we observe that central banks in inflation targeting countries increase the nominal interest rate to prevent excessive food price inflation. Conversely, central banks in non-inflation-targeting countries do not react to an increase in ASI.

We eventually estimated the interactions between weather, macroeconomic and monetary variables in a balanced set of high- and middle-income countries and within a random-coefficients panel VAR approach, in which the autoregressive parameters are allowed to be partially country-specific. The results from this heterogeneous panel model reveal a certain degree of cross-country heterogeneity, but they also remain broadly consistent with the average dynamics estimated using the homogeneous panel VAR, thereby supporting the robustness of our baseline results.

The findings of this study offer a novel perspective of how macroeconomic and monetary policy variables react to less abrupt changes in agricultural conditions. Our analysis, which seeks to provide a global assessment of these interlinkages, is subject to some limitations, mainly related to data availability, especially for least developed countries. Quarterly data are in fact not always available and had to be imputed; also, the analysis is based on an unbalanced longitudinal sample, with the imbalance particularly affecting low-income countries. Future analysis should be based on sub-national data, in which weather disturbances are evaluated also at the local level.

The present study stresses the important role central banks have in helping countries deal with the consequences of climate change. Their role is in fact fundamental not only to support the ecological transition to low-carbon emission economies, but also to undertake the short-run preventive actions to mitigate the economic consequences of climate change and extreme weather events. The results of the present study also suggest that low-income countries may benefit from more flexible policy frameworks that account for temporary food price fluctuations and coordination with fiscal measures such as targeted subsidies or agricultural investment incentives. Central banks could incorporate climate indicators like agricultural stress (Jensen et al. 2019; Ortega-Gaucin et al. 2021) into their forecasting tools to anticipate food inflation and avoid pro-cyclical tightening when shocks are supply-driven. Clearer communication and forward guidance may also help anchor expectations, while regional cooperation could strengthen the collective capacity to manage climate-induced inflation risks.

Though beyond the scope of research, the present study also emphasizes the importance of helping countries adapt to weather shocks and to minimize food price volatility after a worsening in agricultural conditions. For instance, climate adaptation and mitigation finance can play a fundamental role in fostering agricultural resilience (Trentinaglia et al. 2023), thus preventing excessive price variations after weather shocks (Ichoku et al. 2023). In this context, initiatives improving countries' adaptive capacity are particularly relevant also to reduce food price volatility after a worsening in agricultural conditions. Implications regarding specific and feasible technologies should be considered, particularly for low-income economies. ICT-based solutions such as remote sensing (Jensen et al. 2019) and smartphone applications providing localized weather and crop information (Confalonieri et al. 2013) can enhance drought monitoring and support the creation of early warning bulletins. These technologies can also be integrated with poverty alleviation instruments—such as microcredit and insurance schemes—helping farmers manage risks and stabilize income. While traditional microcredit programs often show limited effects (Banerjee et al. 2015; Jordan 2021), innovative remote-sensing-based approaches can reduce credit risk and improve farmers' access to financing (Möllmann et al. 2020). Technological innovation in agriculture should also include Climate Smart Agriculture (Amadu et al. 2020; Lipper et al. 2014), which enhances productivity, supports food security, and mitigates the impact of drought through improved practices, drought-tolerant crops, and soil management.

Appendix

A1. Countries included in the analysis

Table A1.1 reports the countries included in the sample grouped by the World Bank income classification. Tables A1.2-A1.4 list the countries included in the alternative classifications used in the analysis (Sections Data and sources and Methodological approach: the panel VAR model).

A1.1 Income group classification

Income group	Countries
High income countries	Australia, Austria, Belgium, Canada, Chile, Croatia, Czech Rep., Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Poland, Slovak Rep., Slovenia, Spain, Sweden, Switzerland, United Kingdom, Uruguay, USA
Upper middle income	Albania, Argentina, Armenia, Azerbaijan, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Dominica, Dominican Rep., Ecuador, Equatorial Guinea, Gabon, Georgia, Guatemala, Indonesia, Jamaica, Jordan, Malaysia, Mexico, Namibia, Paraguay, Peru, Russian Federation, South Africa, Suriname, Thailand, Turkey
Lower middle income	Algeria, Bangladesh, Benin, Bolivia, Cambodia, Cameroon, Congo, Egypt, Eswatini, Ghana, Honduras, India, Kenya, Kyrgyz Rep., Lao people's dem. Rep., Mauritania, Moldova, Mongolia, Morocco, Myanmar, Nepal, Nicaragua, Nigeria, Pakistan, Philippines, Senegal, Sri Lanka, Tanzania, Ukraine, Vietnam, Zambia
Low income	Burkina Faso, Burundi, Chad, Gambia, Guinea-Bissau, Liberia, Madagascar, Mali, Mozambique, Niger, Rwanda, Sierra Leone, Tajikistan, Togo, Uganda, Yemen

