



BANK ĊENTRALI TA' MALTA
EUROSISTEMA
CENTRAL BANK OF MALTA

A photograph of the interior of the Central Bank of Malta building. The space is characterized by a high ceiling with a dramatic, colorful sky (orange, red, and blue) projected onto it. The walls are made of light-colored stone or concrete, and the floor is dark. On the right, there are several rows of white, rectangular, three-dimensional blocks arranged in a grid pattern. In the foreground, there are long, low, curved reception desks. In the background, there is a large arched doorway leading to another part of the building. The overall atmosphere is modern and architectural.

CENTRAL BANK OF MALTA WORKING PAPER



BANK ĊENTRALI TA' MALTA
EUROSISTEMA
CENTRAL BANK OF MALTA

Short-run spillover effects of climate shocks to small-open economies: An empirical investigation.

Theodossios Drossidis*

WP/06/2026

*Senior Research Economist in the Economic Research Office within the Economic Research Department. The author would like to thank Governor Alexander Demarco, Deputy Governor Rita Schembri, Aaron G. Grech, Noel Rapa, Massimo Giovannini, Germano Ruisi and all attendees to an internal seminar for feedback and comments provided. The article also benefited greatly from valuable suggestions of Friderike Kuik, Angeliki Theophilopoulou and Haroon Mumtaz. The views expressed in this report are those of the author and do not necessarily reflect the views of the Central Bank of Malta. Any remaining errors are the sole responsibility of the author.

Abstract

This study extends recent work in the climate literature by examining how climate shocks, specifically temperature and precipitation anomalies, spill over across borders, influencing inflation and real economic variables. Using high-resolution gridded climate data, I construct sector-sensitive climate shock measures that account for potential sign asymmetries and embed them in a large two-country VAR framework for Italy and Malta. The analysis shows that climate shocks in Italy can generate inflationary pressures in Malta, particularly through processed food prices, services, and producer prices in food manufacturing. Importantly, once a shock crosses borders, the affected inflation components in Malta need not coincide with those in Italy, reflecting country-specific transmission channels. These findings underscore the importance of cross-border climate vulnerability, especially for small open economies that are closely integrated with larger trading partners.

JEL Classification: Q54, E31, C32

Keywords: Climate Shocks, Climate proxies, Spillover Effects, Bayesian VAR

Contents

1	Introduction	5
2	Literature	8
3	Data	10
3.1	Climate proxies	10
3.2	Macroeconomic variables	13
4	Methodology	13
5	The effects of temperature and precipitation shocks	15
5.1	Positive temperature shocks	16
5.1.1	Effects on Italy	18
5.1.2	Spillover effects to Malta	19
5.2	Negative precipitation shocks	22
5.2.1	Effects on Italy	22
5.2.2	Spillover Effects to Malta	25
6	What are domestic variables responding to?	27
7	Robustness	31
8	Conclusion	34
	Bibliography	36
A	Macroeconomic Variables	40
B	IRFs of Aggregate Control variables	41
C	Electricity and Gas Imports of Malta	43
D	Processed and Unprocessed Food Import Share	44
E	Final Energy Consumption by Sector in Italy	45
F	Service Breakdown by Item Weights in Italy	46

G	Energy Production before the inter-connector	47
H	Sign-asymmetry of climate shocks	48
	H.1 Negative temperature shocks	48
	H.2 Positive precipitation shocks	50
I	Complementary IRF Decompositions	54
J	IRFs of the Robustness Section	57

1 Introduction

Climate change is one of the most pressing global challenges of our time, with increasingly visible environmental and economic consequences. Global average surface temperatures have risen by approximately 1.3–1.5 °C relative to the pre-industrial period, and individual recent years (most notably 2023 and 2024) have temporarily exceeded the 1.5 °C threshold on an annual mean basis¹. In Europe, warming has proceeded at roughly twice the global rate, with the 2024 annual European mean reported at about 2.4 °C above the 1850–1900 baseline, and the region has experienced increasingly frequent summer heatwaves, compound drought events, and episodic extreme precipitation over the past decade (C3S and WMO (2025)).

These developments have long attracted the attention of policymakers in the European Union, which has committed to achieving a climate-neutral society by 2050, with interim targets aiming to reduce net greenhouse gas emissions by at least 55% by 2030 compared to 1990 levels. This commitment is reflected in a suite of coordinated EU policy instruments, including the European Green Deal, the EU Emissions Trading System (ETS), the Effort Sharing Regulation (ESR), and the Renewable Energy Directive (RED), each targeting specific dimensions of emission reduction and sustainable transformation.

Rising temperatures have been shown to reduce agricultural yields, labour productivity, and energy efficiency, ultimately leading to lower economic output (Dell et al. (2012), Colacito et al. (2019), Kolstad and Moore (2020), Burke et al. (2023)). Likewise, precipitation shocks—whether from excessive rainfall or prolonged drought—can depress agricultural production and put upward pressure on food prices (Damania et al. (2020), Dasgupta et al. (2021), Kotz et al. (2022)).

While some recent studies recognise the potential for such shocks to be transmitted across borders due to trade linkages (Usman et al. (2025b)), the empirical literature remains predominantly focused on *domestic effects*. Ciccarelli et al. (2024), for instance, analyse the seasonal impact of temperature fluctuations on inflation components in Italy, Spain, Germany, and France, showing that warmer (colder) seasons tend to increase (decrease) inflationary pressures. Yet, such studies largely overlook the extent to which climate shocks originating in one country may propagate to others through real and nominal linkages. Understanding these spillover channels is essential, as emerging evidence suggests that trade and production networks can transmit local climate disturbances across borders, amplifying their aggregate economic impact (Baronetti et al. (2024), Usman et al. (2025b), Kotz et al. (2025)). In contrast, other studies, such as Bilal

¹See World Meteorological Organization (2025) and Copernicus Climate Change Service (C3S) (2025) for the most recent observational assessments.

and Känzig (2026), find little evidence of such spillovers. The lack of consensus in the literature may stem from different sources such as the identification of climate shocks, the modelling frameworks employed, or the set of countries under analysis. This study contributes to this debate by explicitly modelling climate shock transmission within a two-country VAR framework.

The spillover mechanism is particularly relevant for small and highly open economies such as Malta, whose economy is tightly linked to Italy: since 2015, Italian food products have accounted for between 41% and 56% of Malta’s total food imports. Imports of agricultural and hunting products have shown a similar pattern, ranging between 48% and 60%. The dependence is even more pronounced in the energy sector, as Malta’s *electricity, gas, steam and air conditioning supply* is entirely sourced from the Italian market². Such pronounced interdependence creates substantial exposure to external shocks, making the Malta–Italy relationship an ideal setting for investigating the cross-border transmission of climate shocks.

Building on Ciccarelli et al. (2024), this study adapts the framework proposed therein to a two-country VAR framework that explicitly incorporates a small open economy assumption and focuses on cross-border linkages. Following Kotz et al. (2021) and Kotz et al. (2023), I construct sector-weighted *temperature* and *precipitation* proxies by calculating weighted deviations of these variables from their long-term means at the NUTS-2 level in Italy. This approach captures how Italian climate shocks first affect domestic conditions and subsequently spill over to Maltese inflation components and production sectors effectively adding to the literature that looks at the importance of climate spillover effects.

In line with Ciccarelli et al. (2024) I find that *positive temperature* deviations during colder (warmer) months lead to price decreases (increases), reflecting expected seasonal dynamics across the main inflation components. In contrast, *negative precipitation* shocks display a more concentrated impact on the agricultural and food sectors ultimately leading to overall weaker effects compared to temperature shocks. Drier summer conditions are associated with price increases in processed and unprocessed food, services, and producer prices, while also increasing energy production volumes. These findings reinforce the broader narrative that dry conditions during already arid periods amplify inflationary pressures; consistent with evidence from studies on weather shocks and Italian agricultural output (Guerriero et al. (2023), Pulighe et al. (2024), Baronetti et al. (2024)).

Beyond these domestic effects, the analysis reveals important cross-border *spillovers* to Malta. Maltese consumer prices closely mirror Italian dynamics, exhibiting responses of comparable

²See appendix (C).

magnitude and persistence, particularly for temperature shocks. Producer prices also co-move with those in Italy, albeit more weakly. Interestingly, Maltese energy production volumes display an inverse adjustment pattern, offsetting foreign fluctuations and suggesting a compensatory response mechanism to external supply conditions.

The decomposition of impulse response functions sheds further light on the transmission channels. Median responses of Maltese HICP components are largely driven by *domestic factors*, except for service prices, food production and economic activity, where spillover effects dominate. Service-price and food production spillovers originate mainly from Italian unprocessed food prices and energy production volumes, and are large enough that Maltese services inflation overshoots its Italian counterpart in spring and summer. The finding reflects the high HICP weight of catering and accommodation in Malta—items whose input costs are tightly linked to Italian fresh-food and energy inputs, and whose demand is, in addition, sensitive to intra-European tourism reallocation under Mediterranean heatwave conditions—so that an Italian temperature shock, which raises energy production and in turn unprocessed food prices, is transmitted to Malta predominantly through services rather than directly through consumer food prices. The business cycle conditions index—a broader measure of economic activity—is also predominantly shaped by Italian economic activity (industrial production) underscoring the tight trade linkages between the two economies. In contrast, consumer and producer energy prices remain primarily determined by *domestic factors*, consistent with the role of government subsidies in shielding the energy sector from external shocks.

Finally, the results uncover important asymmetries once the sign of climate shocks is accounted for. *Temperature shocks* affect producers symmetrically but generate asymmetric consumer responses, particularly in processed food, unprocessed food, and services during summer months. *Precipitation shocks*, by contrast, display clear sign asymmetries on both the producer and consumer sides. These findings point to the relevance of non-linear or interaction-based specifications—especially for precipitation shocks, where positive and negative deviations from normal rainfall produce distinct economic effects (Damania et al. (2020), Kotz et al. (2022)). Quantitatively, imposing the symmetric shock specification attenuates some estimated temperature responses, pushes several credible sets across zero, and it reverses the sign of a non-trivial subset of the precipitation IRFs. The implication is practical rather than merely technical: models that aggregate positive and negative deviations into a single symmetric climate shock series risk distorting the inflationary impact of temperature shocks. In case of precipitation, a symmetric treatment can even lead to sign reversals. Taken together, these findings suggest

that, for small open economies highly integrated with a single partner, the climate exposure of the partner is a relevant additional dimension of macroeconomic risk to monitor, alongside the conventional trade and financial channels.

The remainder of the paper is structured as follows: section (2) offers a brief overview of the climate-economics literature, section (3) describes all the data used in the study including the procedure of proxy derivation, section (4) explains the methodology, section (5) presents the baseline findings of the study, section (6) conducts the IRF decomposition, section (7) provides a sensitivity analysis of the baseline findings and section (8) concludes.

2 Literature

This study lies at the intersection of two strands of research: it contributes to the literature on the economic impacts of temperature and precipitation shocks and provides new evidence on whether these shocks generate cross-border transmission mechanisms. A natural starting point is the literature on temperature shocks, where Kotz et al. (2021) document that increases in seasonally adjusted day-to-day temperature variability reduce regional economic growth, independently of changes in the annual mean. They find a linear relationship at the national level but significant non-linear effects across countries. Countries located at lower latitudes—which tend to experience less seasonal temperature variability—are more vulnerable. These regions also tend to be poorer, compounding their vulnerability, as lower-income households face greater barriers to building resilience due to both limited exposure and financial constraints. Expanding on these insights, Mumtaz and Theophilopoulou (2024) find that a 1°C increase in temperature leads to a 0.63% rise in the Gini coefficient after six years, based on a panel of 153 countries. They show that climate shocks have stronger distributional effects in poorer, hotter countries with large agricultural sectors and low adaptive capacity.

The study most closely related to this paper is provided by Ciccarelli et al. (2024), who estimate a large Bayesian Vector Autoregression (VAR) for each of the four largest Euro Area economies—Germany, France, Italy, and Spain—to assess the seasonal effects of temperature variability. Their results, obtained by introducing a temperature shock proxy into the VAR, indicate that the inflationary effects of temperature shocks vary both seasonally and geographically. For instance, warmer temperatures in winter can enhance agricultural productivity and reduce food inflation, while similar shocks in summer lead to price increases. This study makes three key extensions to the above. First, I focus on the cross-country spillover effects of these shocks, examining how climate disturbances in a small open economy propagate to its main

trading partner. Second, I broaden the scope of analysis beyond temperature shocks to include the effects of precipitation shocks. Third, I construct both climate shock proxies—temperature and precipitation—using time-varying weights based on the gross value added of the agricultural sector, drawing on gridded temperature and precipitation data to capture sectoral heterogeneity more precisely.

In comparison, the literature has historically struggled to identify significant and consistent impacts of precipitation shocks on economic outcomes (Dell et al. (2012), Burke et al. (2015), Kalkuhl and Wenz (2020)), a phenomenon often referred to as the “precipitation puzzle.” More recent contributions, such as Damania et al. (2020) and Holtermann (2020), argue that these earlier insignificant findings stem from the inappropriate aggregation of precipitation data in empirical analyses. In line with this, Kotz et al. (2022) offer a detailed empirical assessment of rainfall’s economic impacts using a fixed-effects panel regression applied to a global dataset. Their findings show that an increase in the number of wet days, as well as higher levels of extreme rainfall, has a negative effect on economic growth. Analysis of rainfall distributions across multiple timescales further indicates that although higher annual rainfall can support economic growth, these benefits taper off as total climatological rainfall becomes excessive. Moreover, the relationship between economic growth and monthly rainfall deviations is concave: negative rainfall shocks produce strong and statistically significant reductions in growth, whereas the gains associated with positive rainfall shocks are comparatively weaker and less consistent. Similar effects are confirmed for the agricultural sector of Italy (Baronetti et al. (2024), Salinger et al. (2020), Pulighe et al. (2024)). Compared with this line of research, the present study adds to the literature by offering new insights into the seasonal effects of precipitation shocks at the macroeconomic level.

A recent contribution that considers precipitation and temperature shocks alongside other climatic factors (e.g., wind, sea surface temperature) to assess their economic impact at both global and local levels is provided by Bilal and Känzig (2026). They find substantial negative real effects, reporting, for instance, a roughly 10% reduction in GDP resulting from a 1°C increase in average temperature. In contrast, this paper departs from their methodology by defining climate shocks as deviations from the long-term mean rather than as forecast errors derived from a Hamilton filter, and it places greater emphasis on examining cross-country spillover effects.

When analysing the spillover effects of climate shocks, Usman et al. (2025b) draw on the historically estimated average impacts of extreme climate events—floods, droughts, and heat-

waves—reported in Usman et al. (2025a), who employ a panel framework at the European NUTS-3 level. Using these estimates, they quantify the associated losses in gross value added across regions and highlight that such shocks can propagate across borders through the trade linkages that connect national economies. This mechanism is further supported by Kotz et al. (2025) and Peersman (2022), who document substantial price increases in various unprocessed food categories following droughts and heatwaves. By contrast, Bilal and Känzig (2026) find that, although spillover effects are present, they do not play a major role in their analysis. This study challenges that view by showing that spillover effects can be particularly important for small open economies that are highly integrated with larger trading partners.

3 Data

3.1 Climate proxies

To derive temperature and precipitation shocks, I follow the approach presented in Kotz et al. (2021), Kotz et al. (2022) and Kotz et al. (2023). Data comes from the ERA5 reanalysis dataset introduced in Hersbach et al. (2020) which combines model simulations with meteorological data and provides a consistent data set that covers the entire globe at a high spatial resolution (here: $0.25^\circ \times 0.25^\circ$ grid cell). Temperature is measured in Celsius, 2 meters above the surface, and precipitation represents any form of rainfall or precipitation that occurred within the grid cell. Precipitation values represent the water height in millimetres, if it was evenly distributed across the grid cell.

I use hourly data of every $0.25^\circ \times 0.25^\circ$ grid cell above Italy and compute monthly deviations from the long-term mean in each grid cell³. For each monthly observation at time $t = 1, \dots, T$ in each grid cell $i = 1, \dots, I$, I calculate the anomaly as the deviation of the corresponding long-term monthly mean:

$$\Delta Z_{i,t} = Z_{i,t} - \bar{Z}_{i,m} \tag{1}$$

where $Z_{i,t}$ is the observed value in a grid cell i at time t and, $\bar{Z}_{i,m}$ is the long-term mean for month $m \in \{1, \dots, 12\}$ of the same grid cell i . Because the impact of a shock depends on the economic importance of the region in which it occurs, temperature and precipitation anomalies $\Delta Z_{i,t}$ are weighted by each NUTS-2 region’s annual agricultural value added. The weighting matrix is constructed by dividing a region’s value added by the number of grid cells it contains,

³Meteorologically, the long-term mean is computed over 30 years (January 1990 until December 2020). Robustness checks based on different windows are available upon request.

ensuring that the total weight of all grid cells within a region equals its relative value added. This matrix is updated annually and applied to the anomaly measures. This methodological choice departs from other approaches in the literature like Ciccarelli et al. (2024), who weight each 0.25° grid cell by the share of the working-age population (ages 15–65) residing in the cell. Such an approach captures the population exposure of each cell, whereas the proposed baseline weighting here captures the agricultural-output exposure of the cell via NUTS-2 gross value added in agriculture.

The choice between weighting grid-cell anomalies by agricultural gross value added and weighting by population reflects a conceptual trade-off rather than a purely technical one. Agricultural-GVA weighting concentrates the signal on cells whose weather conditions are most relevant for the primary cost channel linking climate shocks to consumer prices, namely the agricultural and food-production stages (Ferrucci et al. (2012), Kotz et al. (2024)). This is the dominant transmission mechanism identified in the euro-area literature on weather-driven inflation and is the mechanism around which other studies like Ciccarelli et al. (2024) organise their analysis. By contrast, population weighting treats every inhabitant as an equally informative point of exposure, which is natural when the object of interest is labour productivity or aggregate demand (Bilal and Känzig (2026)) but down weights sparsely populated agricultural regions that are central to the cost channel. Because the present paper’s primary object of interest is the transmission of Italian climate shocks to Maltese prices — in a small open economy with pronounced one-sided exposure operating primarily through trade linkages and imports — agricultural-GVA weighting is a priori the more conservative choice⁴.

The final shocks series are replicated in figure (1), which displays the temperature (top) and precipitation (bottom) shocks over the observation period. When analysing the effects of these shocks, several aspects must be considered. First, compared with temperature, precipitation is a much more local or idiosyncratic weather condition. This means that the impact of precipitation anomalies is often more geographically concentrated, affecting smaller areas or specific regions, whereas temperature tends to vary more smoothly across space. As mentioned in the previous section, the issue of spatial aggregation of precipitation anomalies has been highlighted in the literature (see Damania et al. (2020) or Bilal and Känzig (2026) and references therein). The 0.25° grid and the GVA-based weighting scheme mitigate this concern. When cell-level anomalies are aggregated with these weights, the resulting series captures an economy-weighted anomaly for Italy as a whole. Second, beyond regional asymmetries, the literature on weather shocks

⁴Reported robustness to the population-based proxy of Ciccarelli et al. (2024) is presented in section (7)

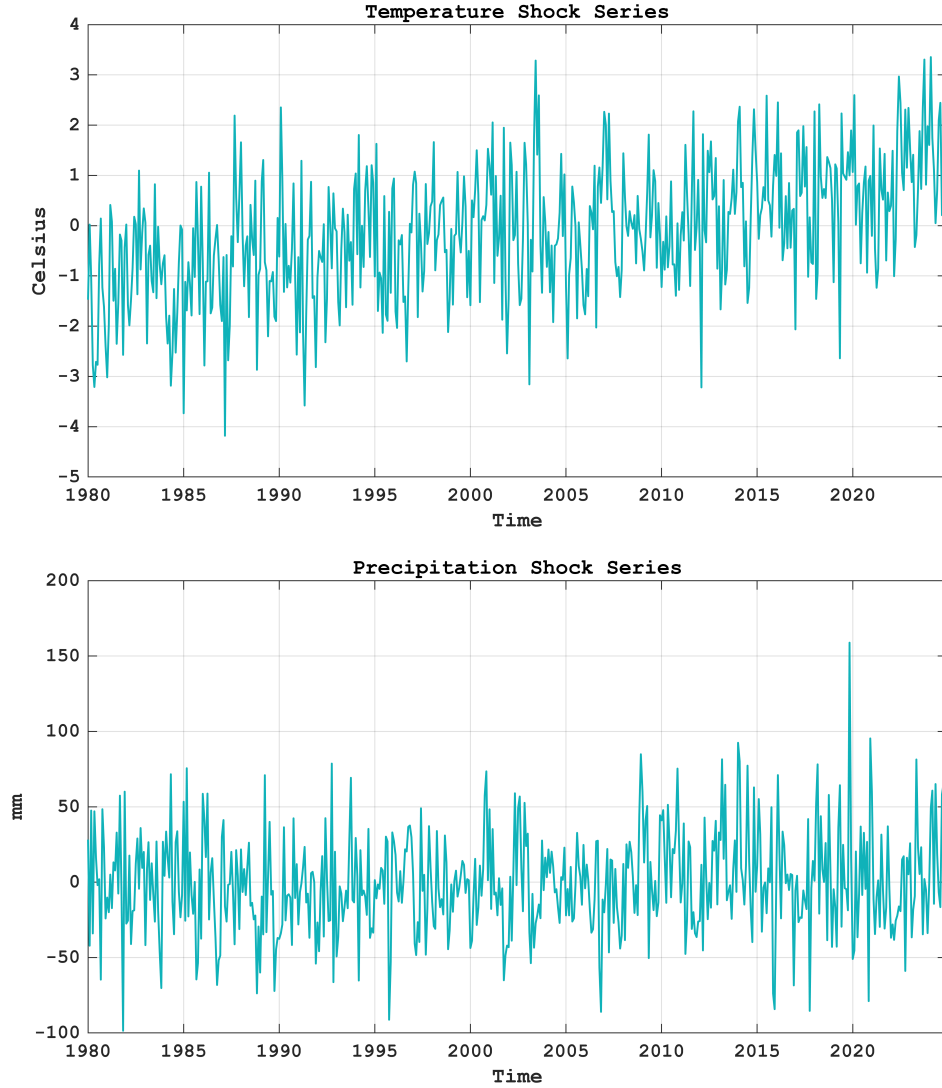


Figure 1: The figure displays the **temperature** (top) and **precipitation** (bottom) anomalies over the Italian territory. At each $t = 1..T$ the value displayed in the figures is the weighted sum of anomalies over all grid cells.

also highlights asymmetries related to the *sign* (Kotz et al. (2022), Usman et al. (2025a)) and *intensity* (Kotz et al. (2022)) of shocks. Since the nature of precipitation shocks—whether extreme or moderate, positive or negative—can significantly affect their economic consequences, it is important to account for the specific characteristics of the shock series under consideration. With regard to non-linear effects related to the *intensity* of precipitation, this study deliberately abstracts from such dynamics by focusing on deviations from the norm, rather than on extreme events⁵. To address potential *sign asymmetries*—and given that this study focuses on positive temperature shocks and compares their effects to negative precipitation shocks—I restrict the

⁵Although extreme events are not the focus of this study, the robustness section derives the baseline results based on the Standardized Precipitation Index (SPI), a widely used measure for capturing drought conditions.

temperature (precipitation) proxy to positive (negative) values.

