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## The asymmetric effects of weather shocks on euro area inflation

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**Abstract**

This paper assesses the impact of weather shocks on inflation components in the four largest euro area economies. We combine high-frequency weather data with monthly data on inflation and output growth within a set of Bayesian Vector Autoregressions which explicitly considers the seasonal dependence of the shock. Results suggest the presence of significant country asymmetries and seasonal responses of inflation to temperature shocks, mainly via food, energy, and service prices. An increase in monthly mean temperatures has inflationary effects in summer and autumn, with a stronger response in warmer euro area countries. An increase in temperature variability has significant upward impacts on inflation rates over and above the impacts of changes in means.

**Keywords:** Temperature shocks, Climate change, Inflation, Vector Autoregression
**JEL codes:** Q54, E31, C32

## Non-technical summary

Human emissions are driving current and future climate change (IPCC, 2021a). The impact of this change on current and future economic performance represents a global political and economic challenge and is becoming increasingly important for central banks' monitoring and forecasting of inflation developments in the conduct of monetary policy. While adverse impacts of climate change on economic growth are widely documented, the evidence about the consequences of (manifestations of) climate change on prices and inflation is still scant. This paper contributes to the growing literature on the impacts of climate change on the macroeconomy by investigating the effects of weather shocks on inflation in the four largest euro area countries.

To evaluate the effects of weather shocks on inflation we use a macroeconometric framework that combines macroeconomic data with weather indicators derived from high-frequency meteorological data – to date not fully exploited in the literature on climate and inflation. We assess the impacts on inflation rates disaggregated by type of product. The weather indicators are based on the ERA5 reanalysis dataset (Hersbach et al., 2018, 2020), which combines model simulations and observed meteorological data into a globally consistent dataset. The data and data processing is described in detail in a companion paper (Vidal-Quadras Costa et al., 2022). Here, we focus on indicators that measure (i) changes in mean temperature with respect to a historical mean, and (ii) changes in temperature variability.

The empirical analysis is conducted with country Bayesian Vector Autoregressions (BVARs) that explicitly consider the seasonal dependence of the shock – thus allowing the presence of important non-linearities in the climate-inflation relationship – as well as a measure of interdependence across countries to account for the possibility of spillovers in the final effects of country specific shocks on prices.

The main findings of this paper point to heterogeneous and asymmetric effects across countries of weather shocks on inflation (and output), implying that non-linear responses

of inflation to weather shocks can be expected with progressing climate change. In particular, we find that an increase in monthly mean temperatures increases inflation in summer and partly in autumn, significantly more than in other seasons of the year, with a stronger response in warmer euro area countries (Spain and Italy in summer, Spain in autumn). Overall, the effects are more mixed in France and often insignificant for Germany outside of the winter months. Moreover, an increase in temperature variability has also significant upward impacts on inflation over and above the impacts of changes in means. The resulting inflationary effects of temperature mean and variability shocks are also heterogeneous across HICP components, being more significant (i) for food (process and unprocessed) and services, (ii) during summer, and (iii) for Spain, Italy and France. This combination – which suggests a possible link of (upward) impacts on inflation of those components with higher baseline temperatures – could imply even stronger inflationary impacts with a changing climate, particularly in southern European countries.

Finally, our results point also to asymmetric and heterogeneous effects of country-specific weather shocks on the euro area aggregate. For instance, euro area inflation tends to decrease after a rising temperature outside the summer, with the largest response following a shock in autumn in Italy and France. Instead, a persistent inflationary pressure follows the same shock when it happens in Italy and Spain over summer. On the other hand, shocks to temperature variability tend to put upward pressure on euro area inflation when they occur in Italy, Spain, and France, particularly in winter. Higher temperature variability in Germany, France and Spain in summer has instead a downward effect on euro area inflation.

Different price settings, production structures, baseline temperatures, and institutional factors among others may be responsible for the heterogeneous and non-linear effects that this paper documents. An accurate analysis of these links – which are very consistent with the available literature – is beyond the scope of the paper and is left for future research.

# 1 Introduction

*"If we do not account for the impact of climate change on our economy, we risk missing a crucial part in our work to keep prices stable."*

Christine Lagarde, 2022

With the publication of its latest assessment reports, the Intergovernmental Panel on Climate Change (IPCC, 2021a) has re-affirmed the human influence on climate. Already now this has led to an increase in the global mean temperature of more than 1.1°C, a signal that is also observed in regional temperatures (Figure 1). Climate change has also started affecting the frequency and intensity of weather and climate extremes world-wide, including more frequent and intense hot extremes and more frequent and intense heavy rain (IPCC, 2021a). Adverse impacts, losses and damages, including economic damages, have been recorded as a result, particularly in the agriculture, forestry, fishery, energy and tourism sectors (IPCC, 2022b). While further impacts in the near term are unavoidable due to the continued impact of past greenhouse gas emissions on climate, future risks depend strongly on global efforts to reduce emissions and mitigate climate change.

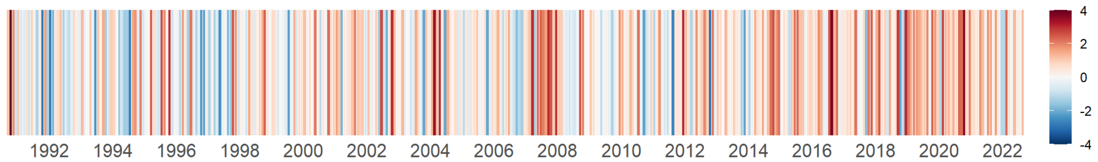


Figure 1: Deviation of euro area monthly mean surface temperature from the 1981-2010 climatological average, weighted using HICP country weights.

Climate change is also becoming increasingly important for central banks' monitoring and forecasting of inflation developments in the conduct of monetary policy (NGFS, 2020; Batten et al., 2020; ECB, 2021; Boneva et al., 2021; Boneva and Ferrucci, 2022; Natoli, 2022). With impacts of climate change increasingly materialising in euro area countries, it is important to understand the impacts of weather shocks on output and inflation now and in the future. This will ultimately help identify the relevant channels through which inflation rates are impacted in a changing climate and help understand the persistence and the potential regionally asymmetric effects from such shocks. Importantly, increased understanding of the climate-inflation relationship will be crucial to understand which baseline central banks should compare to, when assessing the impacts of climate change transition policies on output and inflation.

A growing literature has established links between climate change and aggregate economic growth. In his renowned review "The Economics of Climate Change", Stern (2007) estimates – using an Integrated Assessment Model (IAM) – that the economic cost of 2-3°C warming by the end of the 21st century could lead a decrease of global per capita consumption between 5-20%.[1] Empirical evidence on the climate-economy relationship has also been increasing in recent years and is broadly consistent with Stern's estimates. A negative relationship between higher temperatures and economic output is now well documented – with debate around whether only the level or also growth rates will be affected (e.g., Dell et al., 2012; Carleton and Hsiang, 2016; Hsiang, 2016; Colacito et al., 2019; Kolstad and Moore, 2020). Clear evidence also exists on adverse economic impacts of natural disasters (e.g., Felbermayr and Gröschl, 2014; Kousky, 2014). In addition, studies have investigated the channels through which changes in weather affect the economy, including for example agricultural output, labour productivity and supply, energy demand or health (Auffhammer and Mansur, 2014; Auffhammer and Schlenker, 2014; Dell et al., 2014; Graff Zivin and Neidell, 2014; Kalkuhl and Wenz, 2020; Dasgupta et al., 2021). Furthermore, it is recognised that economic impacts of climate change can be disproportionate and exacerbated in low-income countries and the poorest regions of the world (Stern, 2007; Dell et al., 2012; Kalkuhl and Wenz, 2020; IPCC, 2021b; Ciccarelli and Marotta, 2021). Beyond the impact of changes in mean temperature, studies have also found that increases in day-to-day temperature variability (Kotz et al., 2021b), weather anomalies (Felbermayr et al., 2022), increases in the number of wet days, and extreme daily rain (Kotz et al., 2022) reduce economic growth. Finally, the IPCC con-

[1] With currently implemented policies, the world is on a pathway to global warming of 2.5-2.9°C, and to 2.1°C if all pledges and targets are met (Climate Action Tracker, 2022).

cluded with high confidence that estimates of global aggregate net economic damages increase in a non-linear fashion with global warming (IPCC, 2022b).

Literature on the climate-inflation relationship remains scarce, but first evidence is emerging that establishes a link between weather and the level and volatility of inflation (Parker, 2018; Faccia et al., 2021; Mukherjee and Ouattara, 2021; Natoli, 2022). Similar to the impacts on economic output (Dell et al., 2014) and as illustrated in Section 2, a range of different impact channels are conceivable. These can differ in their effects on prices and output, or interact with each other, and with other, non-climate-related economic developments. Similar to impacts of weather shocks on economic output, the effects on inflation are likely non-linear, depending for example on the baseline temperature level of a country or season. For instance, Faccia et al. (2021) find evidence that extreme temperatures have long-lasting effects on inflation when the shock occurs in the summer, where the main channel of transmission operates via food prices. Beyond seasonally varying impacts, this dependency also implies that impacts of climate change on inflation may be subject to large cross-country heterogeneity, both globally and within the EU.

We contribute to the growing literature on the impacts of climate change on price stability, by investigating the effects of weather shocks on inflation within the euro area. We use indicators based on high-frequency meteorological data (described in a companion paper, see Vidal-Quadras Costa et al., 2022) – to date little exploited in the literature on climate and inflation. We then assess their impacts on inflation rates disaggregated by type of product, including processed and unprocessed food, energy, non-energy industrial goods and services, for each of the largest countries in the euro area. Moreover, our analysis also derives the overall impact of euro area inflation to country-specific temperature shocks. The empirical analysis is conducted with country Bayesian Vector Autoregressions (BVARs) that explicitly consider the seasonal dependence of the shock – thus allowing the presence of important non-linearities in the climate-inflation relationship. We also include a euro area block which captures the interdependence across countries and accounts for the possibility of spillovers in the final effects of country-specific shocks on inflation.