A1.2 Inflation targeting countries

Monetary policy	**Countries**
Inflation targeting	Austria, Albania, Azerbaijan, Belgium, Bolivia, Cambodia, Costa Rica, Croatia, Czech Republic, Dominican Republic, Ecuador, Finland, France, Germany, Ghana, Greece, Hungary, Indonesia, Italy, Iceland, Ireland, Korea, Liberia, Moldova, Myanmar, Netherlands, Peru, Poland, Spain, Sweden, Sierra Leone, Slovakia, Slovenia, Turkey, Tanzania, Yemen

Inflation targeting defined upon the classifications reported in Sect."Data and sources"(Romelli2022, 2024). The following countries have no information: Armenia, Eswatini, Honduras, Israel, Madagascar, Mozambique, Nicaragua, Suriname, Tajikistan. The remaining countries are classified as non-inflation targeting

A1.3 Net agricultural importers

Net agricultural importers	Countries
	Austria, Albania, Algeria, Armenia, Azerbaijan, Bangladesh, Benin, Botswana, Burundi, China, Cambodia, Congo, Croatia, Czech Rep., Dominica, Dominican Rep., Egypt, Equatorial Guinea, Finland, Germany, Gabon, Gambia, Georgia, Greece, Italy, Iceland, Israel, Japan, Jamaica, Jordan, Korea, Kyrgyz Rep., Libera, Mexico, Mali, Mauritania, Mongolia, Morocco, Mozambique, Norway, Namibia, Nepal, Niger, Nigeria, Philippines, Pakistan, Russia, Rwanda, Sweden, Switzerland, Senegal, Sierra Leone, Slovak Rep., Slovenia, Suriname, Tajikistan, United Kingdom, Yemen

Trade classification based on 2000–2019 sample median value (see Sect."Data and sources"). The remaining countries are classified as net agricultural exporters

A1.4 More vulnerable countries

More vulnerable countries	Countries
	Albania, Bangladesh, Benin, Bolivia, Botswana, Burkina Faso, Burundi, Cambodia, Cameroon, Chad, Congo, Rep. Of., Dominican Rep., Ecuador, Egypt, Equatorial Guinea, Eswatini, Gabon, Gambia, Ghana, Guatemala, Guinea-Bissau, Honduras, India, Indonesia, Kenya, Lao, Liberia, Madagascar, Mali, Mauritania, Moldova, Mongolia, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, Peru, Philippines, Pakistan, Rwanda, Senegal, Sierra Leone, Sri Lanka, Thailand, Tanzania, Togo, Uganda, Vietnam, Yemen, Zambia

Vulnerability classification based on 2000 sample median value (see Sect."Data and sources") of the ND-GAIN vulnerability index. The remaining countries are classified as less vulnerable countries

A2. Panel VAR results

Table A2.1 below reports the result of the lag selection conducted using the command *pvarsoc* in Stata18. Figure A2.1-A2.4 below display the IRFs on the entire panel VAR estimated on the entire sample (Fig. A2.1), on the income group subsamples (Figs A2.2-2.4) and on inflation vs. non-inflation targeting countries (Figs A2.5 and A2.6).

A2.1 Panel VAR lag selection

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.940	297.725	0.000	−354.551	147.725	−26.722
2	0.988	222.328	0.000	−212.522	122.328	6.030
3	0.991	168.046	0.000	−49.379	118.046	59.897
4	0.993	.	.	.	.	.