The sign truncation of the climate proxy is not innocuous. As reported in section (7), allowing for symmetric climate shocks materially changes several precipitation impulse responses, with a subset of IRFs reversing sign relative to the baseline specification. This finding is consistent with the concave relationship between precipitation and economic activity documented by Kotz et al. (2022): the effects of drier-than-average conditions need not mirror those of wetter-than-average conditions in either magnitude or direction. Aggregating positive and negative precipitation deviations into a single symmetric shock series can therefore attenuate or even reverse the estimated responses.

For temperature shocks, the symmetric specification leaves the qualitative pattern of the responses broadly unchanged but attenuates their magnitude and, in several cases, pushes posterior credible sets across zero. The baseline temperature results should therefore be interpreted as *conditional* on the one-sided hot-shock specification. While the overall qualitative conclusions remain robust, posterior support at individual horizons becomes weaker under the symmetric specification (see sections (5), section (7) and appendix (H)).

3.2 Macroeconomic variables

For each country, I use the following sub-components of HICP inflation: processed food, unprocessed food, non-energy industrial goods, services, and electricity & gas. Additionally, I include total industrial production (excluding energy), energy production, food production, aggregate producer prices, energy producer prices, and producer prices of food manufacturing⁶. Following the global VAR literature (Burke et al. (2015) and Chudik and Pesaran (2016)), I also incorporate euro area aggregates—HICP, industrial production, and farm-gate prices—alongside global food prices⁷. The inclusion of these variables primarily aims to account for potential second and third-round spillover effects that may influence domestic dynamics. Finally, I transform all macroeconomic variables to year-on-year growth rates. The frequency of the data is monthly.

4 Methodology

I am using the shock series derived in section (3.1) as proxies in a VAR model to estimate dynamic causal effects of temperature and precipitation shocks to macroeconomic variables. Consider the

⁶For Malta, I use the business cycle conditions index which is directly comparable to an overall economic activity index such as industrial production (see Ellul (2016)).

⁷Appendix (A) provides a detailed overview of all macroeconomic variables used in this study.

following VAR:

$$Y_t = C_t + \sum_{p=1}^P B_p Y_{t-p} + AZ_t + U_t \quad (2)$$

where Y_t is a matrix of endogenous macroeconomic variables, C_t collects the constant terms, B_p is a matrix of coefficients of the lagged endogenous data, A is the matrix of coefficients of the exogenous terms Z_t (here: the weather proxy) and U_t collects the reduced form residuals. To highlight the spillover effects in the VAR in (2), let $Y_t = [y_t^{MT'} \ y_t^{IT'}]'$ collect the Maltese (y_t^{MT}) and Italian (y_t^{IT}) endogenous variables. I partition the autoregressive coefficient matrices in (2) conformably:

$$B_p = \begin{bmatrix} B_p^{MT \rightarrow MT} & B_p^{IT \rightarrow MT} \\ B_p^{MT \rightarrow IT} & B_p^{IT \rightarrow IT} \end{bmatrix}, \quad p = 1, \dots, P.$$

The small-country assumption is imposed as a tight prior around zero on the off-diagonal block $B_p^{MT \rightarrow IT}$ for all p , so that Maltese variables do not feed back into Italian equations (Gatt and Ruisi (2022) and Ruisi (2022)). Equation (2) then drops to:

$$\begin{bmatrix} y_t^{MT} \\ y_t^{IT} \end{bmatrix} = \begin{bmatrix} c^{MT} \\ c^{IT} \end{bmatrix} + \sum_{p=1}^P \begin{bmatrix} B_p^{MT \rightarrow MT} & B_p^{IT \rightarrow MT} \\ 0 & B_p^{IT \rightarrow IT} \end{bmatrix} \begin{bmatrix} y_{t-p}^{MT} \\ y_{t-p}^{IT} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & A^{IT \rightarrow IT} \end{bmatrix} \begin{bmatrix} Z_t^{IT} \\ Z_t^{IT} \end{bmatrix} + \begin{bmatrix} u_t^{MT} \\ u_t^{IT} \end{bmatrix} \quad (3)$$

Where in equation (3), an analogous partition of the impact effects is captured by the proxy's coefficient matrix, A . The identification rests on the assumption that Italy is affected by the shock before it reaches Malta, implying that Malta does not respond contemporaneously. This delayed transmission motivates muting Malta on impact, which is imposed through the triangular block of zeros in the A matrix of equation (3). Given this structure, the first effect on the Maltese economy arises through the spillover channel $B_p^{IT \rightarrow MT}$, which affects Malta at horizon 1 of the IRF⁸. Subsequent effects are obtained by tracing the shock through the higher-order dynamics of the model.

Following Ciccarelli et al. (2024), Z_t in equation (3) is a column-wise collection of seasonal temperature/precipitation anomalies:

$$Z_t = [winter * z_t \quad spring * z_t \quad summer * z_t \quad autumn * z_t] \quad (4)$$

⁸To be precise, while this structure ensures that the shock hits Italy first, it does not rule out potential correlation with Mediterranean-wide climate conditions occurring simultaneously. The latter relates to the appropriateness of the proxy and is discussed in section (3.1)

With *winter*, *spring*, *summer*, *autumn* being seasonal dummies that equal 1 for the specific season⁹.

The VAR in equation (2) incorporates a total of $N_y = 26$ endogenous and $N_x = 5$ exogenous variables. Efficient estimation of such large VARs can be achieved by writing the model in Kronecker structure as shown in Chan (2020). Consider the reduced form errors in (2), U_t , to be *iid* i.e., $N(0, \Sigma)$. Vectorising these errors, yields $vec(U_t) \sim N(0, \Sigma \otimes I)$, where Σ is an N_y -by- N_y variance-covariance matrix and I is a T -by- T identity matrix. By leaving the identity matrix to follow a more general structure as shown in equation (5), I allow for non-Gaussian innovations.

$$vec(U_t) \sim N(0, \Sigma \otimes \Omega) \quad (5)$$

This is achieved by setting $\Omega = diag(\lambda_1 \dots \lambda_T)$. Where each λ_t is drawn independently from an inverse gamma distribution $(\lambda_t|v) \sim IG(v/2, v/2)$ and the hyperparameter v is drawn in an MH-step. This specification leads to the marginal distribution of the reduced form errors being a t-distribution with v degrees of freedom¹⁰.

Since $p(B, \Sigma, \Omega) = p(B, \Sigma) * p(\Omega)$, the prior $p(\Omega)$ can be treated independently from $p(B, \Sigma)$ and standard prior settings from the literature can be used. Specifically, a standard normal inverse Wishart prior as in Kadiyala and Karlsson (1997) where $\Sigma \sim IW(S_0, v_0)$ and $vec(B)|\Sigma \sim N(vec(B_0), \Sigma \otimes V_B)$. In the application, I set $vec(B_0) = 0$ and the variance-covariance matrix of the coefficients, V_B , to be diagonal with entries $v_{b,ii} = \kappa_i / (l^2 \hat{s}_r)$, where l is the lag of variable r and \hat{s}_r being the sample variance of an AR-regression. I set $v_0 = n + 3$, $S_0 = I_n$, $\kappa_1 = 0.1^2$ and $\kappa_2 = 10^2$ for the constant.

Each country block is estimated separately using 6 lags in the macroeconomic variables and no lags in the weather proxy. I obtain 100,000 draws, of which I discard the first 50,000.

5 The effects of temperature and precipitation shocks

This section presents the baseline results over the sample period from January 2001 to December 2024. The estimated IRFs trace the transmission of climate shocks originating in Italy and their subsequent spillover effects on Malta. Because the shock is identified as hitting Italy first, the IRFs in all figures should be interpreted chronologically: *Italy* (blue line) reacts contemporaneously to the shock, while *Malta* (red line) responds one period later. To ensure comparability

⁹The seasons are defined meteorologically: *winter* = Dec.; Jan.; Feb., *spring* = Mar.; Apr.; May., *summer* = Jun.; Jul.; Aug., *autumn* = Sept.; Oct.; Nov.

¹⁰See Chan (2020) for the derivation of the posteriors.

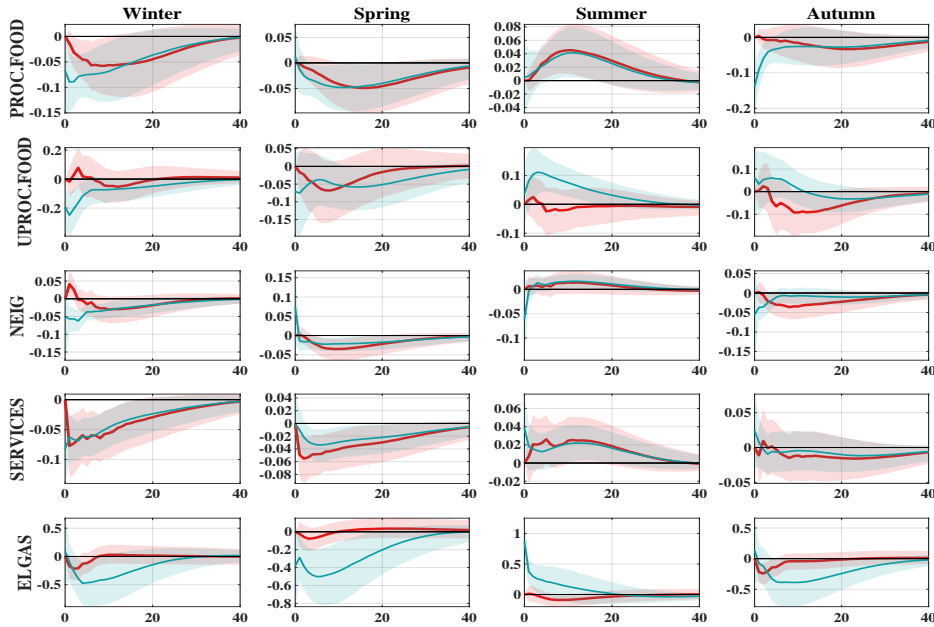
across seasons, the IRFs are normalised to the 75th percentile of each shock distribution (25th percentile for precipitation shocks).

Overall, climate shocks generate significant and highly seasonal spillover effects from Italy to Malta, primarily through energy and food-related channels. Positive temperature shocks produce economy-based effects across energy, food, and services prices, with summer heat generating the strongest inflationary pressures. Negative precipitation shocks, by contrast, have more concentrated but often sharper effects, particularly in food and energy markets during the summer and autumn months. Across both shocks, the clearest transmission mechanisms operate through climate-sensitive sectors—especially energy and unprocessed food prices—with spillovers propagating into processed food and services inflation in Malta. Overall, the findings highlight the importance of cross-border climate transmission channels in closely integrated economies.

5.1 Positive temperature shocks

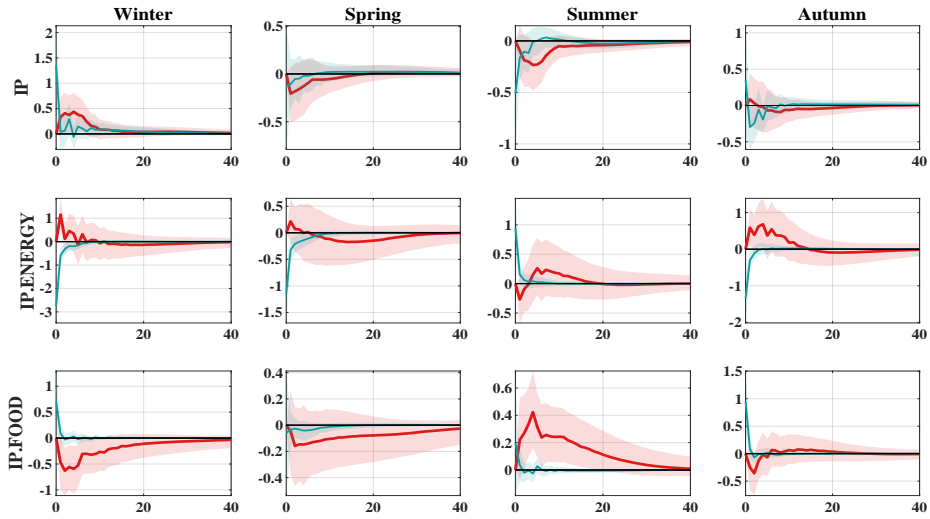
This subsection turns to the effects of positive temperature shocks. Figures (2)–(4) present the corresponding sectoral impulse responses, revealing broad-based adjustments across the economy. Each of these effects is discussed in turn below.

Figure 2: Spillover effects of a **temperature shock** on HICP components in Malta.



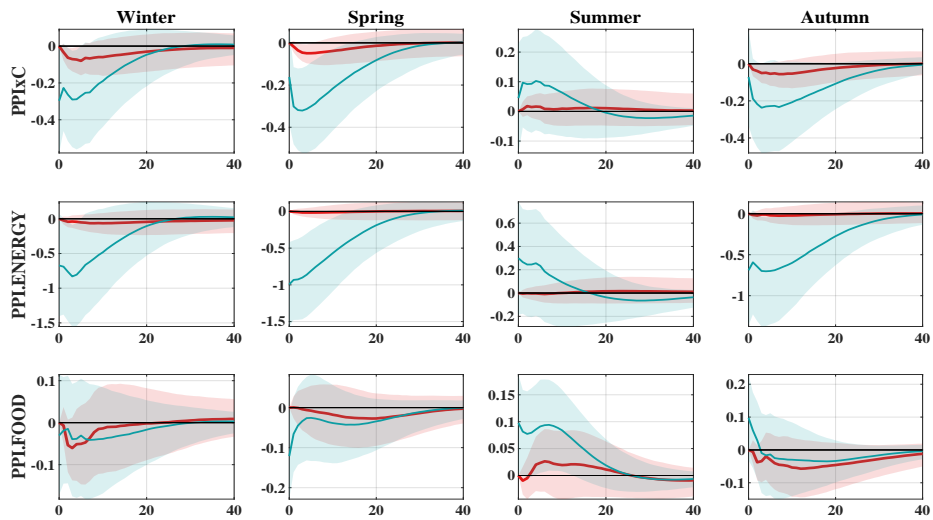
Note: The figure displays impulse response functions (IRFs) for selected Italian (blue) and Maltese (red) macroeconomic variables, with 68% credible sets shown around the median responses. The temperature shock is normalised to represent an increase equal to the 75th percentile of the seasonal temperature distribution, capturing the effect of an extreme temperature event within each season.

Figure 3: Spillover effects of a **temperature shock** on real activity in Malta.



Note: The figure displays impulse response functions (IRFs) for selected Italian (blue) and Maltese (red) macroeconomic variables, with 68% credible sets shown around the median responses. The temperature shock is normalised to represent an increase equal to the 75th percentile of the seasonal temperature distribution, capturing the effect of an extreme temperature event within each season.

Figure 4: Spillover effects of a **temperature shock** on producer prices in Malta.



Note: The figure displays impulse response functions (IRFs) for selected Italian (blue) and Maltese (red) macroeconomic variables, with 68% credible sets shown around the median responses. The temperature shock is normalised to represent an increase equal to the 75th percentile of the seasonal temperature distribution, capturing the effect of an extreme temperature event within each season.

5.1.1 Effects on Italy

Energy sector. The energy sector is crucial for assessing climate shock impacts, due to both direct effects on energy use and its strong interconnections with other sectors. Energy is a key input across the economy, affecting indices such as food, services, and goods. In Italy, warmer winter, spring, and autumn conditions reduce energy production (IP.ENERGY), with clear posterior support, while the opposite holds in summer. Effects are strongest in winter and summer, where production falls by roughly 2.73 percentage points in winter and rises by roughly 0.95 percentage points in summer. Responses are short-lived, fading after about 4 months (winter/spring) and 2 months (summer/autumn). Energy prices show more persistent but smaller effects. Producer prices (PPI.ENERGY) fall in winter, spring, and autumn, with peak responses of roughly -0.83 percentage points (3 months after the shock) and -0.99 percentage points (on impact) in winter and spring, respectively. Consumer electricity and gas prices (ELGAS) show similar but smaller patterns. In summer, ELGAS prices rise on impact by around 0.87 percentage points, while producer prices are not credibly different from zero, limiting pass-through. Overall, increases in production volumes and electricity and gas inflation appear primarily driven by the consumer side.

Food sector. Food prices show clear seasonal responses to temperature shocks. Higher temperatures reduce consumer food prices in winter, spring, and autumn, but increase them in summer, with similar patterns for processed and unprocessed food. Processed food prices are more persistent, especially in winter and summer, where effects last over 10 months. Unprocessed food shows larger short-run responses across winter, spring, and summer, likely reflecting direct exposure to agriculture, which is strongly climate-sensitive¹¹. Peak median responses for unprocessed food inflation are -0.25 percentage points in winter (1 month after the shock), -0.07 percentage points in spring (1 month after the shock), and 0.11 percentage points in summer (3 months after the shock). On the production side, food manufacturing prices (PPI.FOOD) follow a similar seasonal pattern, but persistent declines with clear posterior support occur only in summer, lasting about 13 months and reaching a peak median response of roughly 0.1 percentage points on impact. Results suggest that milder winters support agricultural productivity and lower prices, while extreme summer heat raises costs through production stress and higher energy needs. This pattern is less evident for food manufacturing output (IP.FOOD), where no posterior medians are credibly different from zero. Overall, consumer prices show more frequent

¹¹A variable specific IRF decomposition shows that Italian energy production explains a large share of the IRF displayed here.

and persistent effects across seasons than producer prices.

Services sector. Consumer prices in the services sector exhibit pronounced seasonal patterns, closely mirroring those observed in the energy and food sectors. This alignment reflects the interconnected nature of these components, as energy, food, and goods all constitute essential inputs in the service price index. In particular, a positive temperature shock tends to depress service prices during the colder months while elevating them in the warmer months. The peak median responses reach -0.08 percentage points on impact in winter and 0.04 percentage points in summer (on impact). Both the magnitude and persistence of these effects closely resemble those documented for processed and unprocessed food prices, underlining the similar energy and/or agricultural-pass-through transmission mechanisms that drive price dynamics across these sectors.

Other variables. The response of non-energy industrial goods (NEIG), shows a seasonal pattern in line with the narrative of an energy pass-through to goods inflation. Furthermore, temperature shocks have smaller but longer lasting effects on goods prices than in the other sectors, especially in winter, with a peak median response of roughly -0.06 percentage points 3 months after the shock, which remains credibly different from zero for a total of about 15 months. Compared to that, the effects in other seasons are negligible. Finally, Italian aggregate production (IP) increases (decreases) in the winter (summer) months however, the posterior credible set includes zero¹².