Our findings underline the importance of the recent inclusion of climate-related concerns into central banks' strategies (European Central Bank, 2021), especially in the context of a changing climate and the already observed increased frequency and intensity of weather shocks in Europe. The main findings of this paper point to heterogeneous and asymmetric effects across countries of weather shocks on inflation (and output), implying that non-linear responses of inflation to weather shocks can be expected with progressing climate change. In particular, we find that an increase in monthly mean temperatures increases prices in summer and partly in autumn, significantly more than in other seasons of the year, with a stronger response in warmer euro area countries (Spain and Italy in summer, Spain in autumn). Overall, the effects are more mixed in France and often insignificant for Germany outside of the winter months. Moreover, an increase in temperature variability has also significant upward impacts on inflation over and above the impacts of changes in means. The resulting inflationary effects of temperature mean and variability shocks are also heterogeneous across HICP components, being more significant (i) for food (process and unprocessed) and services, (ii) during summer, and (iii) for Spain, Italy and France. This combination – which suggests a possible link of (upward) impacts on inflation of those components with higher baseline temperatures – could imply even stronger inflationary impacts with a changing climate, particularly in southern European countries. Finally, our results point also to asymmetric and heterogeneous effects of country-specific weather shocks on the euro area aggregate. For instance, euro area inflation tends to decrease after a rising temperature outside the summer, with the largest response following a shock in autumn in Italy and France. Instead, a persistent inflationary pressure follows the same shock when it happens in Italy and Spain over summer. On the other hand, shocks to temperature variability tend to put upward pressure on euro area inflation when they occur in Italy, Spain and France, particularly in winter. Higher temperature variability in Germany, France and Spain in summer has instead a downward effect on euro area inflation. Different price settings, baseline temperatures, and institutional factors among others may be responsible for the heterogeneous and non-linear effects that the paper documents. An accurate analysis of these links is, however, beyond the scope of the paper, and is left for future research. Similarly, the paper refrains from discussing the (possibly exacerbating) effects on the results due to the recent epidemiological and geopolitical shocks whose scarring consequences are still very much uncertain.

The paper is structured as follows: in Section 2 we discuss the transmission channels; in Section 3 we introduce the modelling framework; in Section we present the data; in Section 5 we report the main results and further discuss their potential drivers; in Section 6 we conclude.

## 2 From climate to inflation: transmission channels

Key risks in Europe stemming from climate change include an increased mortality and morbidity from heat (which importantly also impacts labour productivity), agriculture losses from heat and drought, water scarcity and floods affecting people, economies and infrastructure (IPCC, 2022a). In the context of these key risks, possible impact channels from extreme weather and climate to inflation are illustrated in Figure 2 – covering both supply and demand channels, in line with evidence provided by Ciccarelli and Marotta (2021) on the possible nature of climate-related shocks. When a weather shock materialises, the energy, agriculture, manufacturing and services sectors can be directly affected by the shock (green arrows in Figure 2). Economic sectors can also be indirectly affected (thin lines in Figure 2), for instance through external factors (e.g., input and commodity prices) and expectations. The sign and magnitude of the impact depends on the type of weather shock, for example whether it is related to temperature or precipitation, but also on when and where the shock materialises.

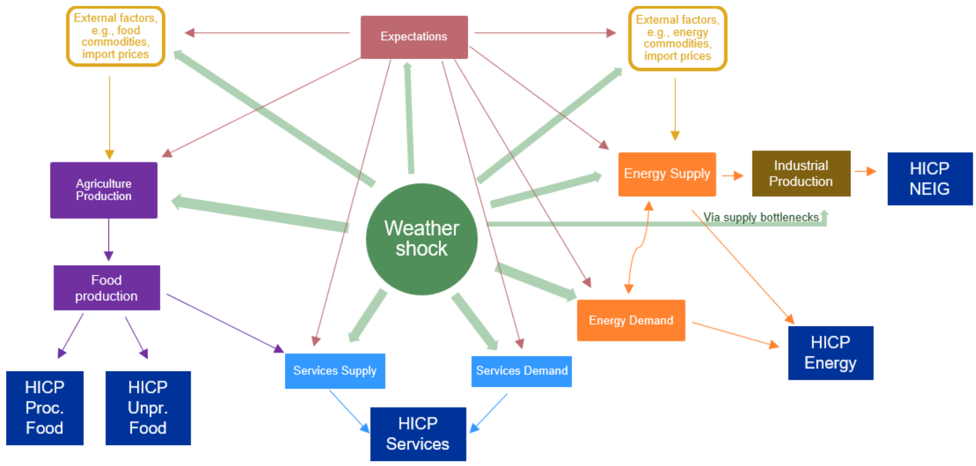


Figure 2: Channels linking weather and prices

The possible final direct effects of weather shocks on consumer price inflation could materialise through (but are not limited to) the following:

- **Food**: Price increases due to reduced agricultural productivity and food supply in increasingly hotter and drier conditions in the summer; increased or more volatile prices due to more variable weather – such as a warmer period followed by frost – destroying crops and reducing food supply; price decreases due to moderate increases in average temperature in cooler countries increasing agricultural productivity and food supply. Processed food prices may react with a lag to impact unprocessed food prices. Prices could increase more persistently or be affected by multiple subsequent or interconnected shocks, for example in case of prolonged drought conditions interacting with an acute heat/drought event.

- **Energy**: Price increases due to extreme heat and higher energy demand for cooling; increased or more volatile prices due to supply disruptions as a result of extreme events such as floods, wildfires or high temperatures resulting in a lack of cooling energy; price decreases due to higher average temperatures in cooler seasons and reduced energy demand for heating.

- **Non-energy industrial goods (NEIG)**: Price increases due to higher input prices (e.g., energy) as a consequence of energy supply disruptions; price increases due a disruption of the supply of inputs as a consequence of extreme weather (e.g., low river water levels disrupting transport); price increases due to reduced labour productivity from extreme heat; price decreases due to more favourable operating conditions with milder temperatures in cold seasons.

- **Services**: Price increases due to reduced labour productivity; price increases in the tourism sector because of more variable/extreme weather affecting both demand and supply; pass-through of food and energy price changes to food-related services potentially with a lag.

In the next two sections we will introduce an empirical specification and the corresponding data to assess aggregate impacts on HICP inflation rates and components.

# 3 A seasonal-dependent BVAR

## 3.1 Model description

The interaction between inflation and climate-related variables is modelled in a relatively standard macroeconometric framework that aims at capturing some of the direct and indirect links of Figure 2 and the seasonal dependencies mentioned in Section 1. Specifically, for each country, we consider the following Vector Autoregression with exogenous variables (VARX):

$$\begin{aligned} y_t =& A_0 + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \\ & \Gamma_{0,w} w_t \times winter_t + \Gamma_{0,g} w_t \times spring_t + \Gamma_{0,s} w_t \times summer_t + \Gamma_{0,f} w_t \times autumn_t + \\ & \cdots + \Gamma_{r,w} w_{t-r} \times winter_{t-r} + \Gamma_{r,g} w_{t-r} \times spring_{t-r} + \\ & \Gamma_{r,s} w_{t-r} \times summer_{t-r} + \Gamma_{r,f} w_{t-r} \times autumn_{t-r} + u_t, \end{aligned} \tag{1}$$

where $y_t$ is an $N \times 1$ vector of endogenous monthly macroeconomic variables and $u_t \sim \mathcal{N}(0, \Sigma)$ is an $N \times 1$ vector of reduced form errors. For $j = 1, \cdots, p$, the $N \times N$ matrices

$A_j$ contain the reduced-form parameters governing the dynamics of the endogenous variables and $A_0$ is an $N \times 1$ vector of intercepts.

Furthermore, we split the vector of endogenous variables in two blocks:

$$y_t = \begin{bmatrix} y_t^c \\ y_t^{ea} \end{bmatrix}, \tag{2}$$

where $y_t^c$ includes the endogenous variables of the single country and $y_t^{ea}$ contains euro area variables. Because the VARXs will be estimated by country, the inclusion of a euro area block is a sensible way of capturing common features (and hence interdependence) across countries and accounting for the possibility of (implicit) spillovers in the final effects of country-specific shocks on inflation.

The vector $w_t$ represents weather shocks, which in this paper is constructed by two measures of temperature-related shocks. We assume that the shocks are exogenous in the model and $\Gamma_{m,\kappa}$ is a vector of parameters ruling the impact of the weather shock on $y_t$, for $\kappa = winter, spring, summer, autumn$ and $m = 0, \cdots, r$. We allow up to $r$ lags of the exogenous variables to enter the VAR.[2]

We further introduce the seasonal dummy variables, $winter_t$, $spring_t$, $summer_t$, and $autumn_t$, which take the value of 1 for the months corresponding to each season.[3] The dummy observations enter the VAR through their interaction with the weather shock, such that the contemporaneous impulse response function of the endogenous variables

[2]We are aware that the exogeneity assumption can be challenged by the argument that human activity has influenced world climate in the last few decades (see IPCC, 2021b). However, the anthropogenic influence on climate is a long-run and slow-moving relationship determined by the long ($>$ 100 years) lifetime of CO2 in the atmosphere. Since we are interested in the short- to medium-term effects of abrupt weather changes on inflation, we assume that for the horizons relevant to business cycles, economic activity will not have a sizeable impact on climate change. The same approach has been taken by similar studies on the relationship between climate change and economic variables, such as Ciccarelli and Marotta (2021), Kim et al. (2021) and Mumtaz and Alessandri (2021).

[3]We consider that $winter_t$ takes the value of one for December, January and February; $spring_t$ for March, April, May; $summer_t$ includes the months of June, July and August; and $autumn_t$ is defined for September, October and November.

$y_t$ to a change in $w_t$ is:

$$\left.\frac{\partial y_t}{\partial w_t}\right|_{season=\kappa} = \Gamma_{0,\kappa}, \tag{3}$$

which depends on the season, $\kappa = winter, spring, summer, autumn$. Higher-order impulse responses can be obtained via the matrices $A_1, \cdots, A_p$.