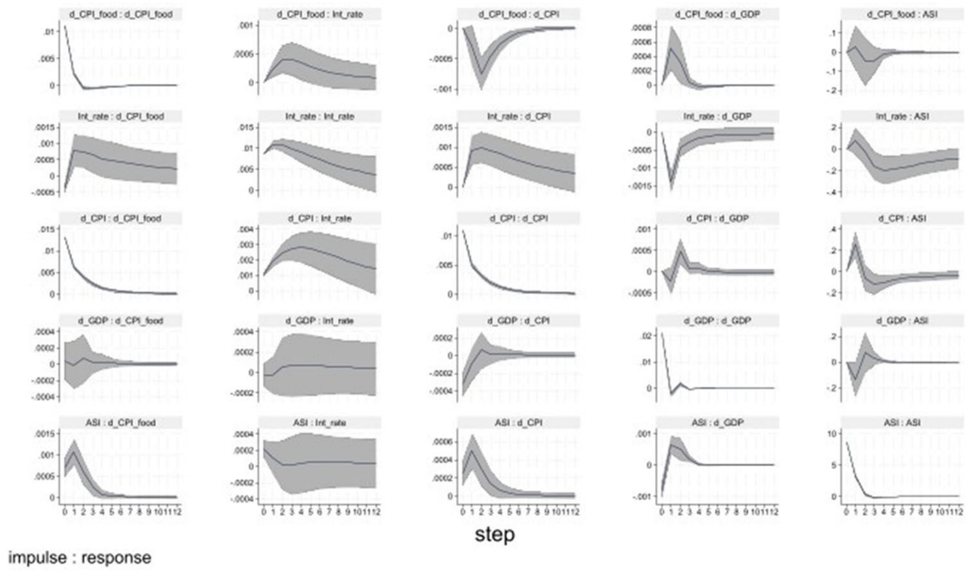

Fig. A2.1. Impulse-responses obtained on the entire sample. *Note: orthogonal and non-cumulated IRFs together with 68% confidence intervals obtained after 1000 monte carlo simulations*

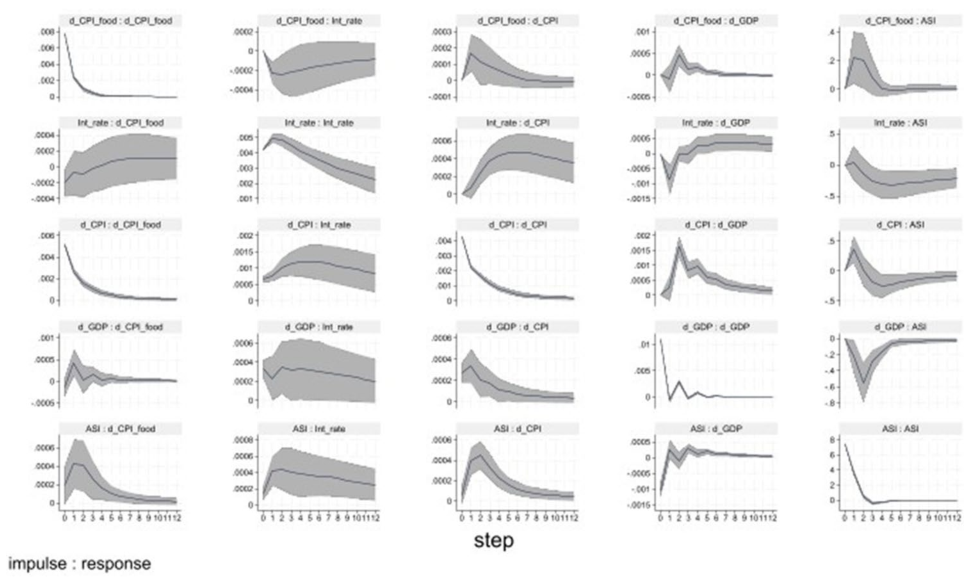

Fig. A2.2. Impulse-responses obtained on the sample of high-income countries. *Note: orthogonal and non-cumulated IRFs together with 68% confidence intervals obtained after 1000 monte carlo simulations*