5.1.2 Spillover effects to Malta

Energy sector. Malta, which experiences among the highest cooling degree days (CDD) in Europe due to high temperatures, relies heavily on imported energy, as domestic production—mainly natural gas and limited renewables—cannot meet demand¹³. Although Italy remains a key supplier, government subsidies largely decouple consumer prices from external shocks, making energy costs primarily dependent on consumption. Consequently, fluctuations in Italian energy prices have only a limited direct impact on Maltese consumer and producer prices¹⁴. These subsidies also shape how shocks propagate, as differences in domestic energy-use patterns matter. As shown in figure (5), the transport sector accounts for a larger share

¹²See appendix (B) for the IRFs on the aggregate control variables.

¹³See appendix (C) for the importance of electricity and gas imports from Italy since 2015.

¹⁴Section (6) shows that domestic effects for electricity and gas (ELGAS) make up the highest contribution to the observed median response shown in figure (2).

of final energy consumption in Malta than in Italy¹⁵, but heavy subsidisation largely mutes pass-through effects via transport. In contrast, Italy lacks such an offset, allowing the transport sector to transmit shocks more effectively across industries. Additionally, a countercyclical pattern emerges in energy production (IP.ENERGY) between the two countries. During the colder months, when Italian production declines, Maltese production rises. This phenomenon may be rooted in the dynamics implied by the interconnector¹⁶.

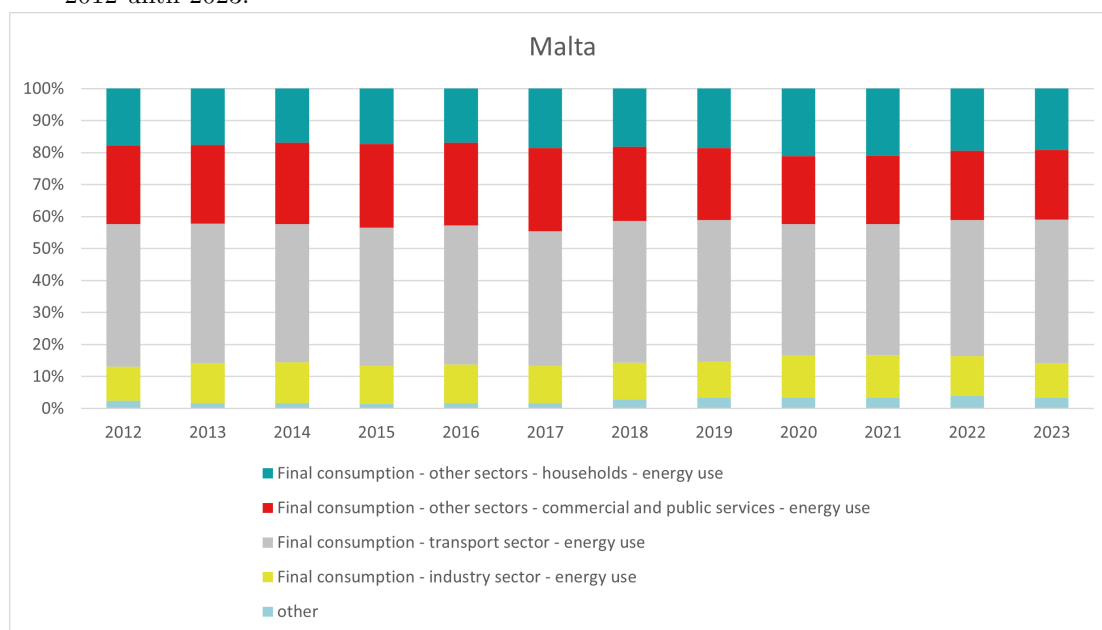
Food sector. Processed food prices in Malta closely mirror the response observed in Italy, both in terms of magnitude and persistence. This co-movement is also reflected, to a slightly lesser degree, in the producer prices of food (PPI.FOOD). However, the effects tend to be weaker for unprocessed food, with the latter's price responses being largely indistinguishable from zero in the posterior, especially when shocks materialise in summer or winter. These results are consistent with Malta's limited yet important reliance on domestic unprocessed food production as well as diversified sources for unprocessed food imports, which partially limit the spillover effects of temperature shocks in Italy. Appendix (D) corroborates the consideration regarding the importance of Italian food imports by illustrating the evolution of Italy's import shares of processed and unprocessed food relative to the rest of the world. Since 2006, both categories have consistently accounted for more than 20 percent of total imports from the rest of the world. Except for the last three years in the observed period, processed food consistently accounted for a larger share of imports from Italy than unprocessed food. However, despite the high degree of interconnection in the food market, spillovers in unprocessed food inflation appear to be modest, if not negligible. Finally, food manufacturing in Malta (IP.FOOD) exhibits a pattern that is opposite to that of its Italian counterpart, particularly during the winter months. In Malta, the effects are negative following a temperature shock, with a peak median response of roughly -0.63 percentage points after 2 months. These responses are driven by the economic interconnections between the two countries, which constitute the primary channel underlying the impulse response functions illustrated in figure (3). A more detailed discussion of these mechanisms is provided in section (6) highlighting that spillover effects from Italy are the main drivers of this finding.

Service sector. Malta's service price responses follow a comparable shape but are marked by some overshooting in some seasons. A spring/summer temperature shock in Italy results in a more pronounced increase in Maltese service prices than in Italy itself. This difference is

¹⁵See appendix (E) for the corresponding figure for Italy.

¹⁶The inverse relationship disappears when estimating the model before 2015.

Figure 5: The breakdown of final energy consumption (in %) in Malta by sector from 2012 until 2023.



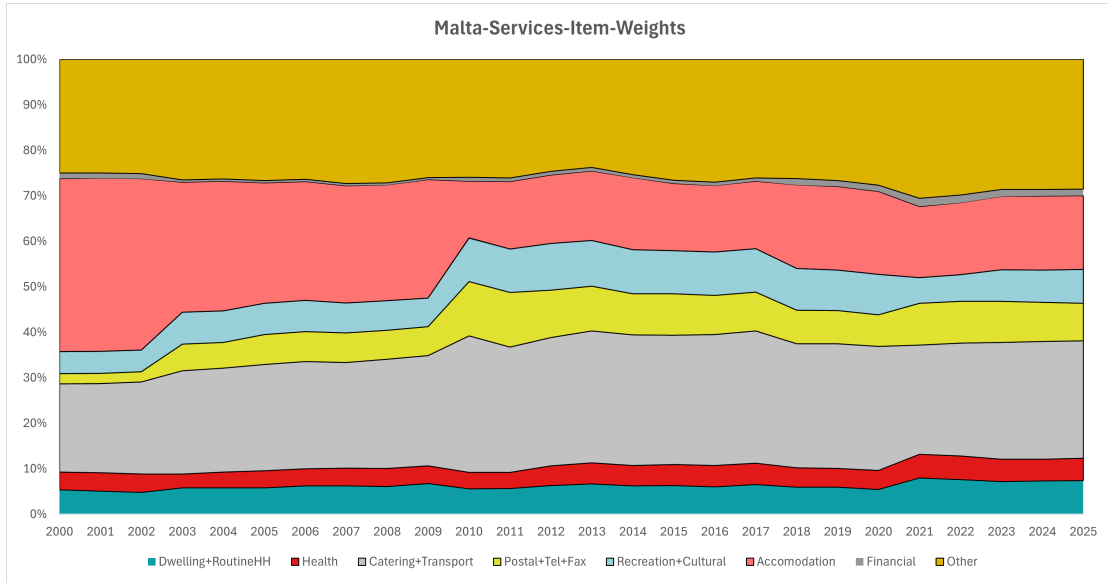
Note: The data is provided by Eurostat.

likely attributable to structural differences in the composition of the service sector across the two countries. Figure (6) presents a decomposition of the service index by item weights over time for Malta¹⁷. Malta's service sector is dominated by accommodation services and catering. By contrast, in Italy, the largest components are dwelling and household-related services, along with catering. Insights from figure (6) suggest that the stronger response in Maltese service prices can be traced to a higher sensitivity of the accommodation and catering sector to external shocks, such as the temperature shocks considered here. This indicates that Malta's service sector is more responsive to external temperature shocks, reinforcing the overshooting effect observed in the empirical findings. In line with these insights, section (6) reveals that unprocessed food prices make up the highest contribution to the observed response further indicating the responsiveness of catering services to external shocks.

Other variables. Non-energy industrial goods (NEIG) prices show only limited spillover from Italian temperature shocks. Nonetheless, Malta's responses seem to be more gradual, showing an element of imperfect pass through in the very short run. Real economic activity in Malta (IP), follows the seasonal pattern of the Italian counterpart with posterior evidence for these effects only in the winter.

¹⁷An analogous figure for Italy can be found in appendix (F).

Figure 6: The breakdown of the service index by item weights from 2000 until 2025.



Note: The data is provided by Eurostat.

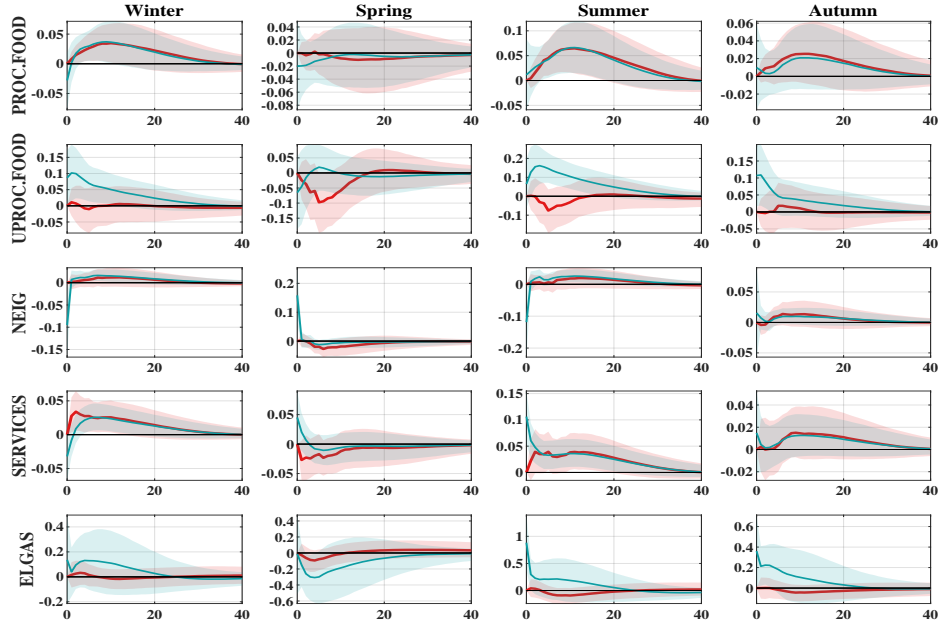
5.2 Negative precipitation shocks

Similarly to the previous section, figures (7) - (9) illustrate the seasonal spillover effects of precipitation. While temperature shocks appear to exert broad macroeconomic effects across multiple sectors, precipitation shocks exhibit a more concentrated impact, primarily affecting the food and energy sectors. This pattern aligns with the expectation that the agricultural sector is particularly sensitive to variations in rainfall (Semenov and Porter (1995), Ceglár et al. (2016)).

5.2.1 Effects on Italy

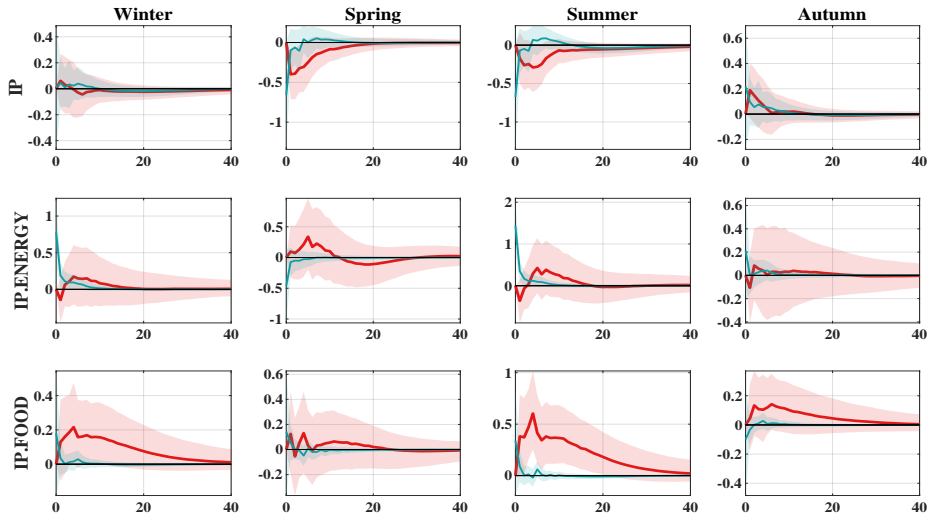
Energy sector. A negative precipitation shock in Italy exerts upward pressure on both consumer (ELGAS) and producer energy prices (PPI.ENERGY). These effects are particularly pronounced and credibly different from zero for the former during the summer months. In the summer, electricity and gas prices exhibit a peak median response of roughly 0.88 percentage points on impact. The corresponding response of producer prices is considerably weaker (around 0.3 percentage points on impact) and not credibly different from zero. Energy production (IP.ENERGY) increases in both winter and summer—periods that, on average, correspond to the driest seasons—suggesting a compensatory response to reduced water availability. The impact increase in winter reaches 0.78 percentage points but is notably larger in summer (1.44 percentage points), with both responses credibly different from zero.

Figure 7: Spillover effects of a negative **precipitation shock** on HICP components in Malta.



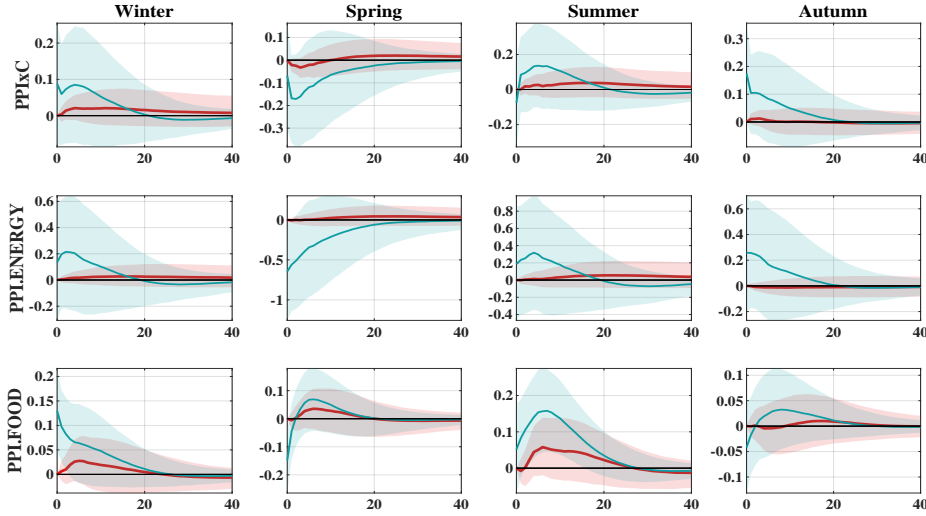
Note: The figure displays impulse response functions (IRFs) for selected Italian (blue) and Maltese (red) macroeconomic variables, with 68% credible sets shown around the median responses. The shock is normalised to represent an increase equal to the 25th percentile of the seasonal distribution of precipitation, displaying the effect of an extreme precipitation event within each season.

Figure 8: Spillover effects of a negative **precipitation shock** on real activity in Malta.



Note: The figure displays impulse response functions (IRFs) for selected Italian (blue) and Maltese (red) macroeconomic variables, with 68% credible sets shown around the median responses. The shock is normalised to represent an increase equal to the 25th percentile of the seasonal distribution of precipitation, displaying the effect of an extreme precipitation event within each season.

Figure 9: Spillover effects of a negative **precipitation shock** on producer prices in Malta.



Note: The figure displays impulse response functions (IRFs) for selected Italian (blue) and Maltese (red) macroeconomic variables, with 68% credible sets shown around the median responses. The shock is normalised to represent an increase equal to the 25th percentile of the seasonal distribution of precipitation, displaying the effect of an extreme precipitation event within each season.

Food sector. As shown in figure (7), drier conditions in Italy generally lead to higher food prices in winter and summer, consistent with the limited agricultural activity during winter and already arid conditions in the summer. In spring, reduced precipitation appears to slightly alleviate supply-side pressures, potentially improving harvesting conditions and passing through to consumer prices. However, these effects remain weak, likely due to offsetting mechanisms such as irrigation, ongoing planting, and trade-related substitution, consistent with existing literature that mentions ambiguous outcomes during this period (e.g., Pulighe et al. (2024)). In contrast, during summer and autumn, precipitation shocks exert a pronounced impact on food inflation. Processed food inflation rises in summer, reaching a peak median response of around 0.66 percentage points 11 months after the shock. This peak materialises considerably later than that of unprocessed food inflation, whose peak median response—close to 0.16 percentage points—is reached after only about 3 months. A similar timing pattern emerges in autumn: processed food inflation peaks at about 0.29 percentage points 11 months after the shock, whereas the peak response of unprocessed food inflation, at about 0.11 percentage points, materialises within the first month following the shock, although with wider credible sets. This suggests heightened price sensitivity when weather shocks occur late in the production cycle, in line with previous findings (Faccia et al. (2021)). Additionally, the stronger response of unprocessed food inflation is consistent with earlier observations regarding the heightened sensitivity of this

component to stress conditions in the agricultural sector. At the same time, the posterior credible sets for food manufacturing (IP.FOOD) include zero, in line with previous findings for temperature shocks.

Service sector. Results on service prices, indicate a limited impact of negative precipitation shocks, except during the winter and summer months. In the summer, service prices rise more than following temperature shocks (see figure (2)). The effects are persistent and last up to 13 months in the winter and 20 months in the summer. The peak median responses in each seasons are 0.026 percentage points and 0.1 percentage points respectively. This increase in Italian service prices primarily reflects the pass-through of higher energy and unprocessed food prices.

Other variables. Prices of non-energy industrial goods (NEIG) and overall real economic activity (IP) appear largely unaffected by short-term precipitation shocks¹⁸.

Taken together these seasonal dynamics are consistent with the agricultural calendar: winter, a period with limited planting and harvesting activity, shows minimal responsiveness (Santeramo and Maccarone (2022)); spring exhibits a modest decline in food inflation following reduced precipitation whose posterior credible set includes zero, possibly reflecting improved harvest conditions and eased supply-side pressures leading to some ambiguity regarding the sign of the effect, which is in line with the literature (see Santeramo and Maccarone (2022) and Pulighe et al. (2024)). However, the weak magnitude of this effect suggests the presence of offsetting factors such as irrigation, continued planting activity, or substitution through imports. In contrast, summer and autumn—corresponding to the main harvest periods—show the most pronounced sensitivity to precipitation deficits, reinforcing the role of rainfall in shaping seasonal food supply conditions (Salinger et al. (2020), Baronetti et al. (2024), Guerriero et al. (2023)).

5.2.2 Spillover Effects to Malta

Energy sector. There is no evidence of spillover effects on energy prices (ELGAS) in Malta. However, energy production in Malta exhibits a similar compensatory pattern, indicating that the transmission channels of precipitation shocks may resemble those observed for temperature shocks in this sector. As previously discussed, government subsidies seem to effectively isolate this sector from foreign shocks.

¹⁸See also appendix (B) on the control variables.

Food sector. Similar to temperature shocks, spillover effects from precipitation shocks are primarily observed in processed food prices, as the posterior credible set for the response of Maltese unprocessed food prices to an Italian precipitation shock includes zero at all horizons, consistent with a weak or unidentifiable transmission channel. Winter, summer and autumn display price increases in Maltese processed food inflation, with peak median responses of roughly matching the Italian counterpart in each case. Interestingly, while Maltese food production (IP.FOOD) increases in summer, Italian food production does not exhibit a corresponding response, highlighting differences in production structures and climate resilience between the two countries. Section (6) offers further insights into this finding by showing that spillover effects – especially Italian unprocessed food prices, see figure (10) – make up the highest contribution to the observed median response effectively showing the cross country interconnection that triggers the observed spillover effects.

Service sector. Spillover effects to Maltese service price inflation generally comparable to those triggered by temperature shocks except for the sign. This also holds for the rise in Italian unprocessed food prices during summer, which appears to transmit to the Maltese service sector, ultimately generating effects whose posterior credible sets exclude zero within this category¹⁹. In summer, service price inflation in Malta reaches a peak median response of roughly 0.04 percentage points. The shape and persistence of the effect roughly matches its Italian counterpart.

Other variables. Negligible effects are found on non-energy industrial goods (NEIG) with mainly muted impulse responses across seasons. Real activity in Malta (IP), follows the sign of the Italian counterpart across seasons in terms of both magnitude and persistence. However, these effects are not strong enough to materially influence this variable.