In compact form the VARX reads as follows:

$$y_t = \Phi z_t + u_t \tag{4}$$

where $\Phi$ stacks the parameters associated to the deterministic components, the reduced-form matrices $A_j$, and the matrices related to the exogenous variables for each season $\Gamma_{\ell,\kappa}$, for $j = 1, \cdots, p$ and $\ell = 0, \cdots, r$. The matrix $z_t$ stacks the deterministic components, $p$ lags of the endogenous variables and $r$ lags of the exogenous variables.

### 3.2 Model estimation

We estimate the model based on Bayesian methods. To be specific, we consider a modified version of the methodology of Giannone et al. (2015) which we adapt to include multiple exogenous variables. Following Giannone et al. (2015) we use natural conjugate priors:

$$\text{vec}(\Phi)|\Sigma \sim \mathcal{N}(\bar{\Phi}, (\Sigma \otimes V_\Phi)) \tag{5}$$

$$\Sigma \sim iW(S_0, d) \tag{6}$$

which we specify following a Minnesota structure (Litterman (1979, 1980) and the assumptions popularised by Kadiyala and Karlsson (1997)). Specifically, we construct the prior mean $\bar{\Phi}$ such that each of the endogenous variables follows a random walk. This means that the parameters of the own variable in the first lag equals one, while all other parameters are set to zero. Moreover, we assume that the prior variance $V_\Phi$ is diagonal whose $i$-th element for lag $j$ equals to $\frac{\lambda^2}{j^2}\frac{d-N-1}{s_{i,0}}$. The scale covariance matrix $S_0$ is diagonal and its element $s_{i,0}$ is obtained by estimating an AR(p) model to each variable. The hyperparameter $\lambda$ governs the overall shrinkage of the model and $\lambda$ imposes a larger shrinkage the larger the lag $j$ is. We further assume diffuse priors for the deterministic components and the exogenous variables. Following Kadiyala and Karlsson (1997), we set the degrees of freedom $d$ to be $N + 2$.

In addition to the Minnesota prior, we also allow for the sum-of-coefficients prior (Doan et al., 1984), which shrinks the sum $(I_N - A_1 - \cdots A_p)$ when the model is re-written in its error correction form. The intuition of this prior is that as the shrinkage hyperparameter on the sum goes to zero, then the model would converge to a VAR specified in differences. However, when the shrinkage hyperparameter goes to $\infty$, no additional shrinkage is imposed in the VAR. In the limit, the sum-of-coefficients prior is not entirely consistent with possible co-integration relationships, therefore we also include the single unit root prior, also known as "dummy-initial-observation" prior (Sims (1993)), which assumes that a random walk is a good forecast for the initial values of the variables in the model. When the shrinkage hyperparameter associated with the single unit root prior goes to $\infty$, the prior is set to be diffuse, whereas when it converges to zero, the variables are imposed to be at their unconditional mean. For details on the implementation see Bańbura et al. (2010) and Giannone et al. (2015).

A key feature of the methodology of Giannone et al. (2015) is that it allows the estimation of the hyperparameters governing the priors, which is in fact an important feature for estimating a large model. To do so, they optimise the marginal likelihood which has a closed-form solution due to the natural conjugate priors. The estimation of the hyperparameters is done by imposing hierarchical gamma priors. We simulate the posterior following the Markov Chain Monte Carlo (MCMC) algorithm proposed in the online appendix of Giannone et al. (2015).

We estimate the BVARX in equation (4) with 6 lags of the endogenous variables and 12 lags of the exogenous variables.[4] We obtain 20000 draws of the posterior distribution

[4]As robustness check, we estimate the models with 3, 6, and 12 lags of the endogenous variables

and use the last 10000 draws for inference.

# 4 Data and indicator definitions

## 4.1 Macroeconomic variables

We use monthly data for Germany, France, Italy, and Spain. The estimation sample spans 1991M1-2019M12 for the first three countries and 1993M1-2019M12 for Spain. The VARX contains two blocks of endogenous macroeconomic variables (vector $y_t$): one block with country-specific data, that includes disaggregated inflation rates as well as country-specific measures of sectoral activity, and one block related to the euro area. The country-specific inflation data includes components of the Harmonised Index of Consumer Prices (HICP) based on the breakdown by type of product. Specifically, we consider: processed food (including alcohol and tobacco); unprocessed food; industrial goods excluding energy (NEIG); energy; and services. For economic activity, we use the industrial production breakdown based on Main Industrial Grouping (MIG) defined by Eurostat. The disaggregation consists of five measures: intermediate goods; capital goods; consumer durables; consumer non-durables; and energy. For the euro area block, we include headline HICP and industrial production. As explained above, the euro area variables allow us to control for possible cross-country interdependencies, spillovers or correlations, similar to the global VAR literature (e.g., Chudik and Pesaran, 2016).

In total, each VAR has 12 endogenous variables where all variables are transformed to annual growth rates (see Annex A for further detail).

## 4.2 Climate indicators

While previous literature studying the climate-inflation relationship has mostly focused on relatively simple aggregate temperature metrics, evidence from the empirical literature on weather, climate, and economic output underlines the importance of also looking

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and 0, 1, 6, and 12 lags of the exogenous variables. We find results qualitatively equivalent to those presented in this paper.

beyond the means. The indicators we use here are therefore based on high-frequency meteorological data. We rely on the ERA5 reanalysis dataset (Hersbach et al., 2018, 2020), which combines model simulations and globally observed meteorological data into one dataset. ERA5 is produced by the European Centre for Medium Range Weather Forecast. In contrast to observations from weather stations, reanalyses provide a consistent dataset covering the whole globe, at a high spatial resolution. Reanalysis datasets are widely used in climate monitoring applications, including by the World Meteorological Organization (WMO) and the Intergovernmental Panel on Climate Change (IPCC) (Hersbach et al., 2020). The data we use is available at hourly frequency since 1959, published with a lag of ca. 5 days.[5] It spans a wide range of meteorological variables, such as temperature, precipitation, wind speed and direction, etc., and is therefore suitable as a consistent basis to calculate a set of extreme indices and climatic impact drivers. The computation of indicators used in this study is based on hourly gridded data for Europe, calculating monthly indicators for each grid cell, and finally averaging over all grid cells of each country. The calculation steps are described in more detail in a companion paper (Vidal-Quadras Costa et al., 2022).

To define the vector $w_t$ in equation (1) we use indicators that describe (i) changes in mean temperature and (ii) changes in temperature variability. Changes in temperature means have been widely focused on in the literature to study the climate-economy relationship (see Introduction). As temperature is usually spatially relatively homogeneous, it is a suitable object for aggregating it at macro level. Beyond changes in means, there is evidence for a relationship between temperature variability and economic output. This is why we complement our indicator on changes in mean temperature with a proxy for temperature variability, namely the intra-monthly standard deviation of daily mean temperatures. As the frequency and intensity of extreme events is expected to increase with climate change, it is of broad interest to study the economic effects of weather extremes. Further details on definitions and statistical properties of the data can be found in Annex A.2 and in Vidal-Quadras Costa et al. (2022). Table 1 contains definitions and

[5]For this paper we use a dataset that dates back to 1979.

the notation used in the paper.

| | | |
|---|---|---|
| (i) Mean temperature | Deviation of monthly mean temperature from the historical mean | $\mathrm{T}_{diff}$ |
| (ii) Temperature variability | Mean intra-monthly standard deviation of daily mean temperature | $\mathrm{T}_{sd}$ |

Table 1: Summary of indicators used in this study to define weather shocks.

## 5 Effects of weather shocks on inflation

We show the responses of disaggregated inflation rates to an increase in the deviation of monthly mean temperature from its historical average by 1°C (Figure 3) and an increase in the intra-monthly standard deviation of temperature by 1°C (as proxy for temperature variability, Figure 4).[6] Furthermore, we also show responses of euro area inflation to both shocks (Figure 7). We show results for up to three years after the shock, a relevant medium-term horizon for monetary policy. As a complement, we also present responses of sectoral industrial production and euro area aggregate industrial production in Annex B.

### 5.1 Food

Rising temperatures tend to have inflationary effects on unprocessed food in all countries considered here when the shock occurs in summer, with significant upward impacts of between 0.1 and 0.2 percentage points when the shock occurs, and a declining but still positive inflationary impact within the first year after the shock. When the shock occurs in autumn, inflationary impacts materialise with a delay in Spain, Italy, and France, with a lower magnitude than in summer. A potential channel associated with these results is a decrease in agricultural productivity. After a temperature shock in summer, increasing temperatures in months already characterised by hot (and potentially also

[6] We also considered a model with de-trended $T_{diff}$, to rule out the possibility of spurious correlation. Our results are practically invariant to those presented in this section. Results are available upon request.

dry) conditions can hamper the harvest, decreasing agricultural productivity, labour productivity (esp. outdoors) and the supply of fresh food. An increase in mean temperature in summer also increases processed food inflation in France and Spain though with a lag, potentially reflecting a delayed pass-through from food commodity prices to processed food. On the other hand, rising temperatures in spring lower unprocessed food inflation when the shock occurs, with a more persistent impact in Spain, but smaller in magnitude than the upward impacts of a summer temperature increase.

The responses of food inflation – both processed and unprocessed – to rising temperature variability tend to be inflationary when the shock occurs in the months outside summer. However, in contrast to the responses to rising temperatures, processed food inflation is more sensitive in winter and spring. Moreover, we also find that unprocessed food inflation increases when the shock occurs in spring for Germany, France, and Italy and in autumn for Italy (in the first months after the shock) and Spain (with lagged but more persistent effects). A channel governing these results could be related to agricultural crop yields. The production of crops is highly sensitive to weather variability, especially in the growing season (e.g., Wheeler et al., 2000; Ceglar et al., 2016). For instance, an abrupt frost in spring could destroy fruit blossoms and damage growth of cereals (see, e.g., Eurostat, 2021), and hot temperatures during flowering can reduce the number of seeds or grains that contribute to the crop yield (Wheeler et al., 2000). Moreover, weather variability can affect prices of fresh food via expectations. Farmers must take decisions about sowing and therefore their expectations on production will depend on weather conditions – but a changing weather variability increases uncertainty (Auffhammer and Schlenker, 2014; Eurostat, 2021; Letta et al., 2022). Finally, a change in fresh food production can transmit further rises of prices in processed food.