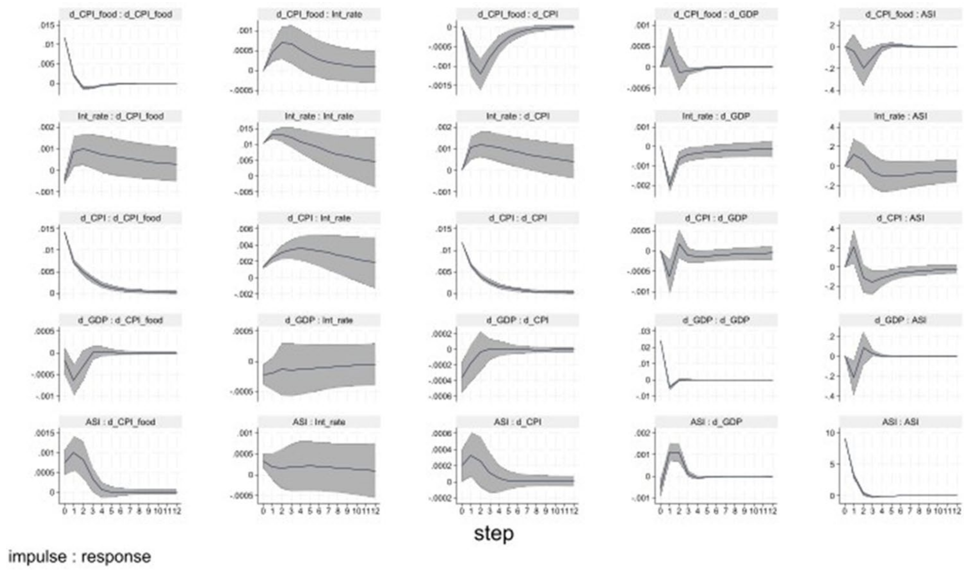

Fig. A2.3. Impulse-responses obtained on the sample of middle-income countries. *Note: orthogonal and non-cumulated IRFs together with 68% confidence intervals obtained after 1000 monte carlo simulations*

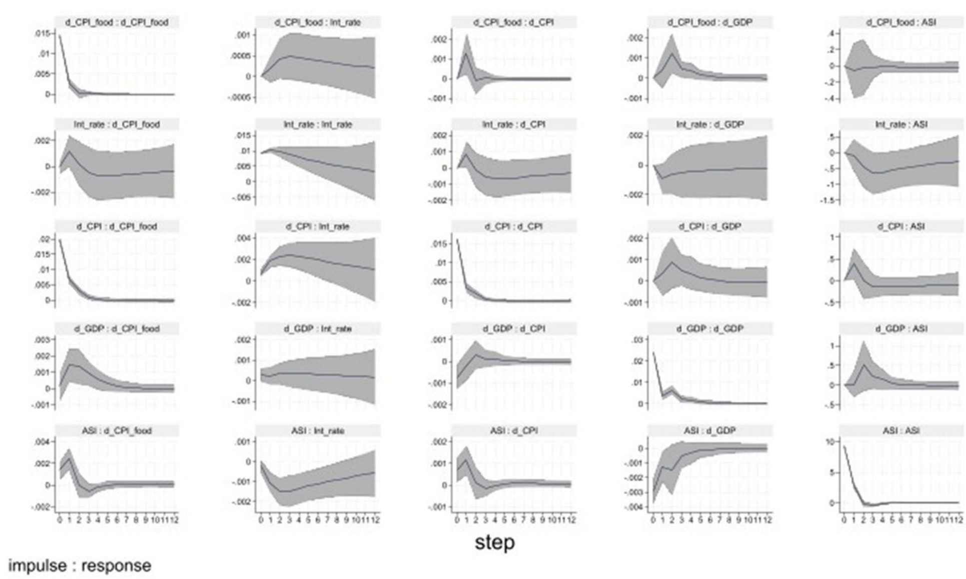

Fig. A2.4. Impulse-responses obtained on the sample of low-income countries. *Note: orthogonal and non-cumulated IRFs together with 68% confidence intervals obtained after 1000 monte carlo simulations*