Taken together, the results indicate that precipitation shocks have measurable, though comparatively modest, spillover effects. Their cross-border transmission remains more limited than that of temperature shocks, even in highly dependent small open economies such as Malta. However, for variables directly linked to the agricultural sector, the effects appear even stronger than those observed for temperature shocks. This suggests that precipitation shocks are more idiosyncratic in nature, yet potentially more intensive in the way they affect specific segments of the economy.

¹⁹See section (6) for this aspect.

6 What are domestic variables responding to?

As shown by Kilian and Lewis (2011), each impulse response function (IRF) in section (5) can be interpreted as the net effect of all endogenous variables' contributions in the system. In the setup presented above, the shock is identified via an exogenous proxy and I decompose the IRF of variable j at each horizon h into the individual contributions of all other variables in the VAR:

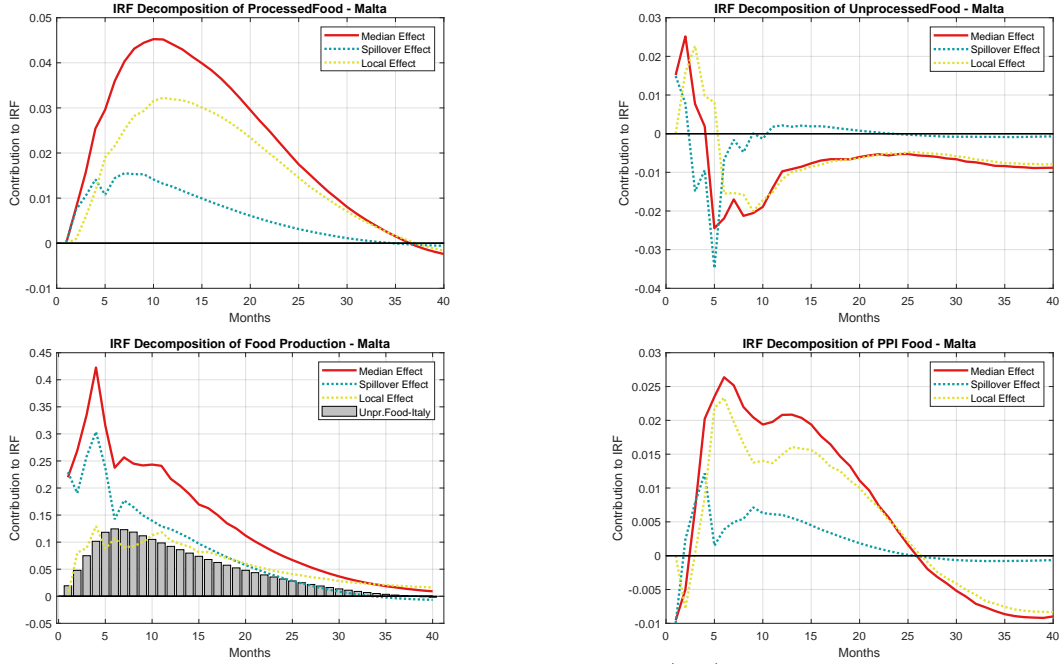
$$D_{k \rightarrow j}(h) = \sum_{l=1}^{\min(p,h)} B_{j,k}^{(l)} * \Psi_k(h-l) \quad (6)$$

Where in (6), $D_{k \rightarrow j}(h)$ denotes the contribution of variable k to variable j at horizon h , $B_{j,k}^{(l)}$ is the coefficient of variable k at lag l in the j th equation and $\Psi_k(h-l)$ is the impulse response of variable k at horizon $(h-l)$. This decomposition attributes the IRF to the lagged propagation channels in the VAR and provides an accounting of how the effect of the proxy shock is transmitted through each variable²⁰.

The following figures illustrate this decomposition for the baseline impulse responses and make the underlying variable-specific contributions transparent. In particular, they allow for a visual assessment of how much of the total response at each horizon is accounted for by domestic versus foreign (Italian and world control) variables. This exercise is conditional on the findings presented in section (5) and should not be interpreted as providing additional evidence on causality. Causal identification is already established through the modelling framework introduced in section (4). Rather, the decomposition provides a horizon-by-horizon snapshot of the variable-specific contributions to each equation's impulse response. Consequently, the distinction between domestic and foreign (i.e., spillover) effects is purely a matter of grouping variables and should not be interpreted as a causal attribution. Throughout, the underlying causal impulse is assumed to originate in Italy. The red line replicates the impulse response function (IRF) shown in the previous section, specifically, the median response from the baseline estimation. In the figures below, the yellow line represents the sum of contributions from all domestic variables and thus reflects the domestic (Maltese) contribution to the total IRF. Conversely, the teal dotted line captures the aggregate contribution from all Italian and control variables in the system, interpreted as the spillover effect on the observed IRF.

²⁰To be precise, Kilian and Lewis (2011) work with the structural MA representation of the VAR and decompose the sequence of *structural transmission channels*. The decomposition above instead operates on the estimated reduced-form VAR and can be interpreted as a dynamic *reduced-form propagation* analysis of a proxy-identified shock.

Figure 10: IRF decomposition of all variables directly related to the food sector following a **temperature shock** for the summer IRFs in section (5.1).

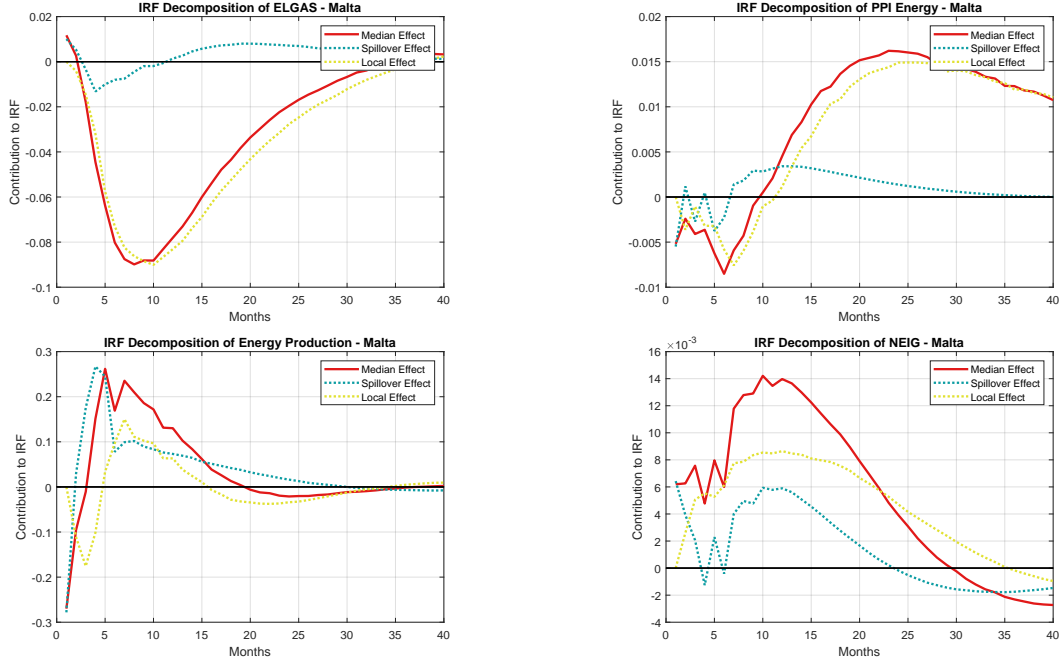


Note: The red line represents the median impulse response function (IRF) of the variable of interest. The yellow dotted line depicts the domestic contribution, while the blue dotted line captures the spillover contribution. Together, the dotted lines sum to the red line, reflecting the total observed effect. The spillover effect comprises the contributions of all non-Maltese (foreign) macroeconomic variables included in the VAR. In contrast, the local (domestic) effect aggregates the contributions from all Maltese macroeconomic variables.

Food sector. Figure (10) presents the outcome of this decomposition for selected variables in the food sector in response to a summer temperature shock²¹. This decomposition deepens the understanding of the IRF compositions behind Italian temperature shocks and complements the patterns shown in section (5). For instance, the decomposition of the two variables of food inflation (processed and unprocessed) shows that while both domestic and spillover effects move in the same direction for processed food, they diverge for unprocessed food. In this case, the spillover contribution offsets the domestic response, resulting in a smaller net effect—closer to zero—when the two are combined. This relationship inverses at higher horizons where domestic and spillover effects align and push the median IRF to the same direction. Looking at the production of food, the decomposition reveals that the contribution of the spillover effect to the observed median response is higher than the domestic contribution over the whole IRF horizon. A more detailed breakdown shows that the highest contribution of the spillover effects comes from Italian unprocessed food, being the main driver of the spillover contribution. Compared to that, producer prices of food manufacturing are displaying larger domestic contributions.

²¹Appendix (I) shows that the same decomposition for a precipitation shock mainly remains unchanged.

Figure 11: IRF decomposition of all variables directly related to the energy sector together with non-energy industrial goods following a **temperature shock** for the summer IRFs in section (5.1).



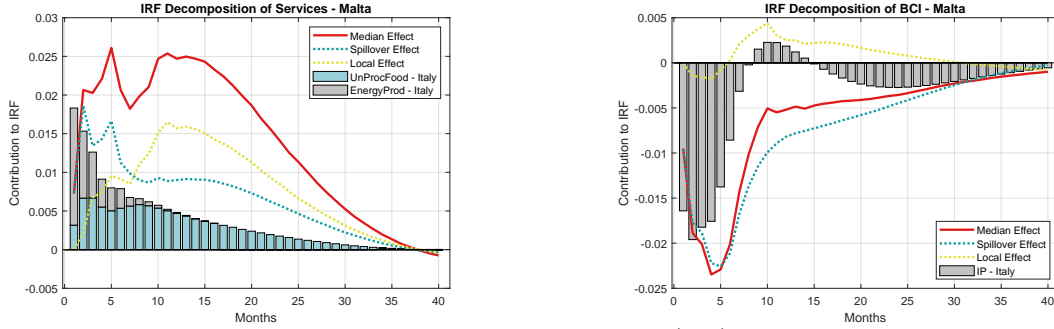
Note: The red line represents the median impulse response function (IRF) of the variable of interest. The yellow dotted line depicts the domestic contribution, while the blue dotted line captures the spillover contribution. Together, the dotted lines sum to the red line, reflecting the total observed effect. The spillover effect comprises the contributions of all non-Maltese (foreign) macroeconomic variables included in the VAR. In contrast, the local (domestic) effect aggregates the contributions from all Maltese macroeconomic variables.

Energy sector. Figure (11) suggests that median responses in energy prices are largely associated with domestic contributions, while spillover effects appear limited. However, posterior credible bands generally include zero, implying substantial uncertainty around these patterns. The decomposition is broadly consistent with the interpretation of offsetting domestic and foreign dynamics in Malta’s energy sector, although the evidence remains weak. For non-energy industrial goods, domestic contributions appear more prominent, with spillovers becoming relatively more important at medium horizons.

Service sector. An interesting insight emerges from the case of service inflation, which exhibits overshooting behaviour in figure (2). The decomposition in figure (12) reveals that the spillover effect dominates, with the contribution from Italian variables exceeding that of the domestic ones over the first 7 horizons. After that, domestic contributions catch up and dominate. A more detailed breakdown shows that unprocessed food inflation and energy production in Italy accounts for the largest share of this spillover, suggesting a key role in driving Maltese service inflation²². This shows that price changes in Italian unprocessed food contribute most

²²This is consistent with the indirect pass-through mechanism previously discussed.

Figure 12: IRF decomposition of services and real activity following a **temperature shock** for the summer IRFs in section (5.1).



Note: The red line represents the median impulse response function (IRF) of the variable of interest. The yellow dotted line depicts the domestic contribution, while the blue dotted line captures the spillover contribution. Together, the dotted lines sum to the red line, reflecting the total observed effect. The spillover effect comprises the contributions of all non-Maltese (foreign) macroeconomic variables included in the VAR. In contrast, the local (domestic) effect aggregates the contributions from all Maltese macroeconomic variables.

to the median responses of food production and service inflation, while the posterior credible set for unprocessed food inflation in Malta includes zero. Figure (12) also reveals that while energy production plays a key role in shaping the IRFs at short-term horizons, the influence of unprocessed food inflation becomes more pronounced over longer horizons. The horizon profile of the unprocessed-food contribution in figure (12) is broadly consistent with the pass-through timing documented for the euro area. Using an error-correction framework spanning the agricultural, producer and consumer stages of the food chain, Ferrucci et al. (2012) find that shocks to international food commodity prices are largely transmitted to euro-area consumer food prices within 6–12 months, with a significant residual component passing through at horizons beyond one year once common agricultural policy buffering is accounted for. Here, the estimated contribution of Italian unprocessed-food inflation to Maltese services inflation is elevated at similar horizons, which is consistent with a cost-pass-through interpretation operating through imported food inputs into the Maltese catering sector, whose HICP weight is disproportionately large (figure (6)). Combined with the illustrations in section (5), these findings suggest that a summer temperature shock increases Italian energy production, which in turn drives up Italian unprocessed food prices. These higher food prices then appear to contribute substantially to inflation in Malta’s services sector²³.

A complementary mechanism operates on the demand side. Italian summer temperature anomalies are correlated with broader Mediterranean heatwave conditions, and a growing body of work documents that such conditions reshape intra-European tourism flows, shifting demand across coastal destinations and across seasons (European Commission, Joint Research Centre,

²³Nevertheless, it needs to be acknowledged that the decomposition is an equation specific accounting identity rather than a formal test of the pass-through channels.

2023; European Commission, 2025). Since accommodation and catering together account for a substantial part of the Maltese services HICP (see section (5) and figure (6)), a reallocation of Italian outbound tourism toward or away from Malta in response to Italian summer heat would move Maltese services prices through a demand channel that is empirically indistinguishable from a cost-pass-through channel within the present specification. The decomposition does not separate the two channels, and therefore interprets the services-inflation spillover as operating through a combination of cost pass-through from Italian unprocessed food and energy inputs and a correlated demand component associated with tourism flows.

Other variables. Spillover effects are also the largest contributor to the median response of the business cycle conditions index (BCI), the measure of aggregate real activity in Malta. Here, a variable-specific breakdown reveals that the main Italian driver of the spillover effect is industrial production, which highlights the close connection between the two economies.

Summing up the insights from the decompositions above, figures (10), (11) and (12) indicate that the spillover effects on consumer inflation are mostly smaller than the domestic contribution with the only exception being inflation of services where the contribution of foreign variables makes up the main effect. On the producer side, the decomposition points to some differences in the relative importance of domestic and spillover contributions across sectors. In the energy sector, domestic contributions appear somewhat more pronounced, while production volumes in energy, food manufacturing, and aggregate economic activity appear more closely aligned with spillover contributions. Nevertheless, posterior credible bands generally include zero, suggesting that these patterns should be interpreted with caution.

7 Robustness

This section presents a series of robustness exercises designed to address potential concerns regarding the sensitivity of the baseline results to alternative modelling choices, identification assumptions, the observation period and data. Collectively, these exercises assess the stability of the estimated effects across a range of specifications and sample restrictions. Given the large number of complementary estimations and impulse response analyses, all robustness figures are reported in appendix (J) in order to preserve the flow of the main discussion while ensuring full transparency and reproducibility of the empirical results.

Model specification. A standard robustness exercise in VAR-type specifications is to assess whether the estimated dynamics are sensitive to the choice of a lag length that is equally well motivated as the one in the baseline. To address this concern, appendix figures (26) - (29) report the impulse responses obtained under alternative lag specifications. Figures (26) and (27) present the results for temperature shocks when reducing the lag length to 3, thereby capturing only one quarter of macroeconomic dynamics, and when extending the specification to 12 lags. In both cases, the baseline findings remain qualitatively unchanged, indicating that the results are not driven by the particular lag selection adopted in the benchmark specification. Figures (28) and (29) provide analogous robustness checks for the seasonal effects of precipitation shocks. As shown, the estimated responses are likewise robust to alternative lag structures, with the main patterns preserved under both the 3-lag and 12-lag specifications.

Shock measure for temperature. As illustrated in figure (1), the temperature shock series exhibits a slight trend, suggesting that the 30-year window used to compute the long-run mean may not fully account for underlying trends. This could bias the estimated shocks by placing excessive weight on recent observations. To address this, I construct a detrended version of the temperature shock series. The resulting estimations, displayed in appendix figure (30), confirm that the observed trend has a negligible impact on the baseline findings. This study also deviates from the existing literature by applying a different weighting scheme when aggregating temperature data across grid cells. As weighting choices can influence the relevance assigned to specific deviations in local temperatures, this could potentially affect the estimated results. To assess the robustness of this methodological choice, I re-estimate the baseline specification using the proxy proposed in Ciccarelli et al. (2024). In particular, the proxy of Ciccarelli et al. (2024) corresponds to a population-weighted aggregation of ERA5 grid-cell anomalies, with weights given by the working-age population share of each cell (ages 15–65). Figure (31) shows that the results remain qualitatively unchanged.

Appendix figure (32) presents the results of an estimation that includes both positive and negative values in the temperature shock series. Compared to the baseline results in section (5), the impulse responses remain qualitatively unchanged. However, the magnitude of the peak effects is somewhat altered. This robustness exercise suggests that while accounting for the sign of a temperature shock does not affect the qualitative nature of the responses, it tends to produce slightly stronger effects. Another potential concern relates to the cosine–latitude correction for grid-cell area. At a 0.25° spatial resolution over Italy, this induces a north–south gradient of about 19% in cell area, implying that northern regions are overrepresented relative to their actual

land area. Appendix figure (33) shows that this adjustment does not impact the main findings presented here.

Shock measure for precipitation. As mentioned in section (3.1) the precipitation shock series used in the baseline estimation closely mirrors the widely used Standardised Precipitation Index (SPI). To compute the SPI, I follow the approach introduced by McKee et al. (1993) and further explained by Edwards and McKee (1997). This involves fitting a gamma distribution to the monthly precipitation data and transforming the resulting cumulative distribution into a standard normal variable via the inverse cumulative distribution function (CDF). The resulting SPI series has a mean of zero and unit variance, allowing for a consistent interpretation of precipitation shocks: values below the value of -1 typically signify dry conditions. Intuitively, a replication of the results based on the SPI reinforces the robustness of the study’s original precipitation-based proxy. Indeed, figures (34) and (35) demonstrate that both the SPI-1 and SPI-3 can replicate the core results of this analysis, with the latter even indicating that accounting for the compounding effect of dry conditions leads to similar findings as shown in section (5)²⁴. Appendix figure (36) presents the results of an estimation that includes positive precipitation values. The findings differ notably, with changes not only in the posterior credibility but also in the direction of effects for certain variables. This exercise highlights the critical importance of accounting for sign asymmetries in the precipitation literature when analysing the impacts of weather shocks. Similar to the case of temperature, figure (37) provides insights from a cosine-adjusted cell weighting and shows that this adjustment does not alter the results qualitatively.

Observation period. Since the baseline estimation in section (5) is including the Covid period, the results might be affected by the extreme change of the volatility in the data. As can be seen in appendix figures (38) and (39), ending the estimation period in December 2019, just before the onset of the Covid period does not alter the results. This holds for both temperature and precipitation outcomes.

Data. As mentioned above, the energy sector is one of the most crucial sectors when looking at climate shocks. In the baseline estimation, consumer prices of energy were captured by electricity and gas (ELGAS). This variable excludes fuel/petrol and liquid gas prices, which make up a substantial part of every economy. Therefore, in appendix figures (40) and (41) I

²⁴SPI- m denotes the accumulation period of the index. For example, SPI-1 and SPI-3 correspond to 1-month and 3-month accumulation period, respectively.

re-estimate the baseline specification based on the total energy prices and confirm the findings in section (5).

8 Conclusion

This study provides new evidence on the macroeconomic consequences of climate shocks, emphasising both domestic effects and cross-border spillovers in a small open economy context. Using a two-country VAR framework, I examine sector-weighted temperature and precipitation deviations in Italy and their transmission to Maltese inflation components and production sectors. Consistent with previous literature, temperature shocks generate broad economy-wide effects, simultaneously affecting consumer and producer prices across multiple sectors, while precipitation shocks exhibit more concentrated, idiosyncratic impacts, primarily through the agricultural sector and associated food prices. Crucially, both types of shocks display pronounced sign asymmetries, with positive and negative deviations producing distinct outcomes. These asymmetries are particularly evident for precipitation shocks, where dry and wet conditions generate divergent responses in prices and production.

Three results in particular stand out as novel and policy-relevant. *First*, Maltese services inflation *overshoots* its Italian counterpart following spring and summer temperature shocks—a pattern that reflects the disproportionately high HICP weight of accommodation and catering in Malta and these items’ tight linkage to Italian fresh-food and energy inputs. *Second*, Maltese energy production responds *countercyclically* to Italian fluctuations, rising when Italian production falls and falling when it rises; this compensatory pattern is enabled by the Malta–Italy interconnector and points to an infrastructure-driven buffering response to external supply conditions. *Third*, the IRF decomposition reveals that Italian *unprocessed food prices* are the dominant driver of the Maltese food-production response—exceeding both domestic contributions and other foreign components—uncovering a previously under-appreciated channel through which Italian agricultural conditions are transmitted to Maltese food manufacturing.