In general, our results of varying effects in different seasons and countries are consistent with the literature on the relationship of crop yields and temperature, which finds important non-linearities, and adverse supply effects materialising predominantly if certain thresholds are exceeded (see Auffhammer and Schlenker, 2014, and references therein).

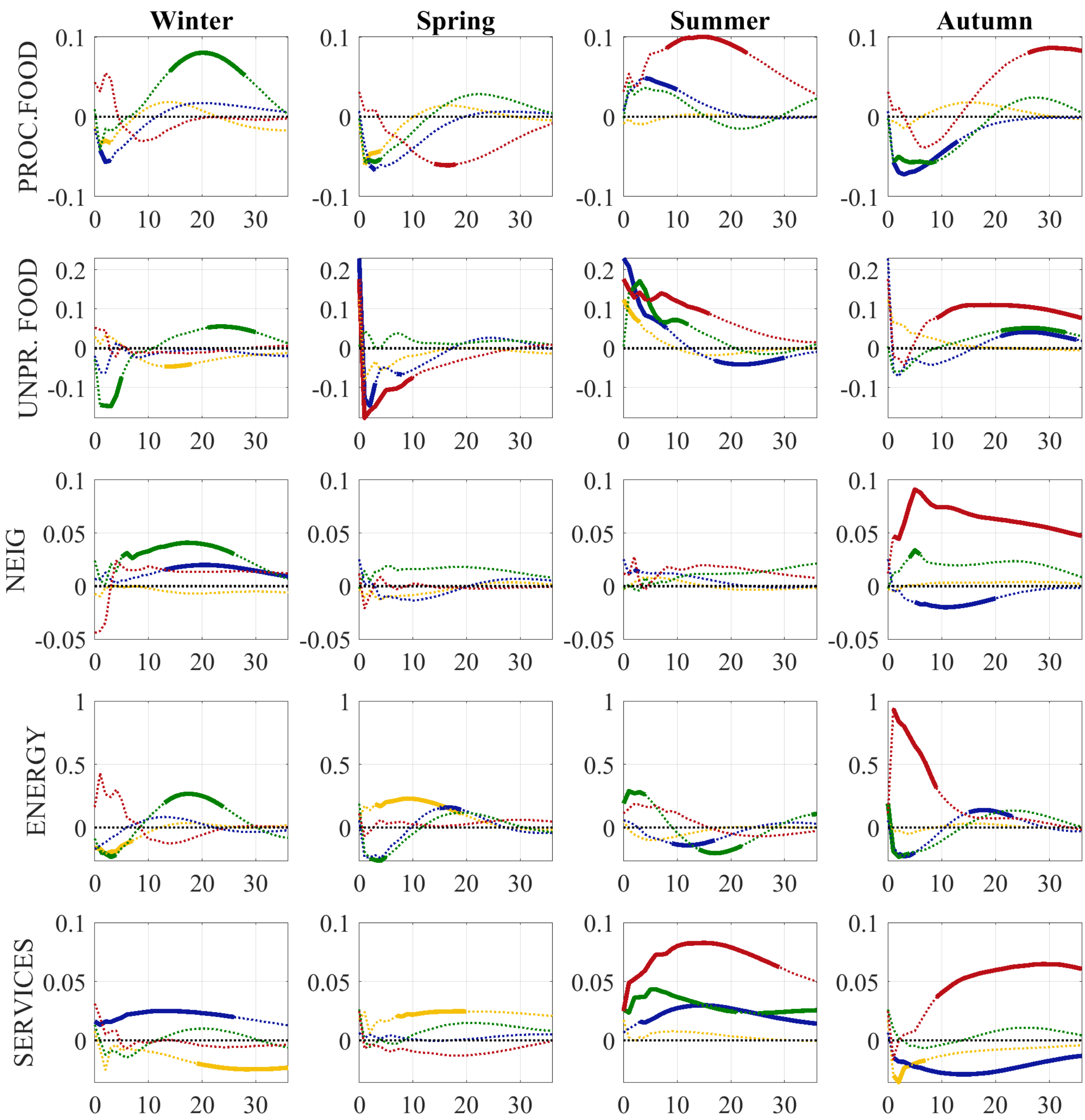



Figure 3: Responses of disaggregated inflation rates to $T_{diff}$

The figure shows the responses of inflation rates to a 1°C deviation of monthly temperature from its historical mean for Germany (yellow), France (blue), Italy (green) and Spain (red). The continuous segments of the lines represent a significant impulse response function based on the 68% credibility bands. The dotted segments represent non-significant responses.

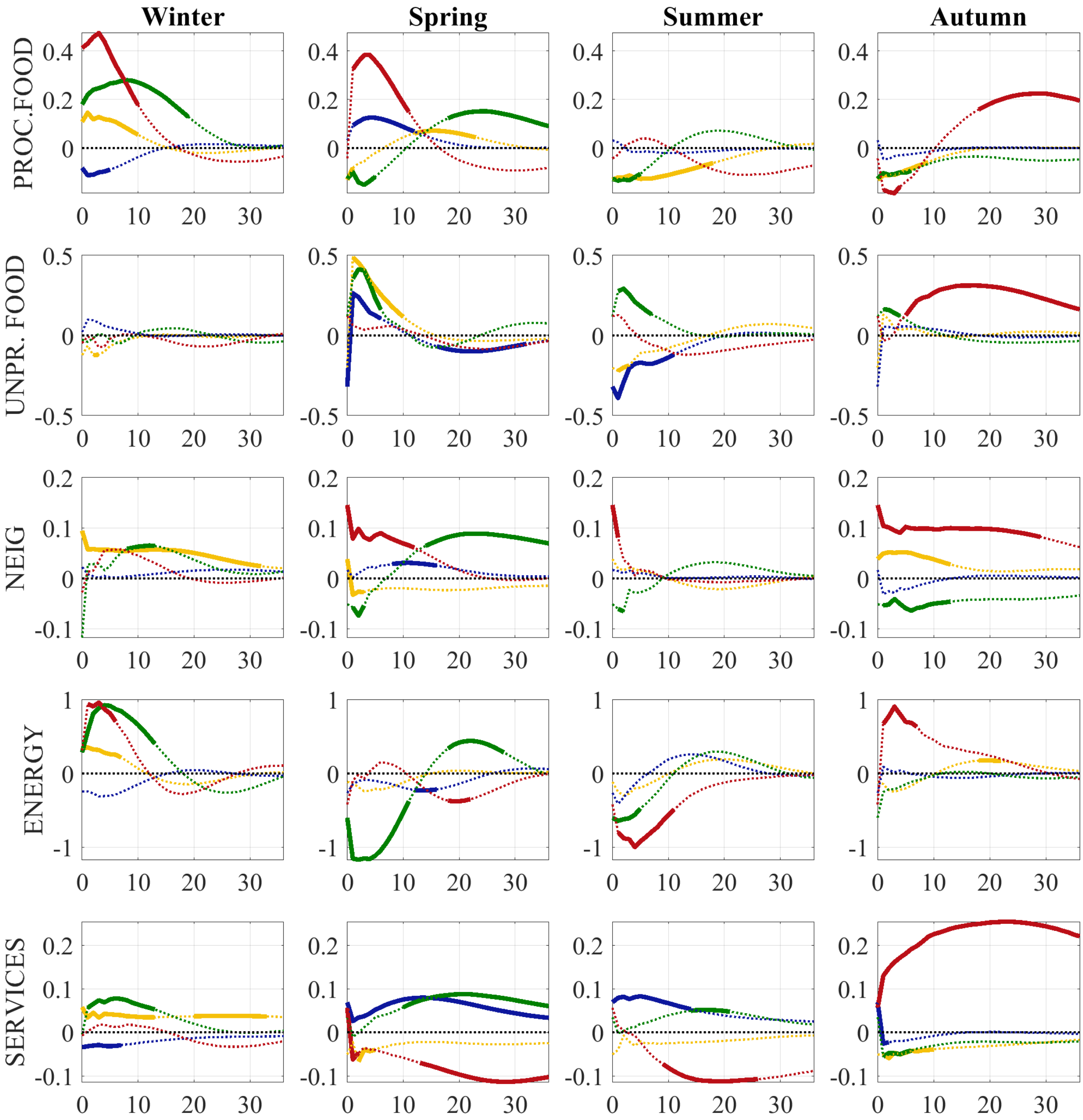



Figure 4: Responses of disaggregated inflation rates to $T_{sd}$

Note: The figure shows the responses of inflation rates to a 1°C increase in the standard deviation of intra-monthly temperatures for Germany (yellow), France (blue), Italy (green) and Spain (red). The continuous segments of the lines represent a significant IRFs based on the 68% credibility bands. The dotted segments represent non-significant responses.

## 5.2 Energy

In response to an increase in monthly mean temperatures, consumers' energy inflation rates decrease in winter in Germany and Italy, however only for the first few months after the shock. A likely explanation could link to a milder winter reducing the demand for heating (Auffhammer and Mansur, 2014, and references therein), and therefore creating downward pressures on prices. The contemporaneous decrease of around 2% in energy production annual growth rates for most countries in the winter is also consistent with these results (see second row in Figure 10 in the Annex). Overall, energy consumption for heating has decreased over the years for the largest countries in the euro area. This is consistent with a 27% decrease between 1979 and 2020 in the annual heating degree days (HD), a temperature-based proxy for days in which heating is usually used (Figure 5) - but likely also complemented by increasing energy efficiency of buildings.

An upward response of energy prices to an increase in temperature in the summer and autumn in some countries could be explained with an increased demand for cooling energy (Auffhammer and Mansur, 2014, and references therein), especially in Southern European countries. As shown in Figure 5, cooling degree days (CD) – as opposed to heating degree days – have a clear upward trend, especially in Southern European countries. However, the immediate response of energy inflation to an increase in summer temperatures is only significant and short-lived in Italy among the countries considered here.