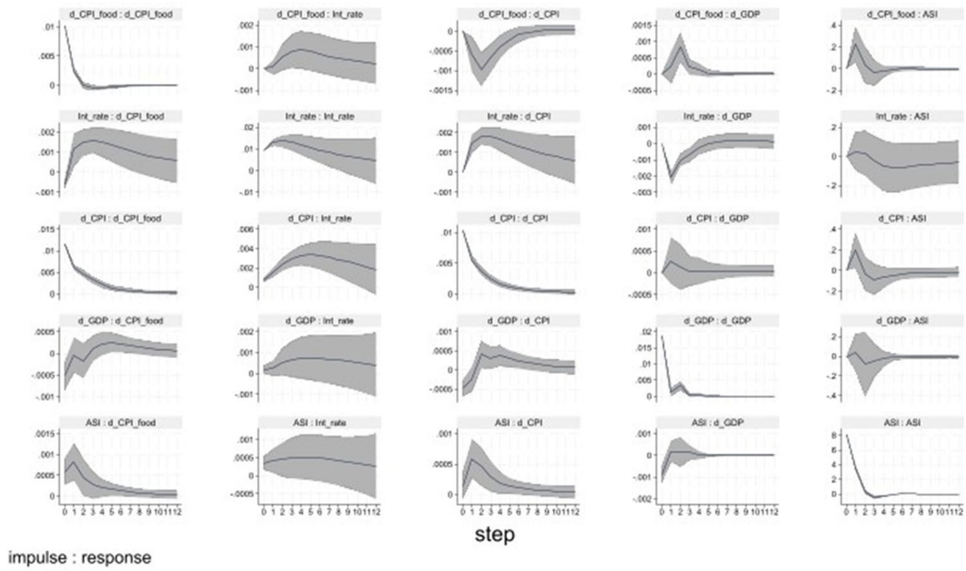

Fig. A2.5. Impulse-responses obtained on the sample of inflation targeting countries. *Note: orthogonal and non-cumulated IRFs together with 68% confidence intervals obtained after 1000 monte carlo simulations*

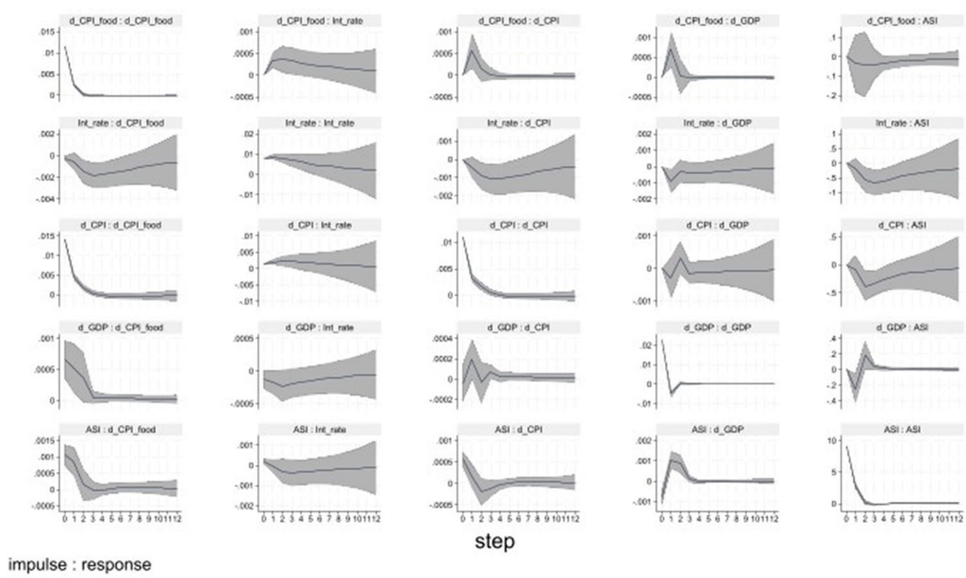

Fig. A2.6. Impulse-responses obtained on the sample of non-inflation targeting countries. *Note: orthogonal and non-cumulated IRFs together with 68% confidence intervals obtained after 1000 monte carlo simulations*

Authors' contributions
The study's conception and design involved contributions from all authors. M.T.T. contributed to Conceptualization, Methodology, Formal analysis, Writing - Original Draft; Writing - Review & Editing. M.P. contributed to Conceptualization, Writing - Review & Editing, Supervision. A.G. contributed to Methodology, Formal analysis, Writing - Original Draft; Writing - Review & Editing. L.B. contributed to Conceptualization, Writing - Review & Editing, Supervision. All authors have read and agreed to the published version of the manuscript.

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Data availability
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests

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