The analysis also highlights the role of cross-border transmission mechanisms. Italian climate shocks influence Maltese inflation and production through trade and energy linkages, but the sectoral pattern of effects differs from the origin country. For instance, while summer temperature and precipitation shocks increase unprocessed food prices through higher energy production in Italy, the corresponding effect in Malta appears in the services sector and domestic food

production rather than directly in consumer food prices. Two caveats apply to the services-inflation result in particular. First, the decomposition in section (6) is an accounting identity and does not discriminate between cost-pass-through from Italian food and energy inputs and a demand-side component associated with tourism reallocation under Italian heat. Second, in the absence of a tourist-flow variable in the Maltese block, the estimated spillover should be read as a reduced-form transmission rather than a causal statement about a specific channel. Additionally, Maltese energy production adjusts inversely to Italian fluctuations, reflecting compensatory domestic responses shaped by infrastructure and policy interventions. These findings underscore the importance of considering both economic interdependence and climate exposure when evaluating the broader impact of environmental shocks.

Overall, the results suggest that small open economies are particularly vulnerable to external climate shocks, and that their effects cannot be fully captured by examining domestic conditions alone. Accounting for sign asymmetries and sectoral heterogeneity is essential for accurate modelling and policy design, as symmetric approaches may underestimate the economic consequences of extreme weather events. Policymakers should thus integrate both domestic and cross-border climate risks when designing mitigation strategies, particularly in sectors that are highly exposed to trade linkages, such as agriculture and energy. By explicitly modelling the spillover channels between Italy and Malta, this study contributes to a deeper understanding of how localised climate events can propagate internationally, reshaping economic outcomes across sectors and highlighting the complex interplay between environmental and economic dynamics.

Bibliography

- Baronetti, A., Menichini, M., and Provenzale, A. (2024). Vegetation response to droughts: The case of northern Italy. *International Journal of Climatology*, 44(2):501–520.
- Bilal, A. and Känzig, D. R. (2026). The macroeconomic impact of climate change: Global versus local temperature. *Quarterly Journal of Economics*. Advance online publication.
- Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.
- Burke, M., Zahid, M., Diffenbaugh, N., and Hsiang, S. M. (2023). Quantifying climate change loss and damage consistent with a social cost of greenhouse gases. NBER Working Papers 31658, National Bureau of Economic Research, Inc.
- C3S and WMO (2025). European state of the climate 2024. Technical Report 102 pp., World Meteorological Organization (WMO) / Copernicus Climate Change Service C3S, Geneva.
- Ceglar, A., Toreti, A., Lecerf, R., Van der Velde, M., and Dentener, F. (2016). Impact of meteorological drivers on regional inter-annual crop yield variability in France. *Agricultural and forest meteorology*, 216:58–67.
- Chan, J. C. (2020). Large bayesian vars: A flexible kronecker error covariance structure. *Journal of Business & Economic Statistics*, 38(1):68–79.
- Chudik, A. and Pesaran, M. H. (2016). Theory and practice of gvar modelling. *Journal of Economic Surveys*, 30(1):165–197.
- Ciccarelli, M., Kuik, F., and Hernández, C. M. (2024). The asymmetric effects of temperature shocks on inflation in the largest euro area countries. *European Economic Review*, 168:104805.
- Colacito, R., Hoffmann, B., and Phan, T. (2019). Temperature and growth: A panel analysis of the United States. *Journal of Money, Credit and Banking*, 51(2-3):313–368.
- Copernicus Climate Change Service (C3S) (2025). Global climate highlights 2024. Technical report, ECMWF.
- Damania, R., Desbureaux, S., and Zaveri, E. (2020). Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). *Journal of Environmental Economics and Management*, 102:102335.
- Dasgupta, S., van Maanen, N., Gosling, S. N., Piontek, F., Otto, C., and Schleussner, C.-F. (2021). Effects of climate change on combined labour productivity and supply: an empirical, multi-model study. *The Lancet Planetary Health*, 5(7):e455–e465.

- Dees, S., Mauro, F. d., Pesaran, M. H., and Smith, L. V. (2007). Exploring the international linkages of the euro area: a global var analysis. *Journal of applied econometrics*, 22(1):1–38.
- Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.
- Edwards, D. C. and McKee, T. B. (1997). Characteristics of 20th century drought in the united states at multiple time scales. Technical Report Climatology Report 97-2 / Atmospheric Science Paper 634, Colorado State University, Department of Atmospheric Science, Fort Collins, Colorado.
- Ellul, R. (2016). A real-time measure of business conditions in malta. CBM Working Papers WP/04/2016, Central Bank of Malta.
- European Commission (2025). Extreme weather risks for tourism in the european Union. Natural Hazards. Springer, doi:10.1007/s11069-025-07516-5.
- European Commission, Joint Research Centre (2023). Global warming to reshuffle europe’s tourism demand, particularly in coastal areas. Technical report, Joint Research Centre.
- Faccia, D., Parker, M., and Stracca, L. (2021). Feeling the heat: extreme temperatures and price stability. Working Paper Series 2626, European Central Bank.
- Ferrucci, G., Jiménez-Rodríguez, R., and Onorante, L. (2012). Food price pass-through in the euro area: Non-linearities and the role of the common agricultural policy. *International Journal of Central Banking*, 8(1):179–218.
- Gatt, W. and Ruisi, G. (2022). The spillover of euro area shocks to the maltese economy. CBM Working Papers WP/03/2022, Central Bank of Malta.
- Guerriero, V., Scorzini, A. R., Di Lena, B., Iulianella, S., Di Bacco, M., and Tallini, M. (2023). Impact of climate change on crop yields: Insights from the abruzzo region, central italy. *Sustainability*, 15(19):14235.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al. (2020). The era5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049.
- Holtermann, L. (2020). Precipitation anomalies, economic production, and the role of “first-nature” and “second-nature” geographies: A disaggregated analysis in high-income countries. *Global Environmental Change*, 65:102167.
- Kadiyala, K. R. and Karlsson, S. (1997). Numerical methods for estimation and inference in bayesian var-models. *Journal of Applied Econometrics*, 12(2):99–132.

- Kalkuhl, M. and Wenz, L. (2020). The impact of climate conditions on economic production. evidence from a global panel of regions. *Journal of Environmental Economics and Management*, 103:102360.
- Kilian, L. and Lewis, L. T. (2011). Does the fed respond to oil price shocks? *The Economic Journal*, 121(555):1047–1072.
- Kolstad, C. D. and Moore, F. C. (2020). Estimating the economic impacts of climate change using weather observations. *Review of Environmental Economics and Policy*, 14(1):1–24.
- Kotz, M., Donat, M. G., Lancaster, T., Parker, M., Smith, P., Taylor, A., and Vetter, S. H. (2025). Climate extremes, food price spikes, and their wider societal risks. *Environmental Research Letters*, 20(8):081001.
- Kotz, M., Kuik, F., Lis, E., and Nickel, C. (2023). The impact of global warming on inflation: averages, seasonality and extremes. Working Paper Series 2821, European Central Bank.
- Kotz, M., Kuik, F., Lis, E., and Nickel, C. (2024). Global warming and heat extremes to enhance inflationary pressures. *Communications Earth & Environment*, 5(1):116.
- Kotz, M., Levermann, A., and Wenz, L. (2022). The effect of rainfall changes on economic production. *Nature*, 601(7892):223–227.
- Kotz, M., Wenz, L., Stechemesser, A., Kalkuhl, M., and Levermann, A. (2021). Day-to-day temperature variability reduces economic growth. *Nature Climate Change*, 11(4):319–325.
- McKee, T. B., Doesken, N. J., Kleist, J., et al. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*, volume 17, pages 179–183. California.
- Mumtaz, H. and Theophilopoulou, A. (2024). The distributional effects of climate change. an empirical analysis. *European Economic Review*, 169:104828.
- Peersman, G. (2022). International food commodity prices and missing (dis) inflation in the euro area. *Review of Economics and Statistics*, 104(1):85–100.
- Pulighe, G., Di Fonzo, A., Gaito, M., Giuca, S., Lupia, F., Bonati, G., and De Leo, S. (2024). Climate change impact on yield and income of italian agriculture system: a scoping review. *Agricultural and Food Economics*, 12(1):23.
- Ruisi, G. (2022). Global oil price swings and shipping disruptions: Do they matter for malta? CBM Policy Papers PP/07/2022, Central Bank of Malta.
- Salinger, M. J., Dalla Marta, A., Dalu, G., Messeri, A., Baldi, M., Messeri, G., Vallorani, R., Morabito, M., Orlandini, S., Altobelli, F., et al. (2020). Linking crop yields in tuscany, italy,

- to large-scale atmospheric variability, circulation regimes and weather types. *The Journal of Agricultural Science*, 158(7):606–623.
- Santeramo, F. G. and Maccarone, I. (2022). Historical crop yields and climate variability: analysis of italian cereal data. *Italian Review of Agricultural Economics (REA)*, 77(2):77–91.
- Semenov, M. A. and Porter, J. (1995). Climatic variability and the modelling of crop yields. *Agricultural and forest meteorology*, 73(3-4):265–283.
- Usman, S., González-Torres Fernández, G., and Parker, M. (2025a). Going NUTS: The regional impact of extreme climate events over the medium term. *European Economic Review*, 178:105035.
- Usman, S., Parker, M., and Vallat, M. (2025b). Dry-roasted nuts: Early estimates of the regional impact of 2025 extreme weather. SSRN working paper, available at <https://ssrn.com/abstract=5484206>.
- World Meteorological Organization (2025). State of the global climate 2024. WMO-No. 1368, WMO.

A Macroeconomic Variables

Beginning with the Italian block, I follow Ciccarelli et al. (2024) and build on the matrix of macroeconomic variables for Italy. Consequently, I am matching the Maltese variables with the Italian block to trace the shock from Italy to Malta. However, some aspects need to be taken into account when matching macroeconomic indicators. Although the breakdown for HICP components from Eurostat offers a perfect match for Malta and Italy, it is mainly the real business cycle indicator that needs to be adapted. In fact, Ciccarelli et al. (2024) use industrial production as a short-term indicator of real activity. This variable is not representative for Malta. To overcome this issue, I am using the real-time business cycle index provided by Ellul (2016). A list of the variables used for each country is shown in table (1). I am using headline

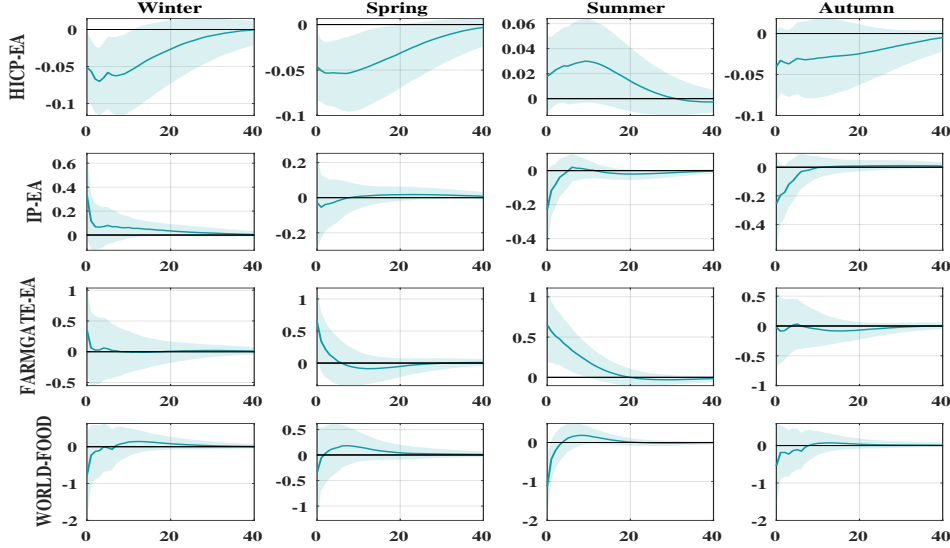
Macroeconomic Variables	
Italy	Malta
Processed Food	Processed Food
Unprocessed Food	Unprocessed Food
Services	Services
Non-Energy Industrial Goods	Non-Energy Industrial Goods
Energy	Energy
IP Italy	Business Cycle Index
Production of Energy	Production of Energy
Overall PPI	Overall PPI
PPI food	PPI food
PPI Energy	PPI Energy
Food Production	Food Production
EA Industrial Production	-
EA HICP	-
EA Farm-gate prices	-
Total World Food Prices	-

Table 1: Data used in the baseline specification. The Italian matrix includes the corresponding macroeconomic totals for Italy as well as controls for possible second-round spillover effects.

HICP, IP, Farm-gate prices and total world food prices in order to capture second-round effects which is motivated by the global VAR literature (see Dees et al. (2007) and Chudik and Pesaran (2016)). All in all, the foreign block comprises 15 endogenous variables of which 11 are Italian and mapped to the corresponding Maltese aggregates.

B IRFs of Aggregate Control variables

Figure 13: Spillover effects of a temperature shock on aggregate control variables.



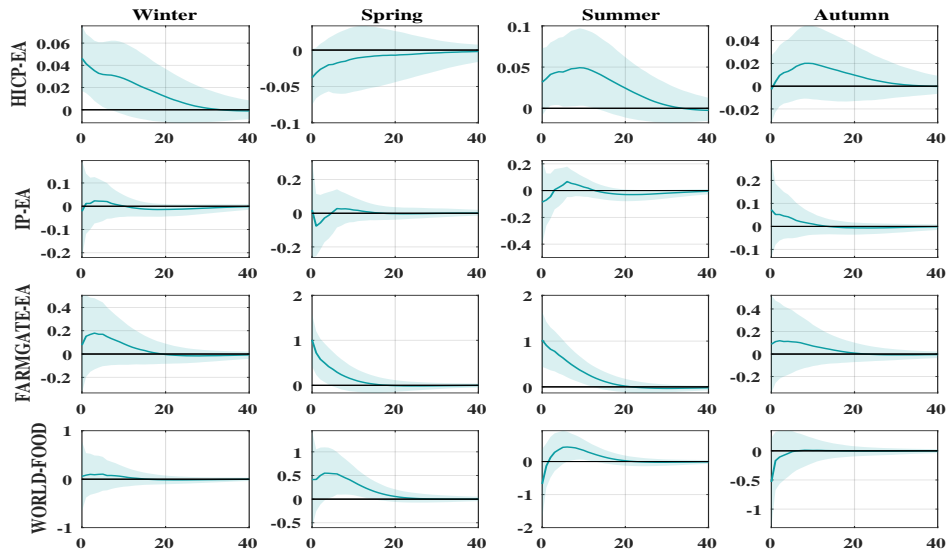
Note: The figure displays impulse response functions (IRFs) for Euro Area and World aggregate macroeconomic variables, with 68% credible sets shown around the median responses. The temperature shock is normalised to represent an increase equal to the 75th percentile of the seasonal temperature distribution, capturing the effect of an extreme temperature event within each season. This figure complements figures (2) - (4) in the main text.

Figure (13) displays the IRFs of aggregate control variables to a temperature shock. Headline HICP in the Euro Area follows the sign of the Italian price movements²⁵. Being a significant player in food manufacturing in Europe, the temperature shock in Italy passes through to the Euro Area totals, albeit with smaller magnitude (a peak decrease of roughly -0.07 percentage points three months after the shock in winter). A temperature shock has no credibly distinguishable effect on Euro Area industrial production. Euro Area farm-gate prices, by contrast, rise on impact by about 0.65 percentage points in the summer months. At the same time, world food prices display negligible effects.

Compared to that, figure (14) shows the analogous effects of a negative precipitation shock as considered in the main text. Euro Area industrial production and world agricultural food prices appear largely unaffected by short-term precipitation shocks. However, Euro Area farm-gate prices increase on impact by roughly 1 percentage point in spring and 1.02 percentage points in summer. This summer response is approximately 60% larger than the corresponding

²⁵Note, that conditional on the season, the sign of the responses of all prices (producer and consumer) is symmetric across sectors.

Figure 14: Spillover effects of a negative **precipitation shock** on aggregate control variables in Malta.

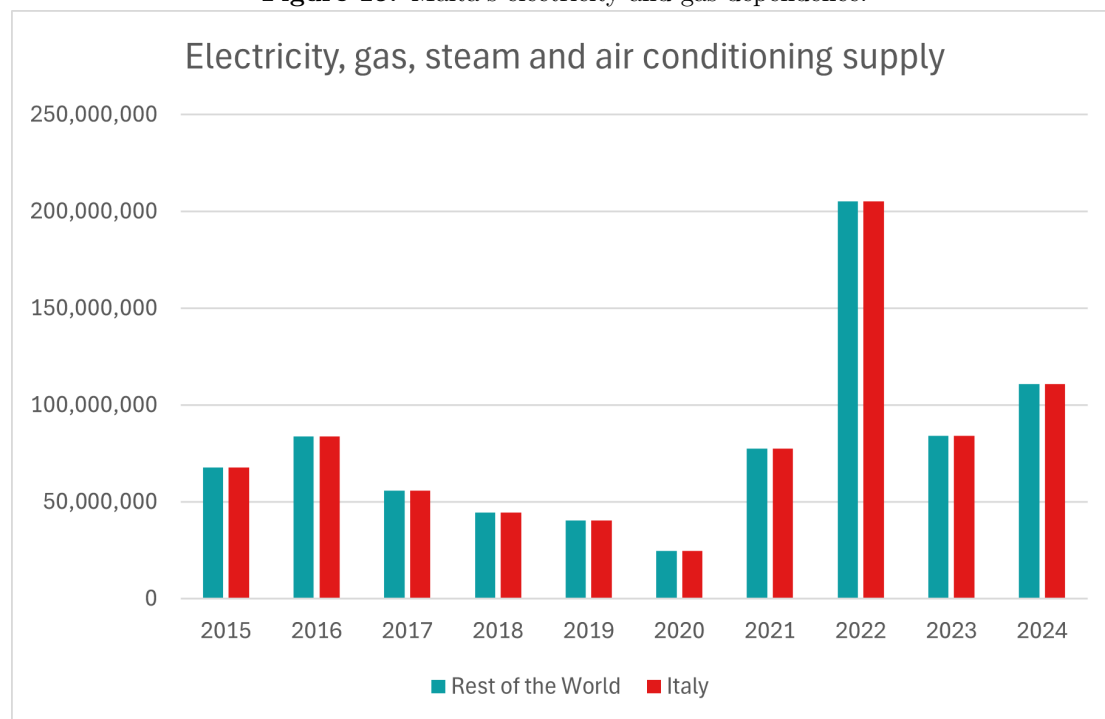


Note: The figure displays impulse response functions (IRFs) for selected Italian (blue) and Maltese (red) macroeconomic variables, with 68% credible sets shown around the median responses. The shock is normalised to represent an increase equal to the 25th percentile of the seasonal distribution of precipitation, displaying the effect of an extreme precipitation event within each season.

temperature shock—underscoring the more concentrated effects of precipitation shocks on the agricultural sector, in contrast to the broader, economy-wide impacts typically associated with temperature shocks. Moreover, the Euro Area HICP exhibits a peak median response of 0.05 percentage points on impact in the winter and a 0.049 percentage points increase after 9 months in the summer season.

C Electricity and Gas Imports of Malta

Figure 15: Malta's electricity and gas dependence.

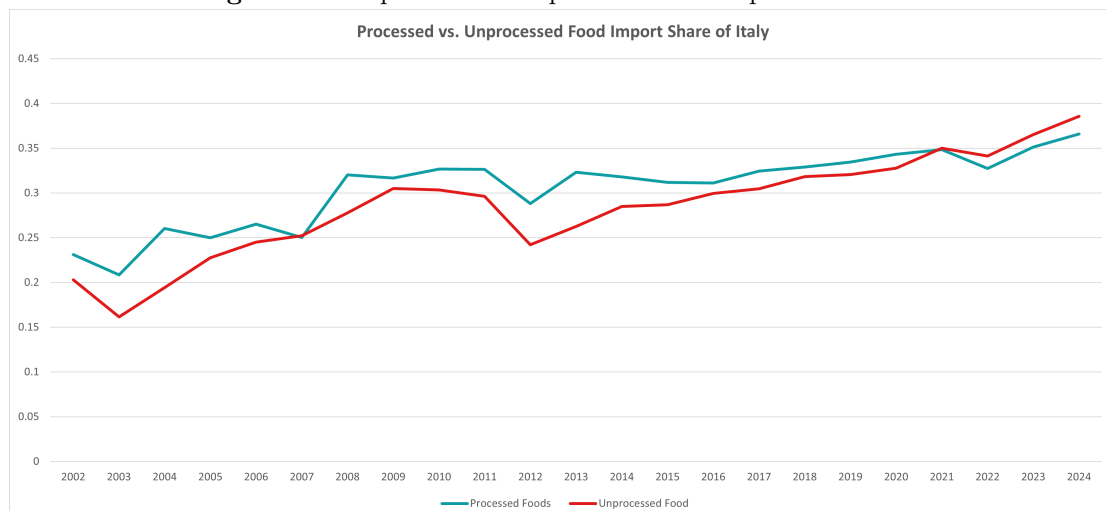


Note: The figure compares the value of Malta's imports from Italy with the total value of imports from all trading partners combined in the *Electricity, gas, steam and air conditioning supply* category. For Malta, Eurostat reports identical values for this category and its subcomponent *Electricity from non-renewable sources*, indicating that the reported imports consist entirely of electricity. The total import series includes imports from Italy. The close correspondence between the two series shows that imports from Italy accounted for virtually all of Malta's imports in this category throughout the period.