Some country-specific responses of consumer energy inflation rates to temperature-related shocks may be grounded in typical price setting characteristics of different countries. For example, differences in persistence may be explained with diverse energy markets (in terms of production, consumption, and price setting) in euro area countries. Moreover, weather-related shocks may have a direct impact on wholesale energy prices which may not necessarily pass-through consumers' energy prices. In general, the final impact of changes in wholesale energy prices on consumers' energy prices depends on country-specific characteristics related to tariffs, price regulation, and taxes (see Box 2 in Adolfsen et al., 2022).

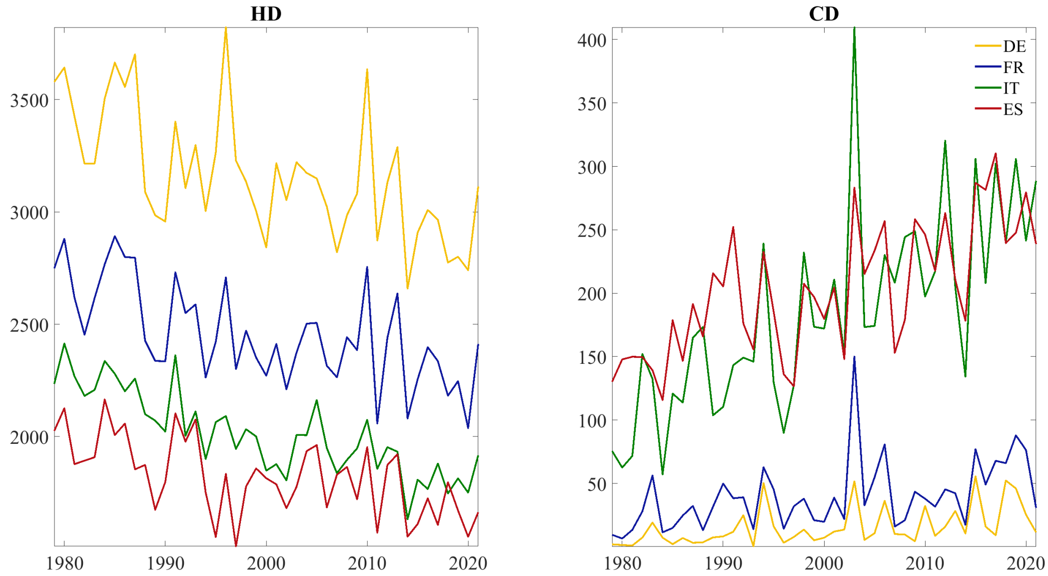



Figure 5: Heating degree days (HD) and cooling degree days (CD)

Note: Annual data. Source: Eurostat.

With increasing progress to transitioning to an energy system based on renewable energies, the relationship between weather and energy prices is likely to change.[7] Notably, on the supply side, the sensitivity of energy prices to weather shocks could increase with a larger reliance on renewable energies, particularly if electricity storage capacities or market integration are still building up and adaptation strategies to climate-related risks are not considered sufficiently.[8] On the demand side, it is expected that demand for heating energy will continue to decrease in winter months, and demand for cooling energy will continue to increase in summer (Auffhammer and Mansur, 2014). In view

[7]In fact, the 2021-22 energy crisis has shown that the current energy system can already be vulnerable to weather shocks - vulnerabilities that are likely not fully captured in our analysis. The 2022 summer heatwave and drought caused cooling water for thermal power plants being too warm, leading to capacity reductions, and reduced the availability of water for hydro energy production. Coinciding with concerns over gas supply shortages, these factors contributed to increasing wholesale electricity prices.

[8]Also see summary of the high-level ad hoc thematic dialogue on energy on 9 November 2022 in Frankfurt am Main and via videoconference, https://www.ecb.europa.eu/pub/pdf/other/ecb.summary-govc-seminar-energy-2022~316bf16043.en.pdf.

of the changing energy system, it is therefore important to further study implications of climate change for the energy system, energy prices and inflation.

### 5.3 Non-energy industrial goods

One important determinant of price developments of non-energy industrial goods (NEIG) is input costs as well as the way they are passed through the pricing chain. The types of relevant cost factors vary depending on the sector but could include energy costs and costs of non-energy commodities. Both costs do not only depend on local or European drivers, but often stem from pressures at global level (see e.g., Koester et al., 2021, and references therein). This could lead to prices of NEIG being less sensitive to local weather and climate shocks compared to other components of HICP.

That said, in selected countries and seasons, NEIG inflation and annual growth rates of production of industrial and consumer goods (Figures in Annex B) react to temperature-related shocks. NEIG inflation rates increase for Italy and France in winter and for Italy and Spain in autumn after an increase in the deviation of monthly mean temperatures from its historical average. These effects are often consistent with an increase in industrial production growth rates (excluding MIG-Energy), suggesting a demand increase with moderately warmer temperatures in winter and autumn. This could potentially be linked to increases in labour productivity or more favourable operating conditions under milder autumn and winter temperatures.

Overall, a higher temperature variability has inflationary effects on NEIG inflation, especially in Spain. The increase could be grounded in a higher difficulty and increased uncertainty around planning industrial processes and logistics.

In a changing climate, supply chains are expected to be increasingly vulnerable to weather shocks from outside the euro area. This is also suggested by results from a recent survey with leading firms, with respondents expecting main risks from climate change to firms – beyond more local factors such as the integrity of production facilities and infrastructure and the well-being of employees – from the sourcing of raw materials and risks to supply chains (for an overview see Kuik et al., 2022). If material sourcing and supply chains are not sufficiently diversified, such shocks could also impact prices of non-energy industrial goods.

### 5.4 Services

To interpret the results for services inflation, it is important to take into account the breakdown of services (Figure 6), which consists of sub-components that can be sensitive to temperature changes directly (e.g., tourism, recreation) or indirectly through their exposure to food and energy sector (e.g., tourism, food services, transportation).

In summer, the reaction of services inflation to an increase in mean temperatures in Spain, France and Italy is positive and persistent for between 20 and 30 months after the shock. The direction of the impact of temperature-related shocks on services inflation rates is generally consistent with the direction of the impact on food inflation, but usually smaller. This suggests that a change in food (commodity) prices driven by weather shocks may feed through to services inflation, notably to prices of food services (e.g., restaurants, cafes, canteens, fast food). However, the more persistent reaction suggests that other drivers may be at play. Together with food services, tourism and recreation-related services have an important contribution to the overall index for services for all countries (Figure 6). It is reasonable to expect that tourism- and recreation-related services are sensitive to changes in weather as well, which could explain the more persistent reaction. As services are sensitive to changes in labour, an additional channel could be through impacts on labour productivity. The negative relationship between warmer temperatures (once exceeding a critical threshold) and labour supply and productivity is well-documented in the literature, with outdoor labour being more sensitive to temperature than indoor labour (Dasgupta et al., 2021).

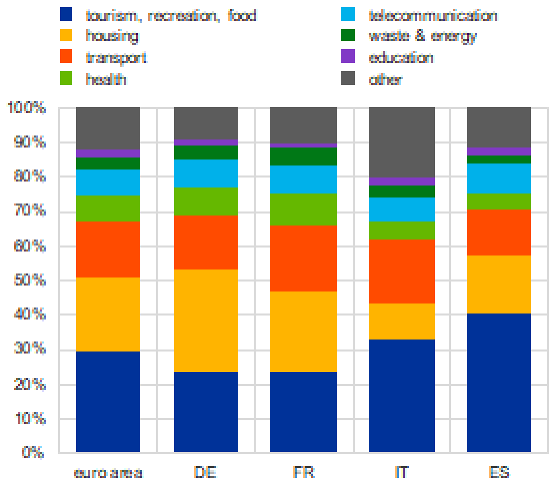



Figure 6: Composition of HICP services by country, using HICP weights.

Note: Own, judgemental classification based on ECOICOP level 4 categories. The chart reflects weights for 2016-2020 (euro area: 2017-2020), excluding the impact of years where weights were strongly influenced by pandemic-related developments. Data source: Eurostat.

An instantaneous reaction of services inflation to an increase in temperature variability can be observed across most seasons and countries (Figure 3), with the most pronounced reaction being an increase in services inflation in Spain after a temperature variability shock in autumn. It is conceivable that warmer weather in this season could lead to increased demand for tourism- and recreational services, pushing up prices instantaneously.

A sensitivity of services to food, and for some sub-sectors of services also energy input prices, amplified by the sensitivity of important services components to weather-related shocks, could, overall, imply an increasing sensitivity of services prices to weather-related shocks in a changing climate. In addition, though currently only representing a comparable small share of the overall HICP services sub-index, prices of health-related services could in the future become more sensitive to weather-related shocks. With increased mortality and morbidity being one of the key risks from a changing climate (see Section 2), the reaction to temperature shocks could be characterised by important non-linearities, being more intense in a warmer climate with stronger heatwaves.[9]

### 5.5 Implications for the euro area economy

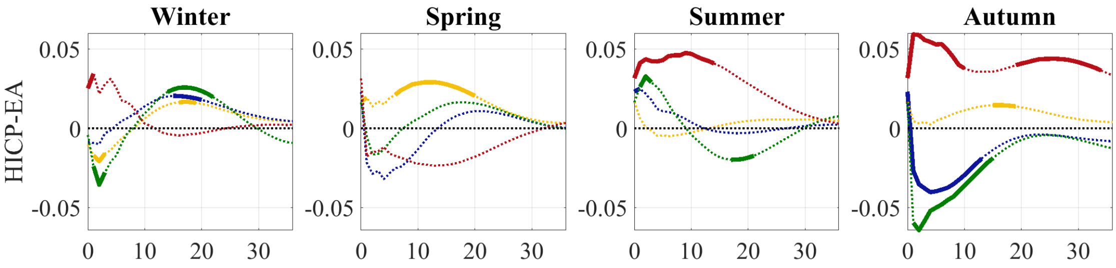
Overall, the results discussed in the previous sections suggest the presence of asymmetries and non-linearities in the response of inflation to temperature shocks, depending on the country, HICP component and season. Among the four largest euro area economies, inflation rates in Spain are more sensitive to temperature-related shocks especially in summer and autumn. Responses in Italy and France are more mixed, and results in Germany are often insignificant outside of the winter months. Results often differ between seasons with both upward and downward impacts in seasons outside of summer. In terms of affected HICP components, most significant impacts are found for processed food, unprocessed food, and services, with inflationary impacts of a temperature shock in summer in Spain, Italy, and France. This suggests a link of (upward) impacts on inflation of these components with higher baseline temperatures (depending on both season and country). Such link would imply potentially stronger inflationary impacts with a changing climate, particularly in southern European countries.

To complement the above, we further assess the implications of country-specific temperature shocks on euro area inflation in Figure 7.[10] Panel (a) shows the responses to higher mean temperature and panel (b) depict the responses to higher temperature variability. Contrary to the charts presented before, each of the impulse responses represent the reaction of euro area HICP to a shock occurring in Germany (yellow), France (blue), Italy (green) or Spain (red). Results for industrial production annual growth rates are shown in Figure 12 in Annex B.

[9] For instance, at the time of writing this paper, a series of heat waves affected Europe in summer 2022, especially in Southern countries. An early estimate of deaths attributable to extreme hot temperatures is of 510 persons in Spain, one of the most affected countries due to heatwaves. See https://elpais.com/sociedad/2022-07-18/la-ola-de-calor-deja-510-muertes-en-espana-entre-el-10-y-el-16-de-julio.html.

[10] Realistically, temperature shocks in different European countries are likely contemporaneous or correlated. Here, we only look at the impact of a shock in one country in isolation.

(a)




(b)

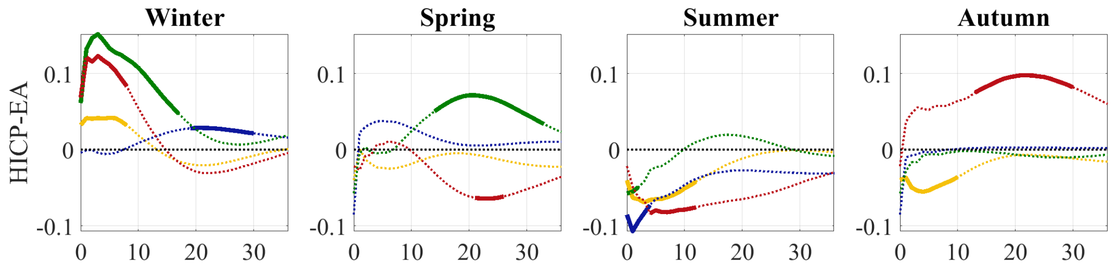



Figure 7: Responses of euro area inflation temperature-related shocks

Note: The figure shows the responses of the euro area inflation to country-specific weather shocks. Panel (a) shows the responses to a 1°C deviation of monthly temperature from its historical mean and Panel (b) depicts responses to a 1°C rise in temperature variability. The variables correspond to inflation in annual percentage change. The continuous segments of the lines represent significant IRFs based on the 68% credibility bands. The dotted segments represent non-significant responses.

Consistent with disaggregated inflation rates, we observe asymmetric and heterogeneous effects of the idiosyncratic weather shocks on the euro area aggregate. In particular, we find that euro area inflation tends to decrease when shocks related to rising temperatures materialise outside of summer, with the largest response stemming from a shock in autumn in Italy and France. We observe the opposite effect on euro area inflation from summer temperature shocks in Italy and Spain, with a persistent impact for more than 12 months from a temperature shock in Spain. Higher temperature variability tends to put upward pressure on euro area inflation when the shocks occur in Italy, Spain and France in the seasons outside the summer, particularly in winter. Higher temperature variability in Germany, France, and Spain in summer has a downward effect on euro area inflation.

With a changing climate, the IPCC expects increasing average temperatures, but also increases in frequency and intensity of hot extremes – in all scenarios considered (IPCC, 2022b). While already observed in the Mediterranean region, a (further) increase in warm and dry conditions, amongst others, is projected both for the Mediterranean, and for Western and Central Europe, with global warming at 2°C and above. Such climatic changes – as suggested especially by our results for Spain in summer – could exert upward and persistent pressures on inflation across a larger set of euro area countries. Increases in temperature variability with a changing climate – which are documented in the literature (Kotz et al., 2021a; Wan et al., 2021) – could further exacerbate these effects. Given varying responses depending on the season in which the shock occurs, these results could also imply higher euro area inflation volatility throughout the year.

## 6 Conclusions

In this paper we study the effects of local weather shocks on inflation in the four largest euro area economies and in the euro area, distinguishing between different impacts in different seasons. We consider impacts on country-specific inflation rates of processed and unprocessed food, energy, non-energy industrial goods and services, and on euro area headline inflation. Going beyond most of the existing literature on the climate-inflation relationship, we define indicators based on high-frequency meteorological data, studying the response of prices to increased monthly mean temperatures and higher temperature variability. We model the impacts using seasonally-dependent, country-wise BVARs.

Temperature-related shocks can significantly – and in some cases persistently – impact inflation, depending on the country and season. An increase in monthly mean temperatures generally increases inflation in summer and decreases inflation in other seasons of the year, with a stronger response in warmer countries. In summer, the response of unprocessed and processed food and services prices to an increase in mean temperatures is generally the strongest, and also results in upward inflationary pressures on euro area inflation. An increase in temperature variability can have significant upward impacts on inflation beyond the impacts of changes in means, especially when occurring in winter.

Our results strongly underline the likelihood of uneven effects of weather shocks on inflation. Responses to weather shocks were generally found stronger in Spain, and also often stronger in Italy and France compared to Germany. It is likely that these results are associated with differences in their baseline climates. This is consistent with a dependence of economic impacts of climate change on baseline temperature levels. Such dependency on baseline climates could also explain differences in impacts across different seasons of the year (especially in summer compared to the rest of the year), in line with findings in the literature.

With a changing climate implying an increased frequency and severity of extremes in Europe the shocks studied here can be expected to occur more frequently and could lead to persistent upward pressures on inflation especially from extreme temperatures in summer. The uneven effects of weather shocks across countries and seasons found here further imply that non-linear responses of inflation to weather shocks can be expected with progressing climate change. Given the differing impacts of shocks in different seasons and across countries, our results also suggest that climate change could enhance heterogeneity of inflation developments across euro area countries and increase inflation volatility.

Overall, our results suggest that indicators defined based on high-frequency, granular meteorological data can help disentangle impacts of weather shocks on inflation. Future analysis would benefit from further work on identifying indicators that can best proxy extremes and their impacts. This includes indicators to proxy droughts and heavy rain or floods, and their interaction with temperature-related effects. In addition, different aggregation techniques or studying possible impacts at higher spatial resolution using granular price data may help identify further important relationships.

Some important interactions between weather and inflation were beyond the scope of this study, including the impact of non-euro area weather shocks on euro area prices, spillovers of weather shocks, a changing response to shocks with a changing climate, and the interaction of weather with other shocks to the economy. Climate change may make euro area prices more vulnerable to non-euro area climate shocks, which can affect commodity prices, supply chains and production facilities located outside of the euro area. A study focusing on the impacts of local weather shocks on inflation will therefore fall short of capturing the whole range of risks to inflation, and further work is needed. In addition, our approach also does not allow to draw conclusions on the spillovers of weather shocks between countries considered in this analysis. As weather shocks of euro area countries are often correlated, cross-country relationships may reinforce the impact of a shock. In addition, our approach allows to consider non-linearities in the climate-economy relationship only to the extent that they depend on seasons. As we use a linear model, we are not able to comprehensively capture non-linearities in the response with increasing shock sizes. Yet, there is strong evidence that economic impact rise with increasing climate change in a non-linear fashion. Based on our results we expect this to hold also for prices and inflation, and further work is needed to study such non-linearities and state-dependencies more comprehensively. Steps in this direction could be taken by using panel approaches, and by combining empirical evidence with climate model results. Finally, it is conceivable that weather shocks do not impact prices and inflation in isolation but may interact with (and potentially reinforce) other shocks to the economy. This is an important field for future work.

## 7 Acknowledgements

Hersbach et al. (2018) was downloaded from the Copernicus Climate Change Service (C3S) Climate Data Store.

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# A Data description

## A.1 Macroeconomic data

Table 2 gives an overview of the macroeconomic data used in the BVARX model from equation (1). We downloaded the data from the ECB Statistical Data Warehouse. The last four columns of the table refer to whether the raw data was available in a non-seasonal adjustment (NSA), Working day adjusted, not seasonally adjusted (WSA-NSA) or seasonal adjusted (SA). Whenever the data was NSA or WSA-NSA we carried out a seasonal adjustment using the Matlab toolbox X-13.[11] All variables are transformed to annual growth rates, i.e., $y_{i,t} = 100 \times \frac{Y_{i,t} - Y_{i,t-12}}{Y_{i,t-12}}$, where $Y_{i,t}$ stands for the seasonal adjusted data in levels.

| Variable | Description | Seasonal adj. | | | |
|---|---|---|---|---|---|
| | | **DE** | **FR** | **IT** | **ES** |
| | **Prices** | | | | |
| PROC. FOOD | HICP - Processed food incl. alcohol and tobacco, Monthly Index | NSA | NSA | NSA | NSA |
| UNPR. FOOD | HICP - Unprocessed food, Monthly Index | NSA | NSA | NSA | NSA |
| NEIG | HICP - Industrial goods excluding energy, Monthly Index | NSA | NSA | NSA | NSA |
| ENERGY | HICP - Energy, Monthly Index | NSA | NSA | NSA | NSA |
| SERVICES | HICP - Services, Monthly Index | NSA | NSA | NSA | NSA |
| HICP-EA | Euro area 19 (fixed composition) as of 1 January 2015, Overall index, Monthly Index | NSA | | | |
| | **Output** | | | | |
| MIG-INTER. GOODS | Industrial Production Index, MIG Intermediate Goods Industry - NACE Rev2 | SA | SA | SA | SA |
| MIG-ENERGY | Industrial Production Index, MIG Energy - NACE Rev2 | WSA-NSA | SA | SA | WSA-NSA |
| MIG-CAP. GOODS | Industrial Production Index, MIG Capital Goods Industry - NACE Rev2 | SA | SA | SA | SA |
| MIG-DUR. CONS GOODS | Industrial Production Index, MIG Durable Consumer Goods Industry - NACE Rev2 | WSA-NSA | SA | SA | WSA-NSA |
| MIG-NON-DUR. CONS. GOODS | Industrial Production Index, MIG Non-durable Consumer | SA | SA | SA | SA |
| | Goods Industry - NACE Rev2 | SA | SA | SA | SA |
| IP-EA | Euro area 19 (fixed composition)- Industrial Production Index, Total Industry - NACE Rev2 | SA | | | |