D Processed and Unprocessed Food Import Share

Figure (16) illustrates the import shares of processed and unprocessed food in Italy over time. For most years, unprocessed food imports represent a relatively smaller proportion compared to global trends. However, this pattern shifts in 2021. The figure also highlights the close trade relationship between Italy and Malta, particularly underscoring Italy's role as a key exporter of food to the Maltese economy.

Figure 16: Import shares of processed and unprocessed food.

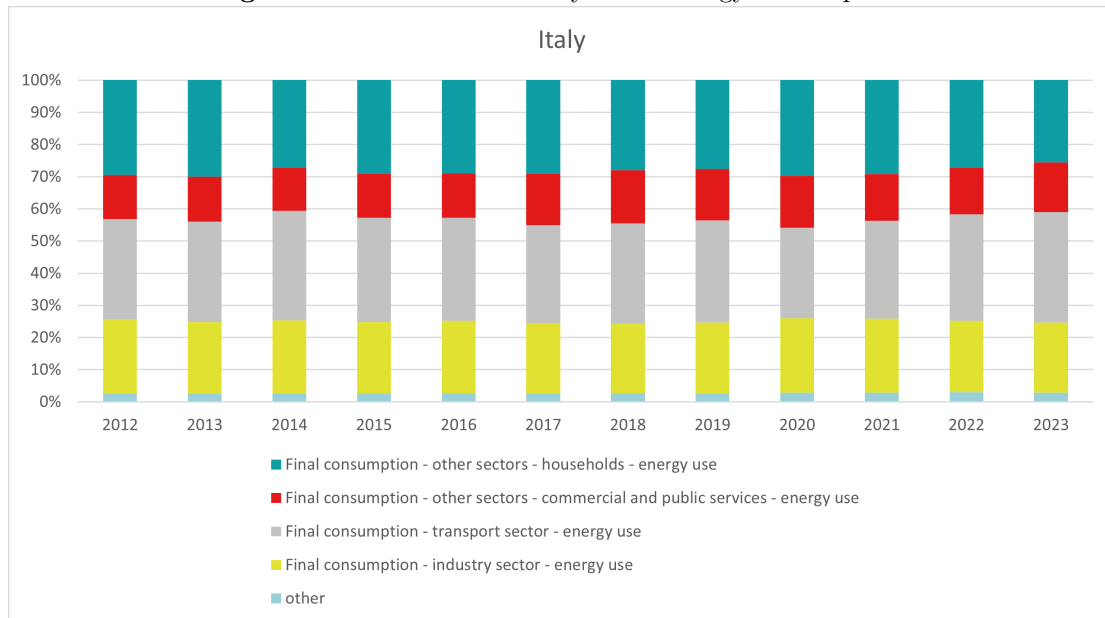


Note: A time series of unprocessed and processed food import shares from Italy relative to the whole world. The categories are derived based on own judgment on the 3-digit breakdown to approximate the COICOP category of processed and unprocessed food.

E Final Energy Consumption by Sector in Italy

Figure (17) presents the composition of final energy consumption in Italy. This figure is directly comparable to figure (5) in the main text and underscores the differences in energy use by sector between Malta and Italy. These distinctions shed light on the country-specific transmission mechanisms of climate shocks, as the primary industry of final energy consumption may vary across countries. For example, households account for a smaller share of final energy consumption in Malta than in Italy. Consequently, an increase in energy prices in Malta is more likely to be transmitted to other sectors, such as transport, rather than to households. This difference in the transmission, in turn, affects how an economy is hit by the shock.

Figure 17: Breakdown of Italy's final energy consumption.

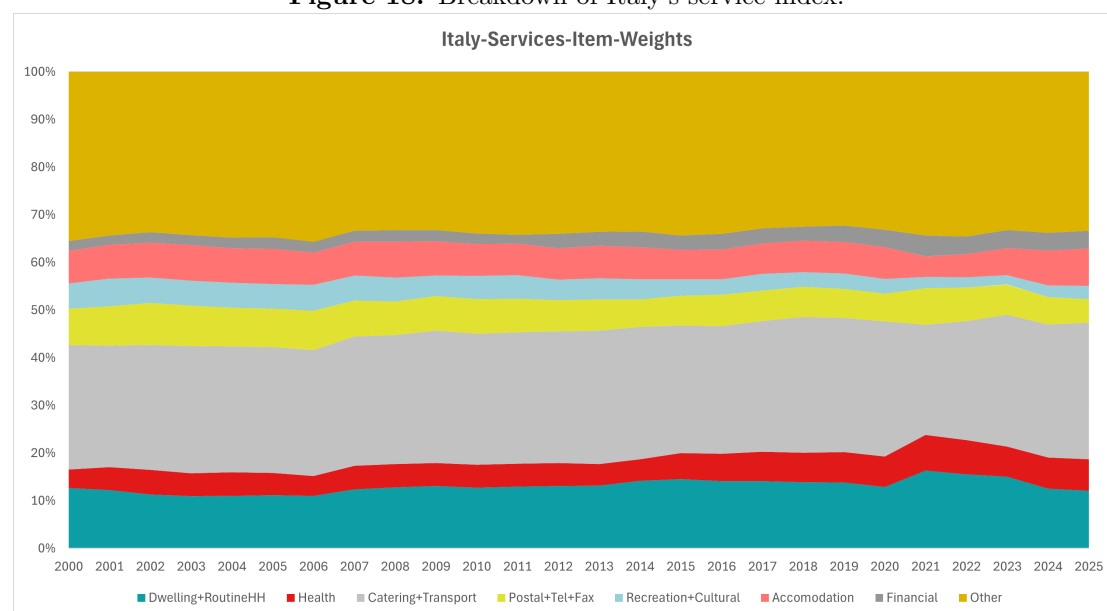


Note: This figure shows the analogous breakdown of Italy's final energy consumption by sector from 2012 until 2023 and can be directly compared to figure (5) in the main text.

F Service Breakdown by Item Weights in Italy

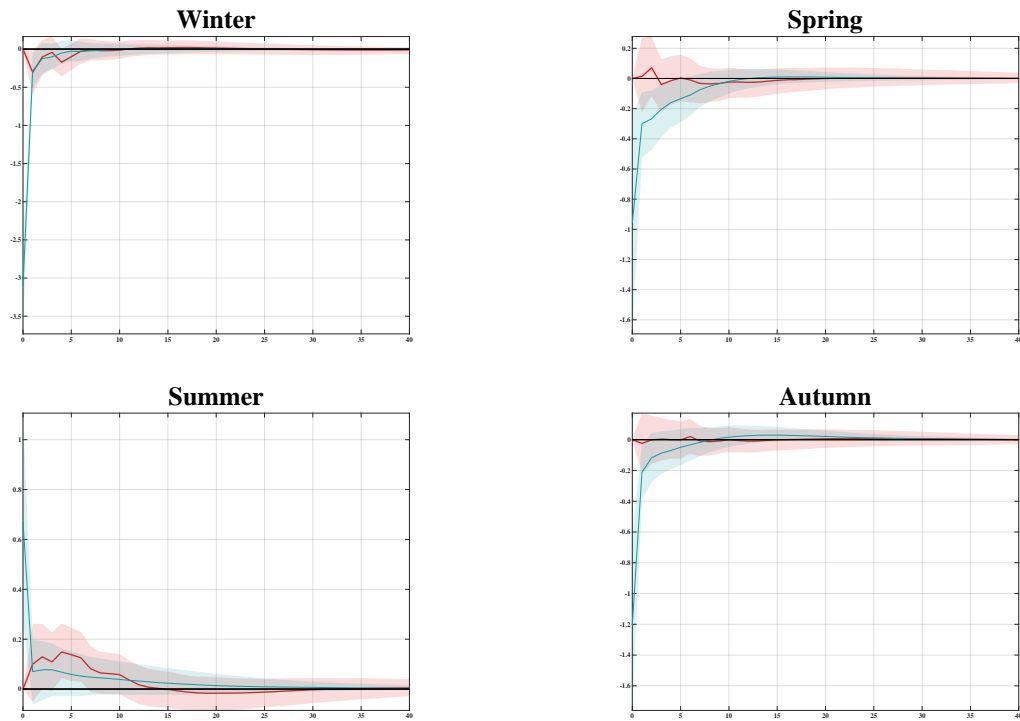
Examining the item weights that constitute the service index provides valuable insights into the response of this HICP component to a climate shock, as discussed in the main text. In comparison to the decomposition of the service sector presented in section (5), figure (18) displays the corresponding breakdown for Italy. Notable differences emerge in the relative weights of dwellings, accommodation, and financial services. As a result, observed price increases in the Italian service sector may originate from different subcomponents than in Malta, suggesting that distinct underlying forces are shaping the service price dynamics in each country.

Figure 18: Breakdown of Italy's service index.



Note: This figure shows the analogous breakdown of Italy's service index by item weights from 2000 until 2025 and can be directly compared to figure (6) in the main text.

G Energy Production before the inter-connector



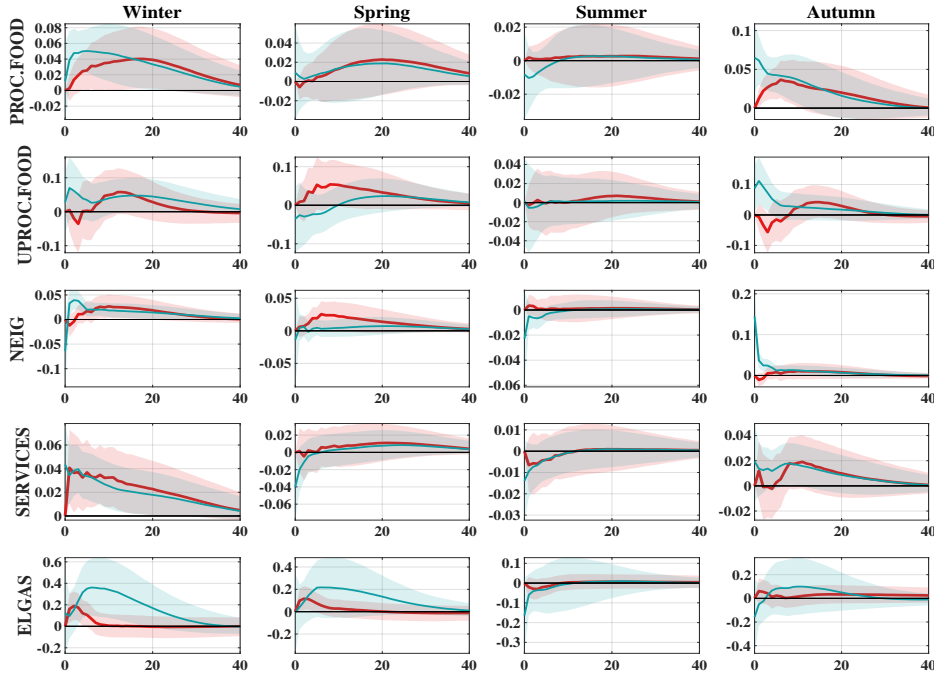
Note: The spillover effects of a **temperature shock** to energy production. The estimation sample ranges from January 2001 until December 2014 and excludes the period of the inter-connector between Sicily and Malta.

H Sign-asymmetry of climate shocks

In section (3.1), the IRFs presented in the baseline analysis are based on a proxy that excludes negative values in the temperature shock series and positive values in the precipitation shock series. Section (7) complements this by presenting estimations using a proxy that includes all observations, showing that accounting for this distinction materially alters the results. This section presents the corresponding IRFs based on the opposite shock considered in the baseline analysis (section (5)). While the spillover effects to Malta remain robust across all specifications, the focus here is primarily on the immediate impact of the shock under consideration. Accordingly, the discussion centres on the IRFs of the Italian variables (depicted in light blue), as Italy is the origin of the shock.

H.1 Negative temperature shocks

Figure 19: The spillover effects of a **negative temperature shock**.



Note: The figure displays the IRFs to a negative temperature shock and is directly comparable to the baseline estimates.

Figure (19) illustrates the seasonal effects of a negative temperature shock on inflation components and serves as the direct counterpart to figure (2), which presents the effects of a positive temperature shock. This comparison is particularly insightful, as it helps assess whether the esti-

mated responses are symmetric—a natural assumption under the symmetric framework adopted in Ciccarelli et al. (2024). Intuitively, if sign-symmetry holds and a positive temperature shock generates the effects shown in figure (2), then a negative shock should lead to opposite outcomes.

Indeed, in several cases, the IRFs confirm this intuition. For example, the baseline results indicate that an unexpected increase in winter temperatures reduces pressure on processed food inflation (see figure (2)). Consistently, figure (19) reveals that a negative temperature shock in winter exerts upward pressure on processed food prices. A plausible explanation, as suggested in the main text, is that lower-than-usual temperatures during an already cold season may severely constrain agricultural activity, thereby affecting input costs and supply chains.

However, this pattern does not extend uniformly across all seasons. In the summer months, processed food inflation appears largely unresponsive to negative temperature shocks. While higher summer temperatures have been shown to raise processed food inflation, cooler-than-usual summers show little posterior evidence of an effect. This suggests a possible asymmetry in how temperature deviations affect inflation across different seasons.

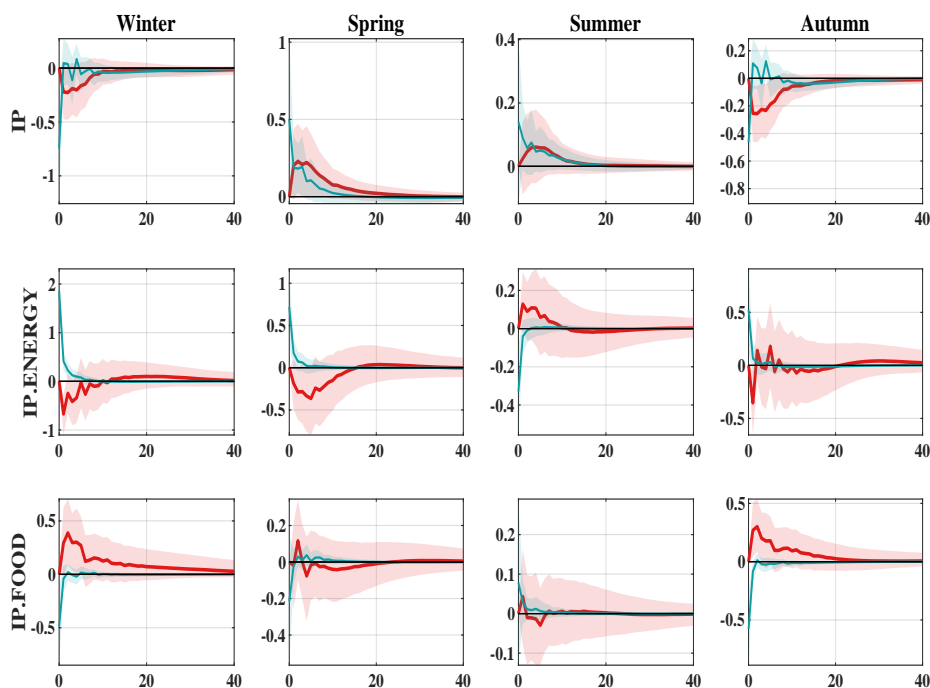
Another notable finding is that unprocessed food inflation shows posterior estimates near zero in response to negative temperature shocks across most seasons, with the exception of a modest effect in autumn. Similarly, services inflation remains largely unaffected. These observations point to sector-specific and season-specific sensitivities, highlighting that the inflationary impact of temperature shocks is not uniformly reversible or symmetric.

The findings become even more compelling when incorporating evidence from the production sector, as shown in figures (20) and (21). With the exception of producer prices in food manufacturing (PPI-FOOD), all variables display the opposite responses compared to the baseline results in figures (3) and (4) in section (5). Notably, PPI-FOOD closely mirrors the movements of unprocessed food prices, suggesting a potential pass-through mechanism from producer to consumer prices in this specific category.

These results indicate that temperature shocks affect the producer side in a manner consistent with linearity in the sign of the shock: variables such as overall real activity, energy production, food manufacturing output, overall producer prices, and producer prices for energy all exhibit a flipped response relative to a positive shock. This symmetry supports the assumption of linear effects on the supply side.

However, this linear relationship does not hold on the consumer side, where the response of prices—particularly for processed food, unprocessed food, and services—remains largely muted, especially during the summer months. These asymmetries underscore the complex transmis-

Figure 20: The spillover effects of a **negative temperature shock**.



Note: The figure displays the IRFs to a negative temperature shock and is directly comparable to the baseline estimates.

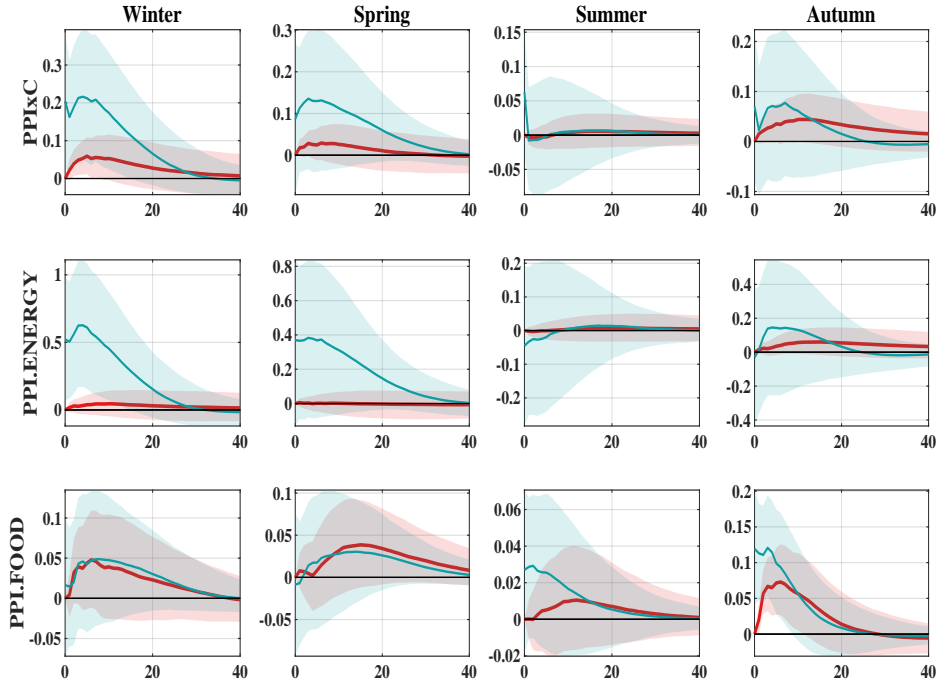
sion of temperature shocks through the economy: while production and upstream prices adjust predictably, downstream consumer prices show non-linear or seasonally dependent behaviour.

H.2 Positive precipitation shocks

Figure (22) presents the corresponding results for positive precipitation shocks, i.e., instances of unexpectedly higher-than-usual rainfall. Contrary to what one might expect under a symmetric, linear framework, the effects of a positive precipitation shock do not mirror those of a negative shock as discussed in section (5).

As with the temperature shock analysis, the food-related consumer price categories stand out in their responses. Processed food inflation reacts notably to increased precipitation during the winter months, displaying a response that is not only the inverse of the negative shock effect discussed in the main text, but also larger in magnitude with strong posterior evidence of an effect. However, this symmetric pattern does not extend to the summer months, where responses are again muted. In particular, while a negative precipitation shock during summer leads to an increase in food prices (figure (7)), a positive precipitation shock yields posterior estimates close to zero with credible intervals overlapping zero.

Figure 21: The spillover effects of a **negative temperature shock**.