Table 2: Macroeconomic data - Description

[11] This toolbox was developed by Yvan Lengwiler and available at https://de.mathworks.com/matlabcentral/fileexchange/49120-x-13-toolbox-for-seasonal-filtering

## A.2 Time series of climate indicators used in this study

We analyse two types of weather shocks related to temperature. Specifically, we consider the deviation of monthly mean temperature from the historical mean temperature (denoted as $T_{diff}$). For each grid cell $i$ and month $m$ of year $y$, the indicator is defined as follows:

$$T_{diff,i,m_y} = T_{i,m_y} - \bar{T}_{i,m}, \tag{7}$$

with $\bar{T}_{i,m}$ denoting the historical monthly mean temperature for each grid cell $i$ and month m over the years 1980-2011.[12] The final variable used in the analysis at monthly frequency, $T_{diff}$, is then calculated by averaging over all grid cells i within each euro area country (Figure 8).

As a proxy of temperature variability (denoted as $T_{sd}$), we consider the intra-monthly standard deviation of daily mean temperatures. This means that for each grid cell $i$ and day $d$ in month $m$ of year $y$, temperature variability is defined as follows:

$$T_{sd,i,m_y} = \frac{1}{D} \sum_{d_{m_y}=1}^{D} \left( T_{i,d_{m_y}} - \bar{T}_{i,m_y} \right)^2, \tag{8}$$

with $D$ denoting the number of days in month $m$ of year $y$, $T_{i,d_{m_y}}$ is the temperature on day $d$ of month $m$ in year $y$, $\bar{T}_{i,m_y}$ is the mean temperature in month $m$ of year $y$. Similar as for $T_{diff}$, the monthly indicator of temperature variability is obtained by taking the average of all cell grids belonging to each of the considered euro area countries (see Figure 9)

A more detailed description is available in a companion paper (Vidal-Quadras Costa et al., 2022).

[12] A climatological mean is normally defined over a period of 30 years.

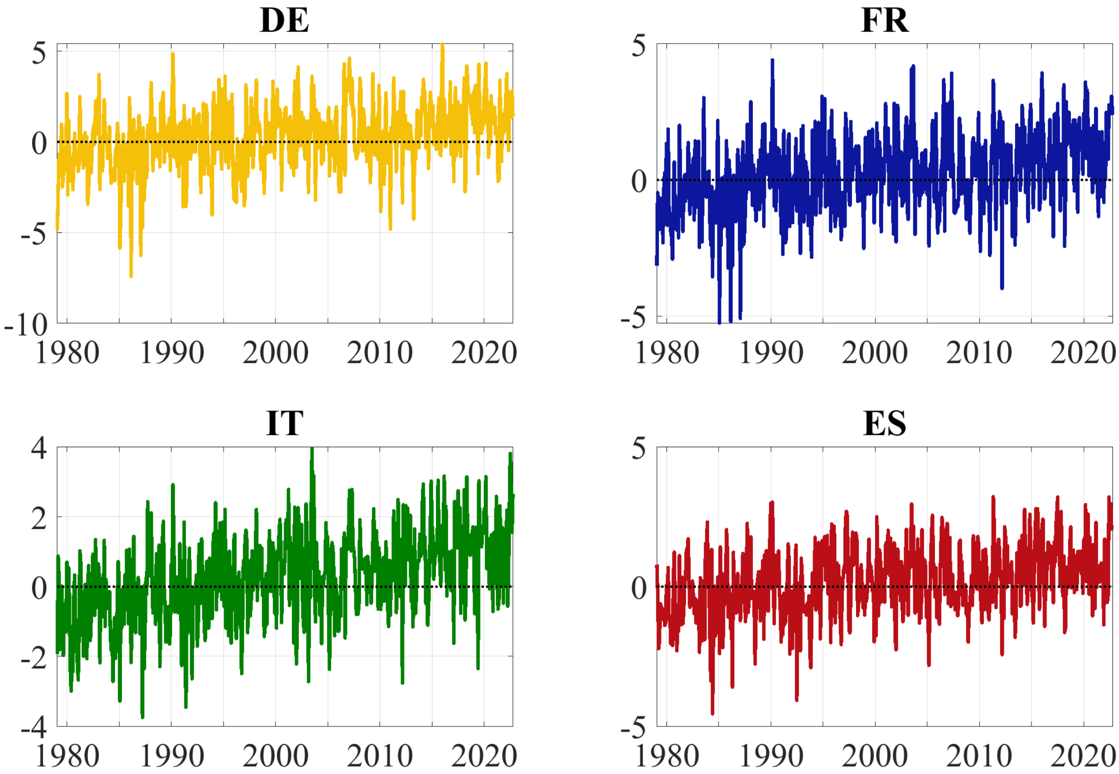


Figure 8: Deviation of monthly mean temperature from the historical mean

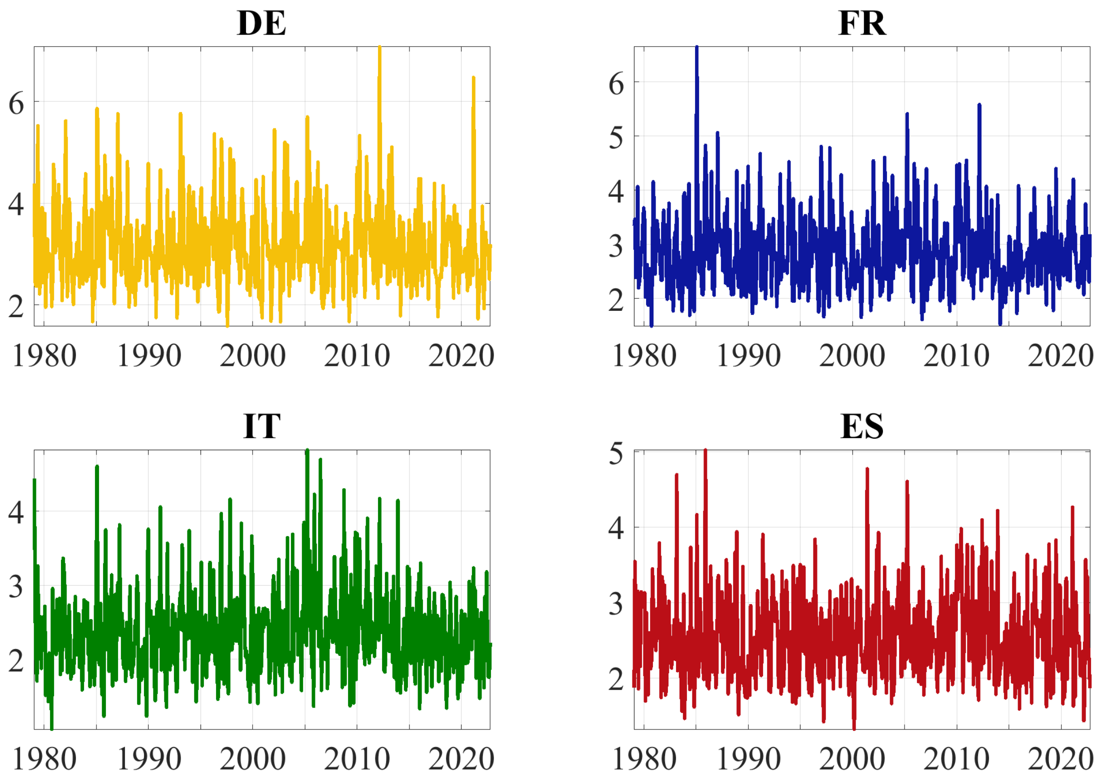


Figure 9: Intra-monthly standard deviation of daily mean temperatures

# B Results for industrial production

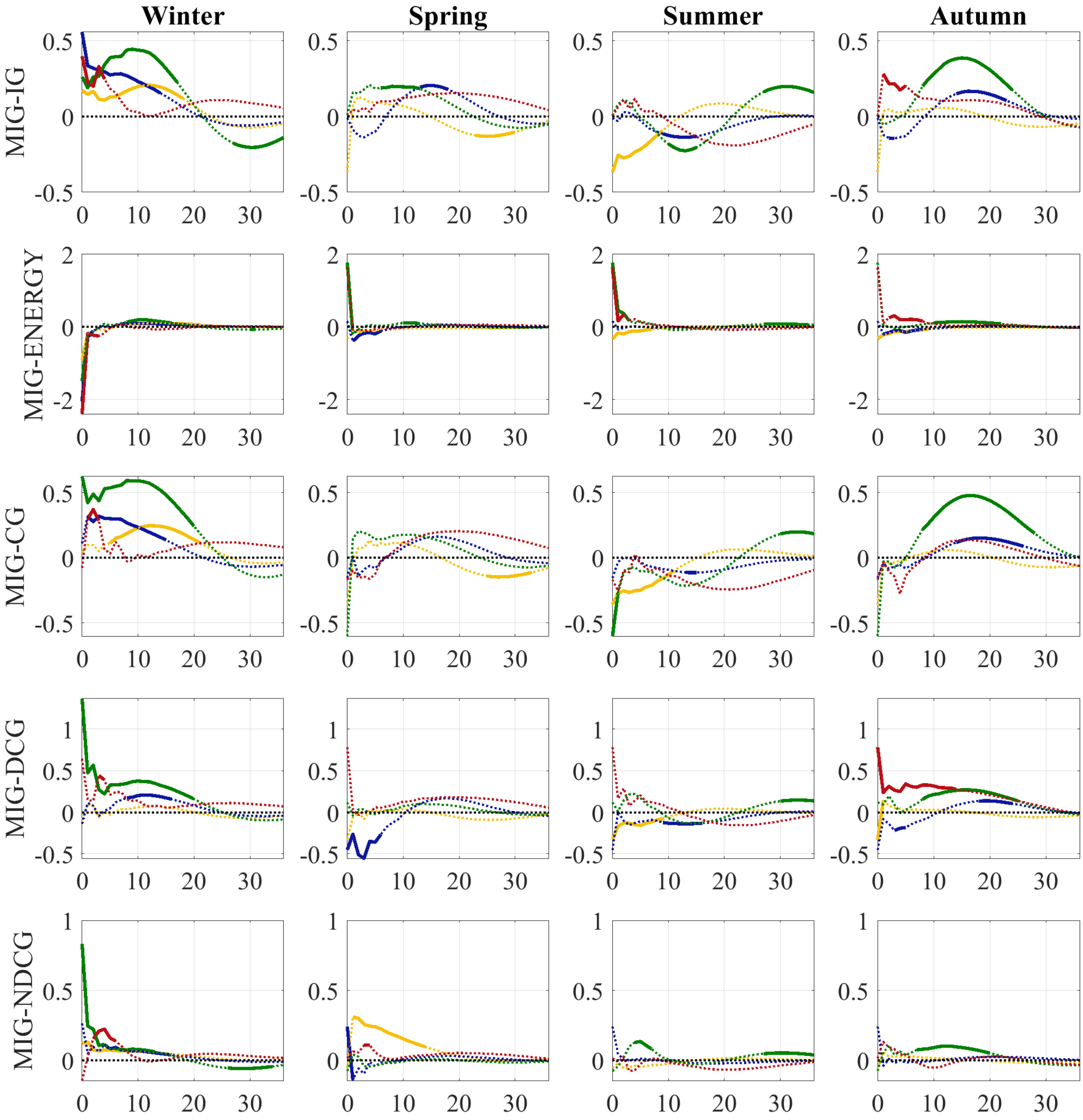


Figure 10: Responses of sectoral output rates to $T_{diff}$

Note: The figure shows the responses of sectoral industrial production growth rates to a 1°C deviation of monthly temperature to its historical mean for Germany (yellow), France (blue), Italy (green) and Spain (red). The continuous segments of the lines represent a significant impulse response function based on the 68% credibility bands. The dotted segments represent non-significant responses.

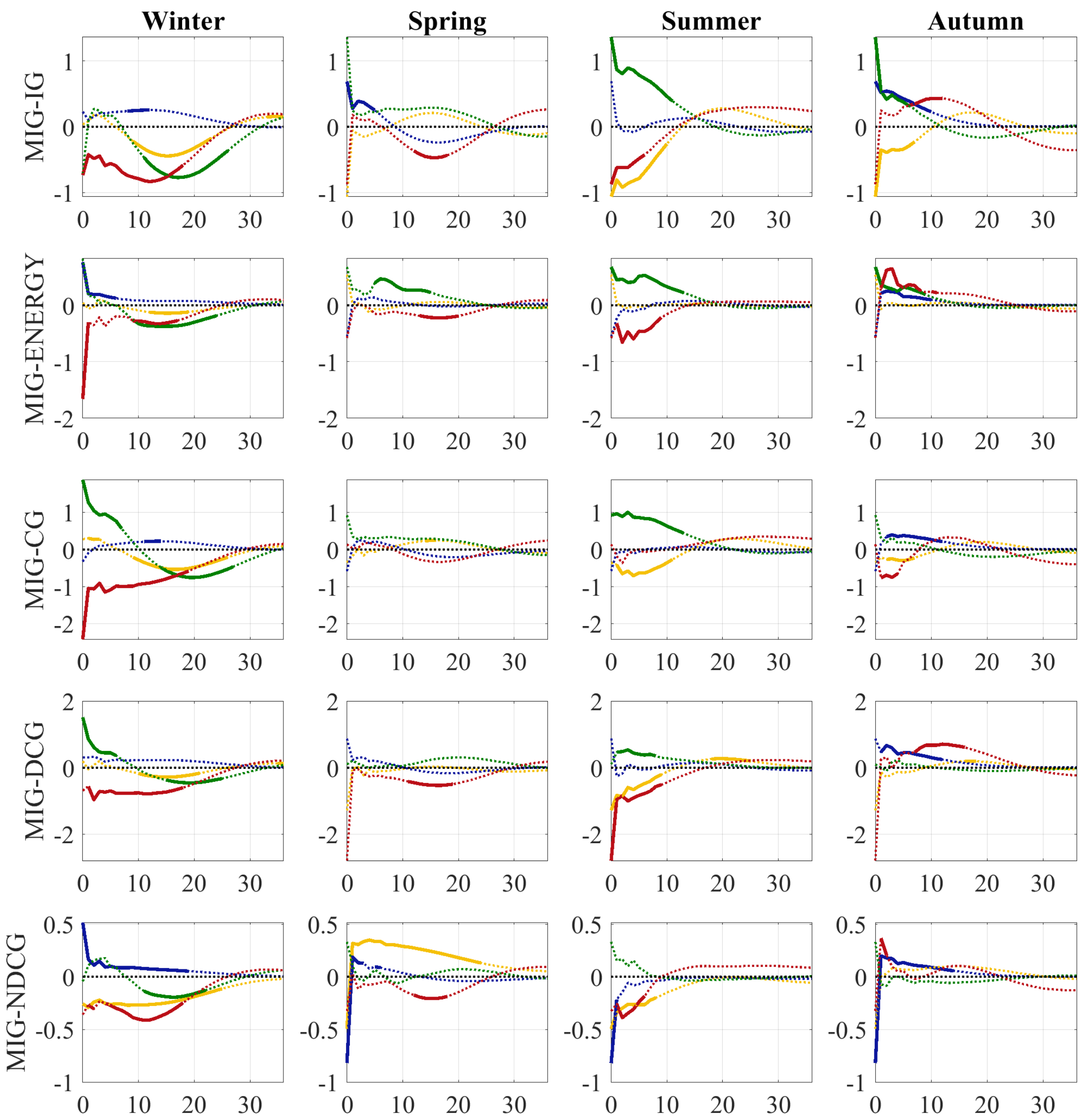


Figure 11: Responses of sectoral output rates to $T_{sd}$

Note: The figure shows the responses of sectoral industrial production growth rates to a 1°C increase in the standard deviation of intra-monthly mean temperature for Germany (yellow), France (blue), Italy (green) and Spain (red). The continuous segments of the lines represent a significant impulse response function based on the 68% credibility bands. The dotted segments represent non-significant responses.

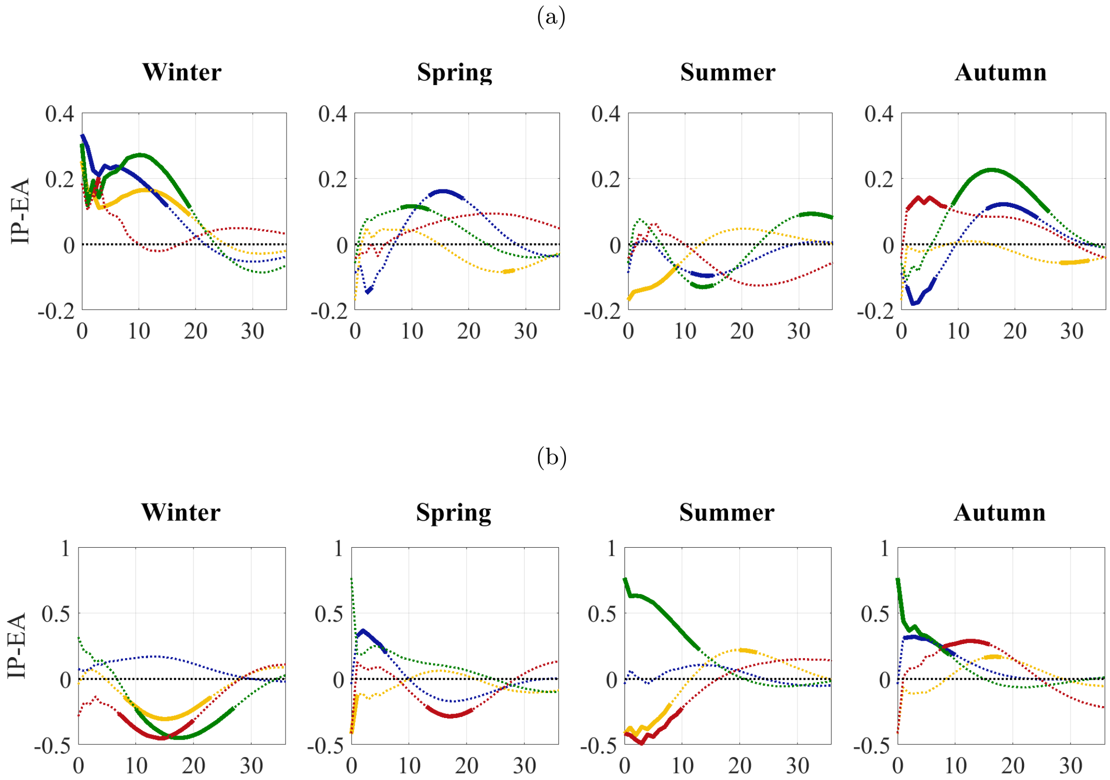


Figure 12: Responses of euro area output to temperature-related shocks

Note: The figure shows the responses of the euro area industrial production annual growth rates to country-specific weather shocks. Panel (a) shows the responses to a 1°C deviation of monthly temperature from its historical mean and Panel (b) depicts responses to a 1°C rise in temperature variability (Panel b). The variables correspond to inflation in annual percentage change. The continuous segments of the lines represent significant IRFs based on the 68% credibility bands. The dotted segments represent non-significant responses.

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The views expressed are those of the authors and should not be reported as representing the views of the European Central Bank (ECB) or the Eurosystem.

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