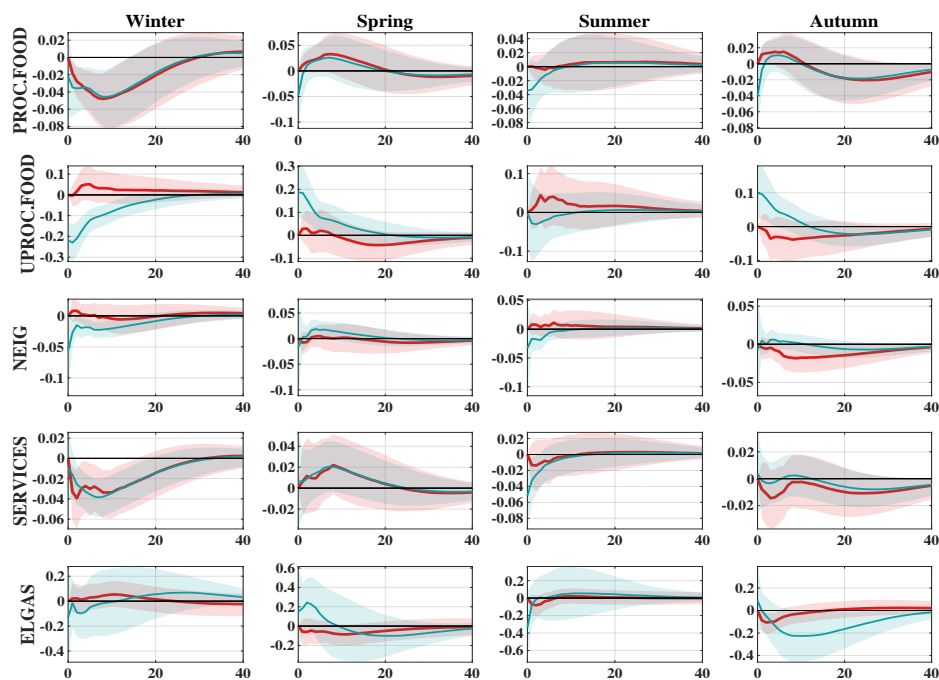
Note: The figure displays the IRFs to a negative temperature shock and is directly comparable to the baseline estimates.

A similar asymmetry is observed in unprocessed food inflation, which shows no meaningful response during summer months either. Interestingly, increased rainfall in autumn does lead to price increases, but the magnitude is smaller compared to the price pressures resulting from reduced precipitation. These patterns reinforce the notion that the transmission of precipitation shocks to consumer prices is non-linear and season-dependent, particularly for food-related inflation components. Examining the producer side in the context of precipitation shocks reveals further evidence of sign asymmetries, particularly for this type of climate shock. As illustrated in figures (23) and (24), several real-side variables—including industrial production (IP) in spring, food production (IP-FOOD) in summer, and producer prices in food manufacturing (PPI-FOOD) during the same season—do not exhibit the expected mirrored responses relative to the negative precipitation shocks presented in the main analysis (see figure (9)).

These results suggest that precipitation shocks generate asymmetric effects depending on the sign of the shock, affecting both the producer and consumer sides of the economy in a non-linear manner. This stands in stark contrast to the findings for temperature shocks, where producer-side variables generally respond in a more symmetric and predictable fashion.

The observed asymmetries underscore the importance of considering non-linear specifications

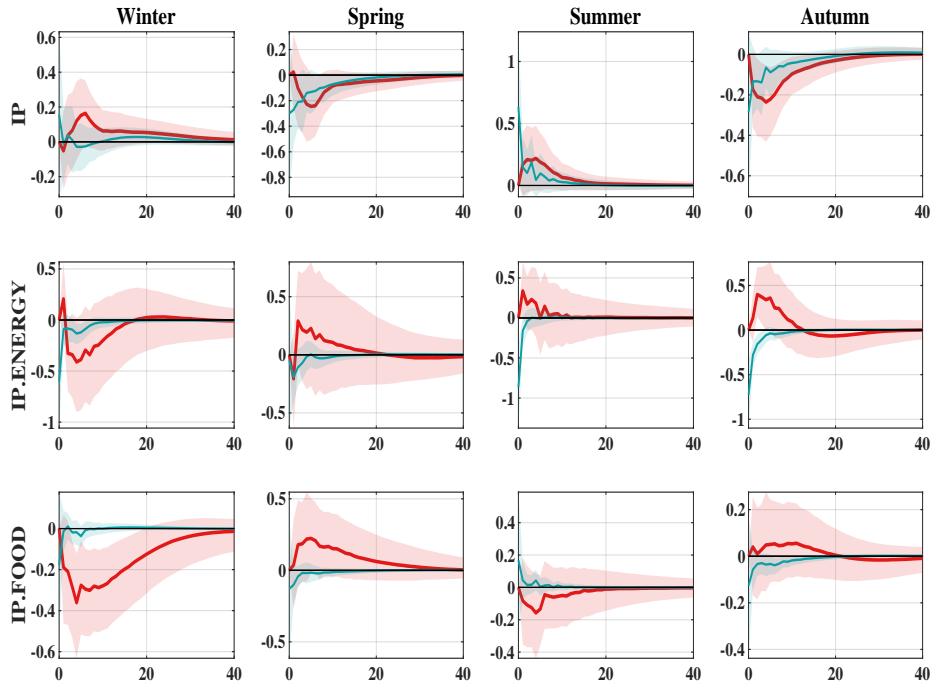
Figure 22: The spillover effects of a positive precipitation shock.



Note: The figure displays the IRFs to a positive precipitation shock and is directly comparable to the baseline estimates.

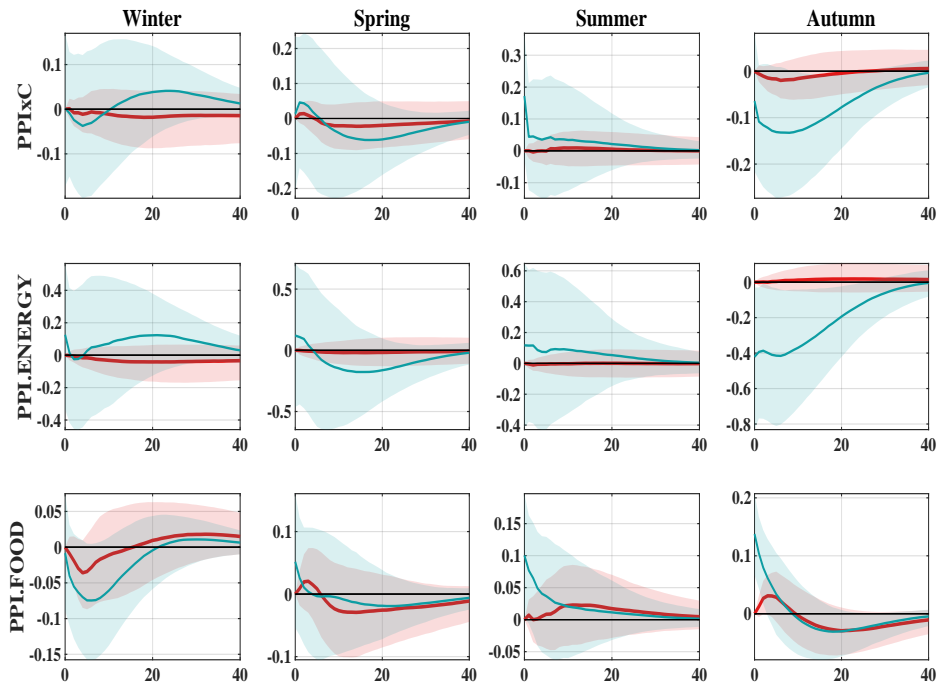
or interaction effects in empirical models analysing climate-related shocks—particularly for precipitation, where the direction of the deviation (more or less rain) appears to matter substantially in shaping economic outcomes (see Damania et al. (2020), Kotz et al. (2022)).

Figure 23: The spillover effects of a positive precipitation shock.



Note: The figure displays the IRFs to a positive precipitation shock and is directly comparable to the baseline estimates.

Figure 24: The spillover effects of a positive precipitation shock.

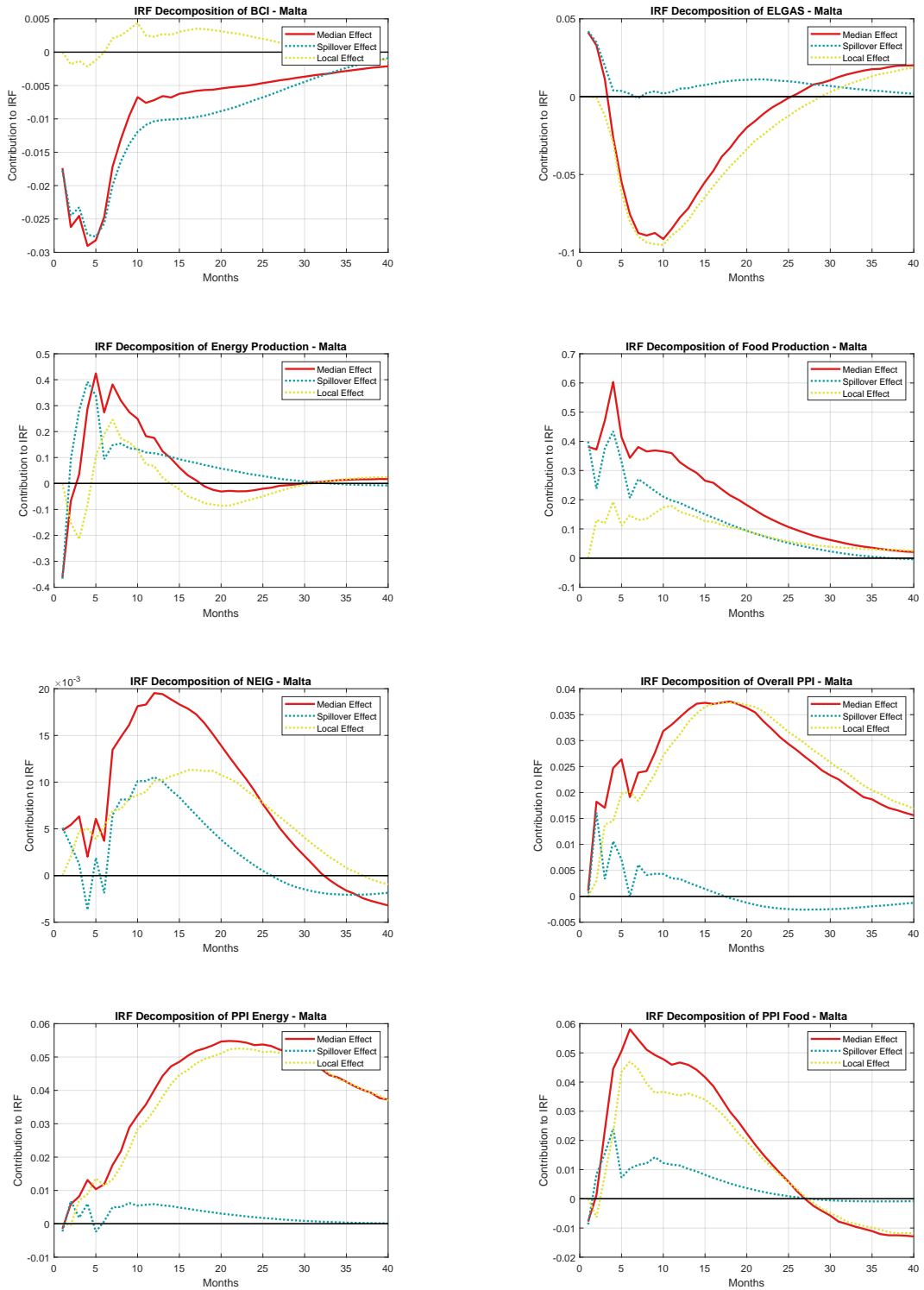


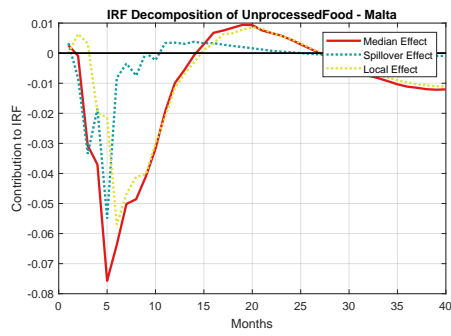
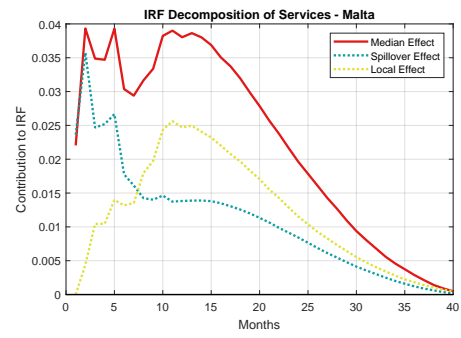
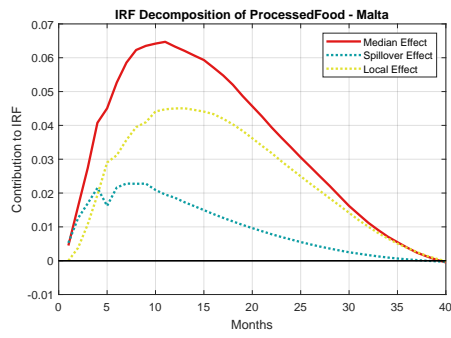
Note: The figure displays the IRFs to a positive precipitation shock and is directly comparable to the baseline estimates.

I Complementary IRF Decompositions

This section presents the corresponding set of IRF decompositions for a summer precipitation shock as well as more granular breakdowns of the temperature decompositions in the main text (section (6)). Figure (??) confirms an identical transmission mechanism for precipitation shocks. However, while the main transmission mechanisms outlined in the main text remain unchanged, this does not imply that the effects of the shocks are identical. Different shocks influence different variables; however, the relative importance of each variable within the VAR framework remains constant. For example, if a summer precipitation shock leads to an increase in Italian unprocessed food prices—similar to the effect of a summer temperature shock—the pass-through to Maltese service prices will persist under both scenarios.

Figure 25: IRF decompositions of a summer precipitation shock.

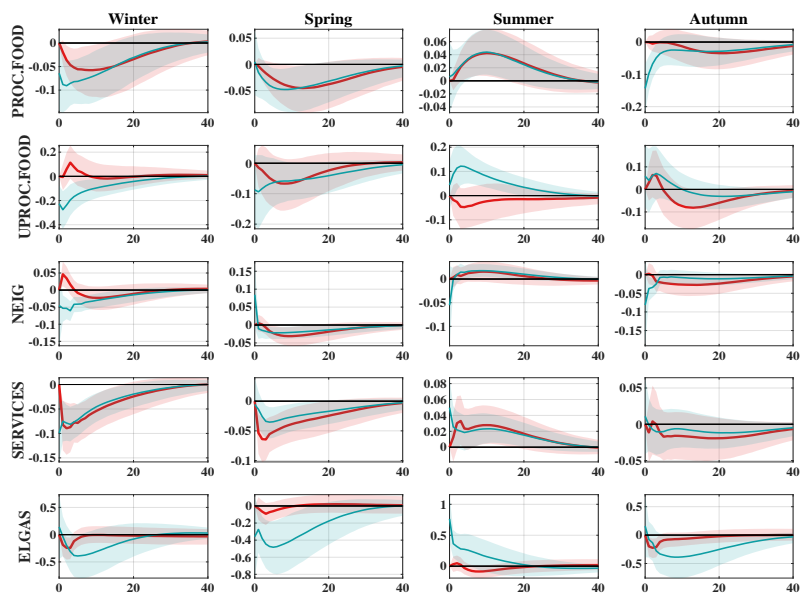




Note: The figure displays the corresponding IRF decomposition of a **summer precipitation shock** for all variables in the system and can be interpreted as direct counterpart to the figures presented in section (6). The red line in each panel corresponds to the Maltese median impulse response of the baseline estimation in section (5). The light blue dotted line is the sum of contributions coming from all foreign variables in the system. The light yellow dotted line corresponds to the sum of all domestic contributions. The light blue and light yellow line add up to the red line at each horizon of the IRF.

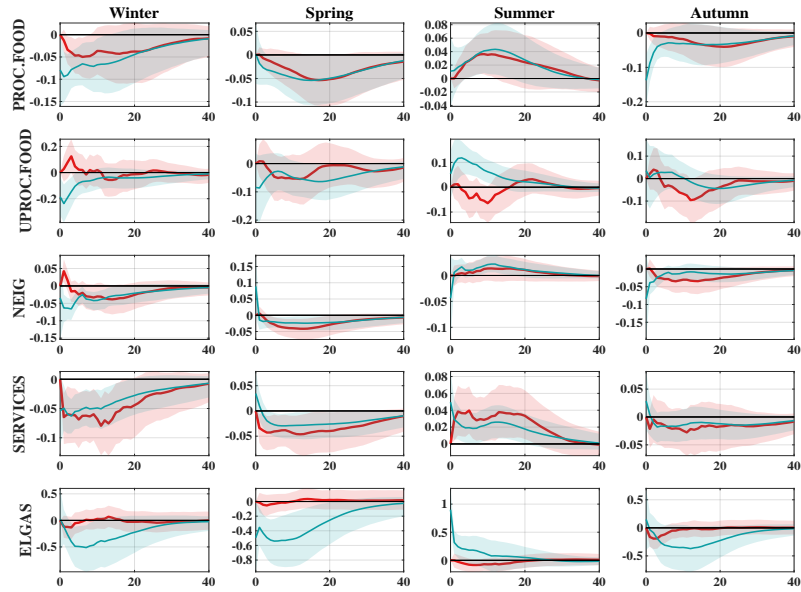
J IRFs of the Robustness Section

Figure 26: Robustness: 3 lags - temperature.



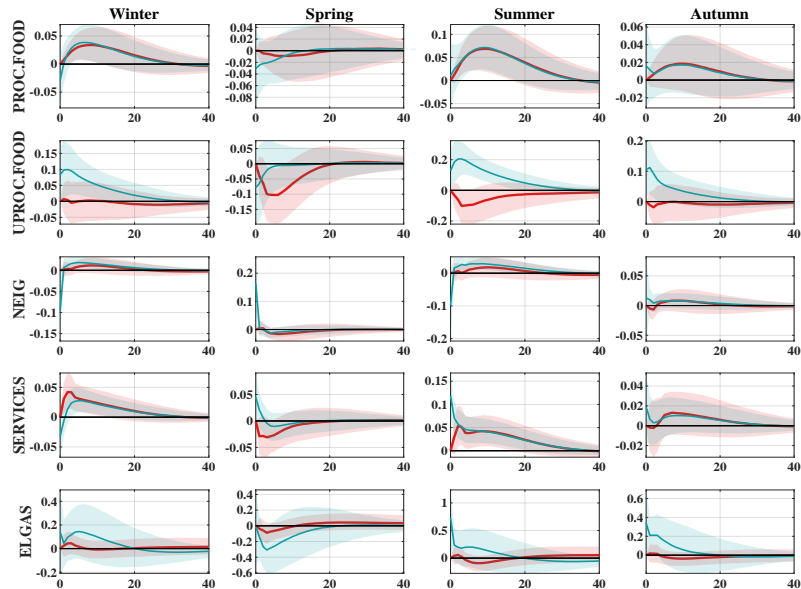
Note: The figure illustrates impulse response functions (IRFs) to a **temperature shock** based on 3 lags. All other specifications are equal to the baseline.

Figure 27: Robustness: 12 lags - temperature.



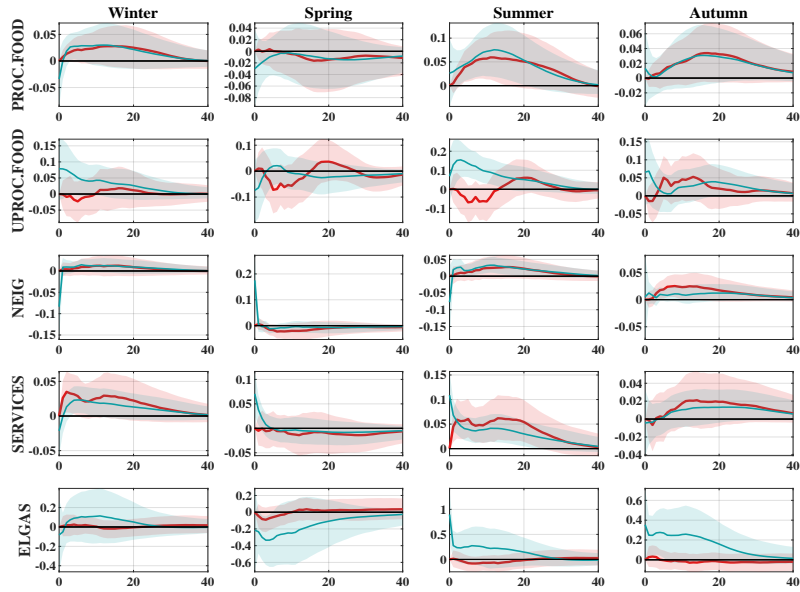
Note: The figure illustrates impulse response functions (IRFs) to a **temperature shock** based on 12 lags. All other specifications are equal to the baseline.

Figure 28: Robustness: 3 lags - precipitation.



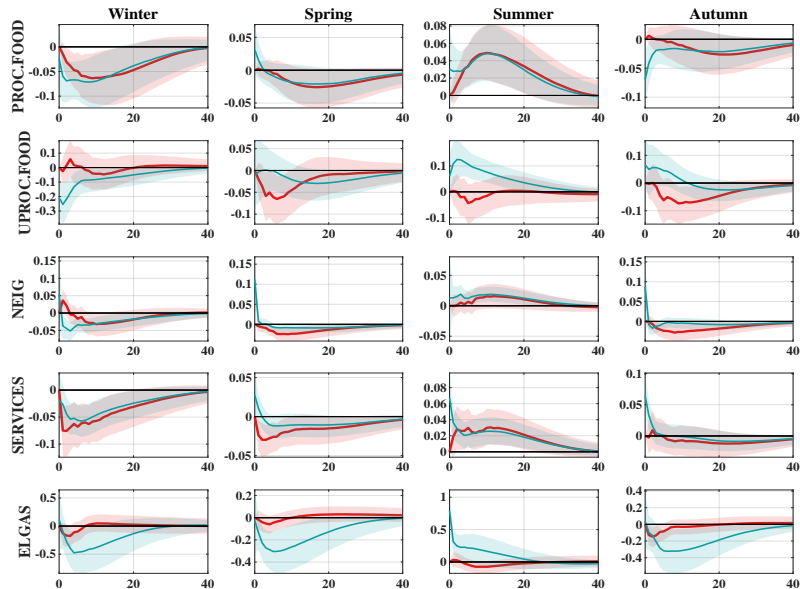
Note: The figure illustrates impulse response functions (IRFs) to a **precipitation shock** based on 3 lags. All other specifications are equal to the baseline.

Figure 29: Robustness: 12 lags - precipitation.



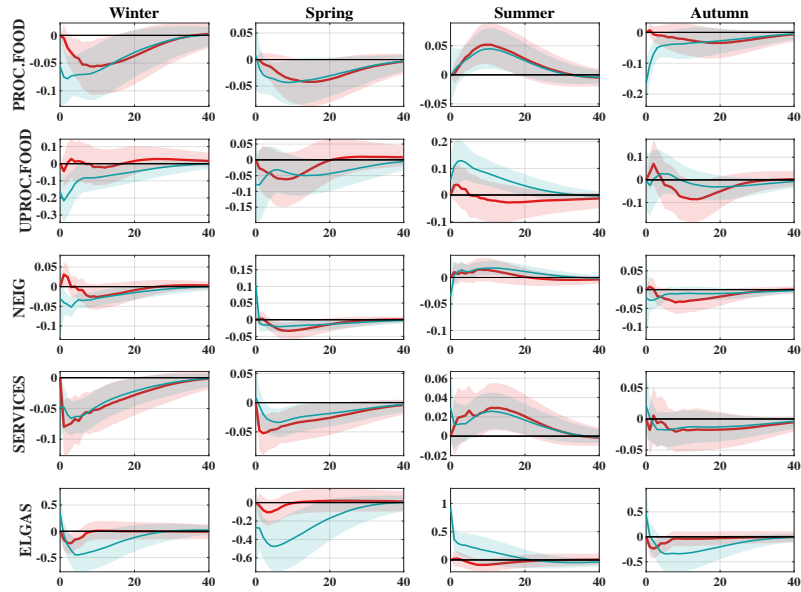
Note: The figure illustrates impulse response functions (IRFs) to a **precipitation shock** based on 12 lags. All other specifications are equal to the baseline.

Figure 30: Robustness: detrended shock series - temperature.



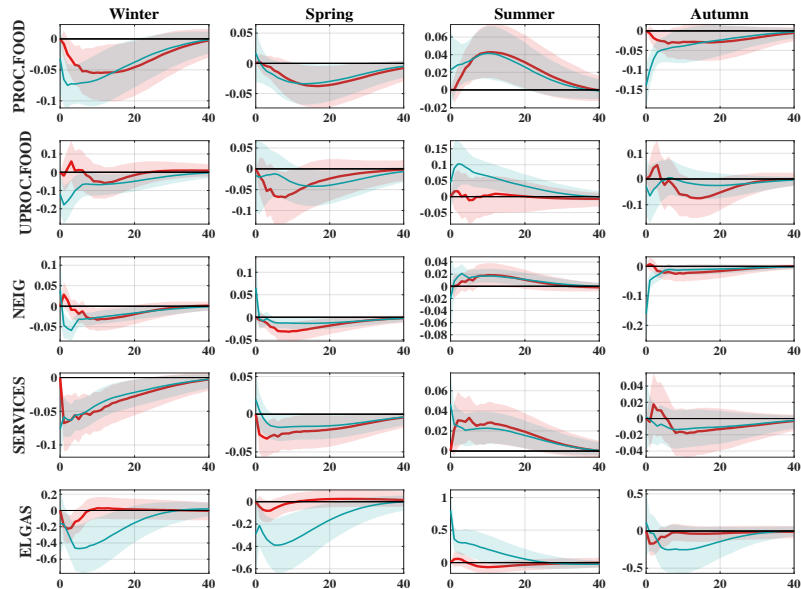
Note: The figure displays IRFs to a **temperature shock** based on a detrended shock series. All other specifications are equal to the baseline.

Figure 31: Robustness: shock series of Ciccarelli et al. (2024).



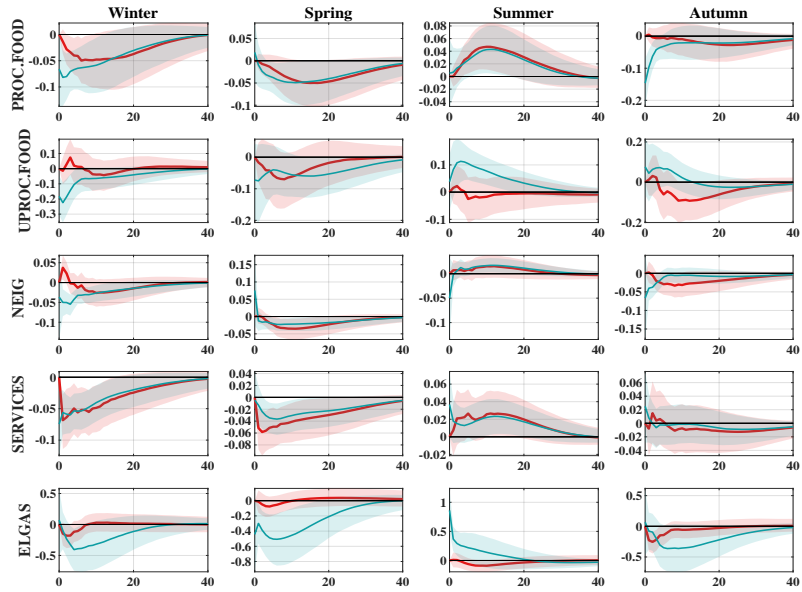
Note: The figure displays IRFs to a **temperature shock** using the shock series of Ciccarelli et al. (2024). All other specifications are equal to the baseline.

Figure 32: Robustness: no sign asymmetry - temperature.



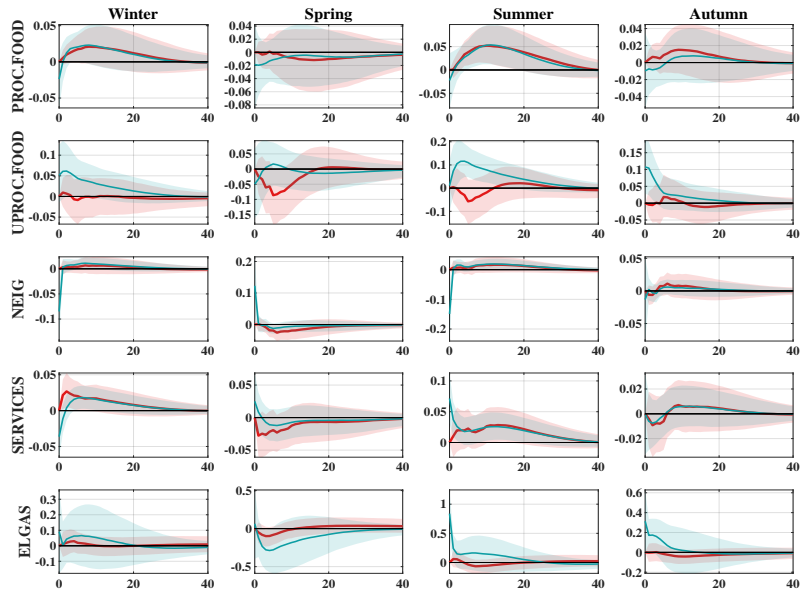
Note: The figure displays IRFs to a **temperature shock** without excluding the negative values in the shock series. All other specifications are equal to the baseline.

Figure 33: Robustness: cosine latitude adjustment - temperature.



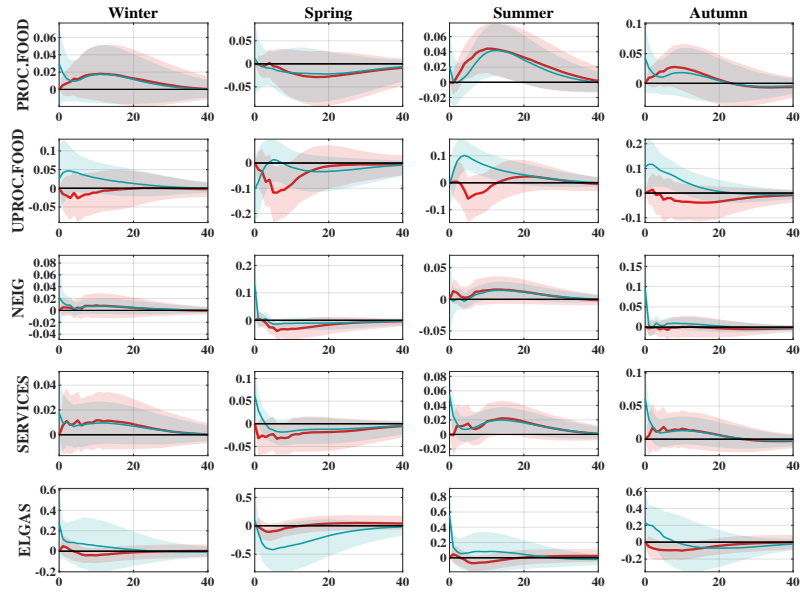
Note: The figure displays IRFs to a **temperature shock** incorporating a cosine latitude adjustment for the grid cell area. All other specifications are equal to the baseline.

Figure 34: Robustness: SPI-1.



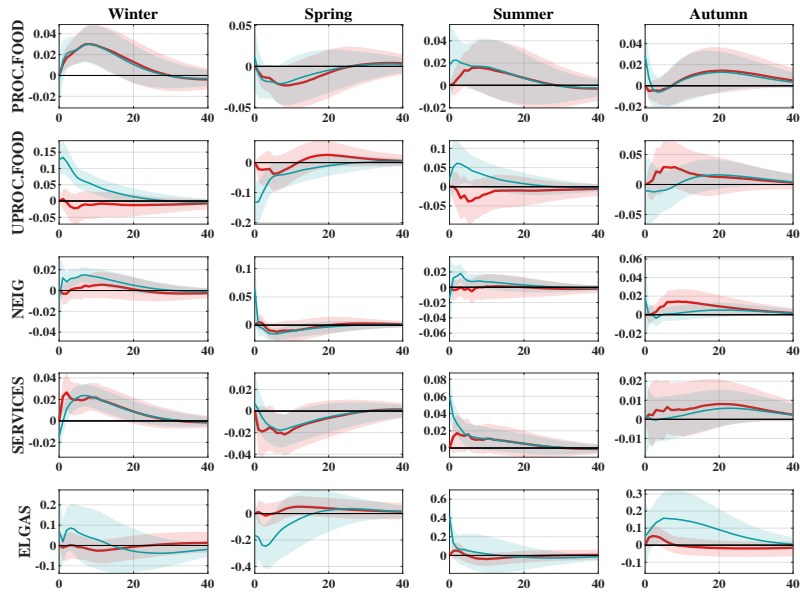
Note: The figure displays IRFs to a **precipitation shock** using the SPI-1 as a proxy. All other specifications are equal to the baseline.

Figure 35: Robustness: SPI-3.



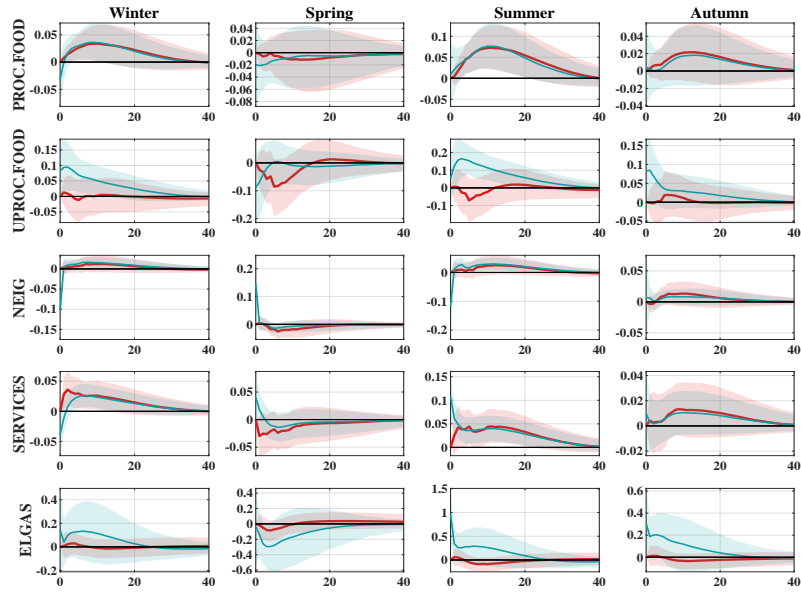
Note: The figure displays IRFs to a **precipitation shock** using the SPI-3 as a proxy. All other specifications are equal to the baseline.

Figure 36: Robustness: no sign asymmetry - precipitation.



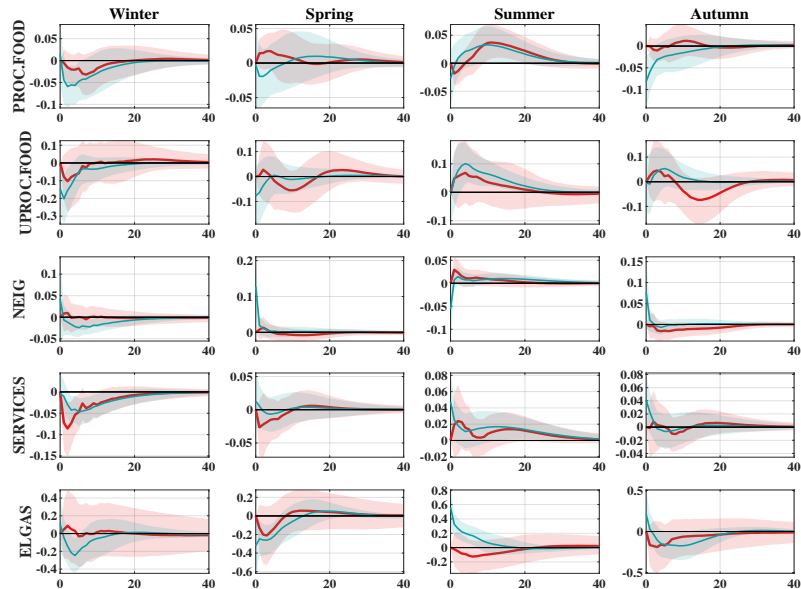
Note: The figure displays IRFs to a **precipitation shock** without excluding the positive values in the proxy. All other specifications are equal to the baseline.

Figure 37: Robustness: cosine latitude adjustment - precipitation.



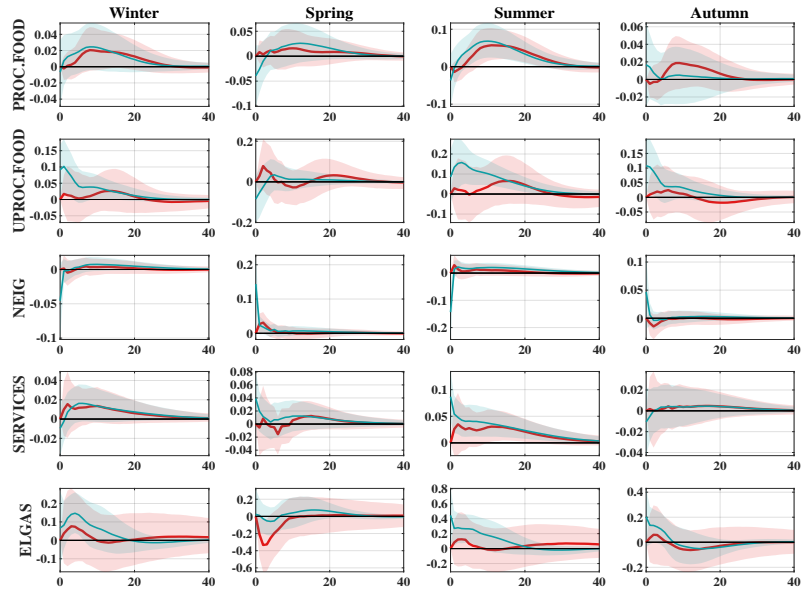
Note: The figure displays IRFs to a **precipitation shock** incorporating a cosine latitude adjustment for the grid cell area. All other specifications are equal to the baseline.

Figure 38: Robustness: no covid - temperature.



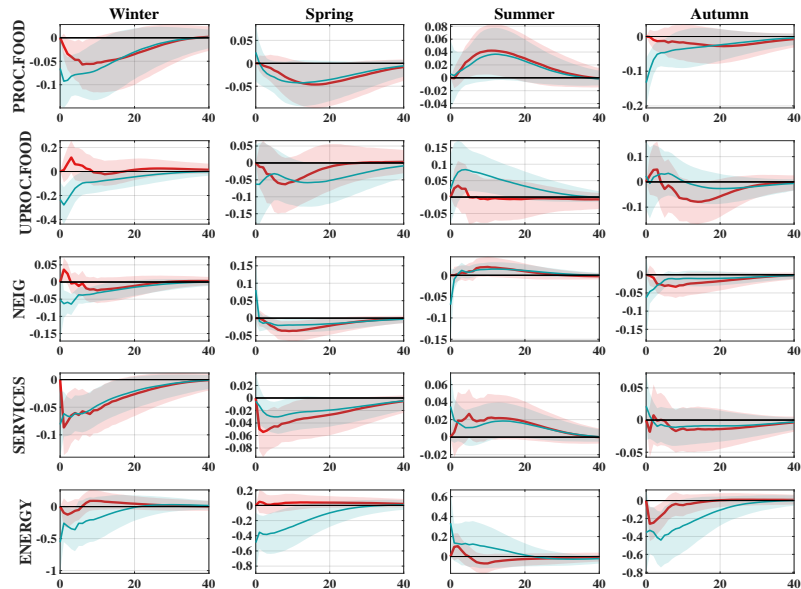
Note: The figure shows the IRFs to a **temperature shock** excluding the Covid Period. All other specifications are equal to the baseline.

Figure 39: Robustness: no covid - precipitation.



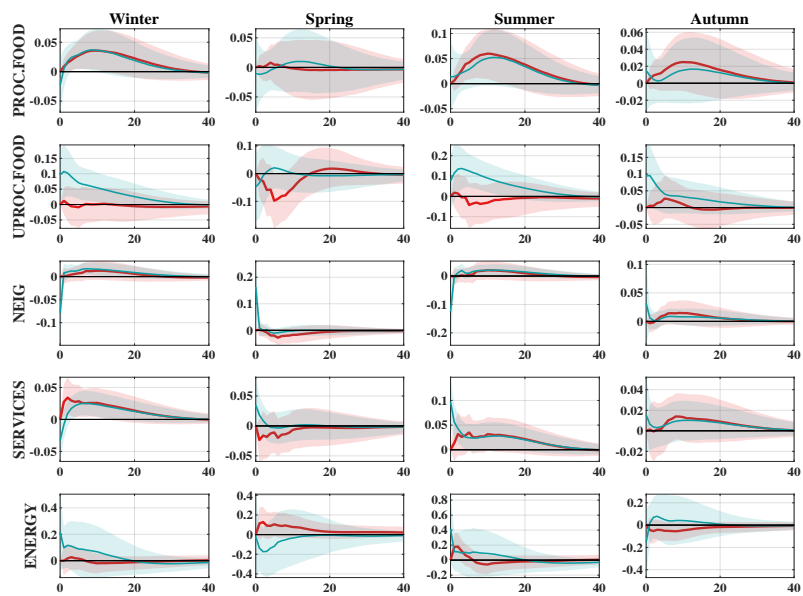
Note: The figure shows the IRFs to a **precipitation shock** excluding the Covid period. All other specifications are equal to the baseline.

Figure 40: Robustness: energy measure - temperature.



Note: The figure shows the IRFs to a **temperature shock** when replacing the electricity and gas (ELGAS) measure by overall Energy prices. All other specifications are equal to the baseline.

Figure 41: Robustness: energy measure - precipitation.



Note: The figure shows the IRFs to a **precipitation shock** when replacing the electricity and gas (ELGAS) measure by overall Energy prices. All other specifications are equal to the baseline.