Dynamic effects of weather shocks on production in European economies

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Abstract

This paper evaluates the dynamic impact of weather shocks on economic activity within the three main European countries. To consolidate meaningful variation in weather patterns, we propose a novel monthly composite weather index (CWI). This index captures relevant information on severe cold and heat conditions, drought, heavy precipitation, and intense wind events. We estimate a series of country-specific Bayesian Structural Vector Autoregressive models to assess the effects of weather shocks on distinct production sectors, namely energy, construction, manufacturing, and services. The findings reveal evidence of a significant impact of weather shocks on economic activity in Europe, with each component of the CWI exerting heterogeneous effects across different countries and production sectors.

Keywords: Weather shocks, European production, Bayesian SVAR
JEL classification: C32, E23, Q54.

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1 Introduction

The intricate relationship between economic activity and climate events has been widely recognized, with a consensus among experts that economic activity contributes to long-term negative effects on the climate. Nevertheless, until recently, empirical evidence of reverse causality from climate shocks to aggregate economic activity, has been relatively scarce. In recent months, there has been a notable increase in research efforts seeking to identify the distinct impact of severe climate events on the business cycle. Noteworthy examples include Kim et al. (2021) for the U.S. and Billio et al. (2020) for European countries. In the context of this literature, the term "climate" denotes the joint probability distribution of outcomes describing the state of the atmosphere, oceans, and fresh water, encompassing ice. Throughout the remainder of this paper, we will refer to the empirical realization of climate: weather conditions and their variations over time. Against this background, the literature suggests that weather shocks tend to have adverse effects on short-run aggregate activity, as measured by industrial manufacturing production, but with a large country-specific heterogeneity. Other economic sectors, with the exception of agriculture (Gallic & Vermandel, 2020), are generally neglected when assessing short-run effects. It is important to distinguish this literature on the macroeconomic effects of weather shocks from research focusing on the impacts of *extreme* weather events commonly classified as natural disasters (e.g., hurricanes or major earthquakes). We refer for example to Strobl (2011) or Felbermayr and Gröschl (2014) for economic impacts of natural disasters on economic activity or to Kruttli et al. (2023) and Ferriani et al. (2023) on the financial system.

As temperature time series are easily available over a long historical sample, it is more common to find studies that try to identify economic responses to changes in temperature, rather than to other aspects of climate. This is the approach taken by Natoli (2022) for the U.S. economy, Lucidi et al. (2022) for several European economies, or by Burke et al. (2005) and Acevedo et al. (2020) for a large panel of high- and low-income countries. Some research also focuses on severe precipitation events and droughts, such as Billio et al. (2020) for several European economies. The latter study the interplay of weather shocks with business and financial cycles, and differentiates across countries and weather shocks. The authors mainly focus on the effects of weather shocks on industrial production growth and find evidence of an uneven impact across the different phases of the business cycle and across the considered countries. Kim et al. (2021) investigated potential time-varying effects of extreme weather on the U.S. economy over the past 60 years using the Actuaries Climate Index (ACI, provided by the American Academy of Actuaries and Canadian Institute of Actuaries). The monthly ACI consolidates physical and meteorological observations of high and low temperatures, rainfall, drought, wind speed and sea level, into a unique measure of severe weather. By estimating a SVAR model accounting for standard macroeconomic variables, the authors show evidence of an adverse aggregate macroeconomic impact of weather shocks that significantly reduce output and increase inflation. In contrast, Lucidi et al. (2022) focus on European economies and find that higher temperatures tend to reduce inflation through the energy prices channel.

Our objective in this paper is to assess short- to medium-run sectoral production effects of several types of weather shocks in Germany, France and Italy, the three largest European economies. Inspired by the new database of European Extreme Events Climate Index (E^3CI),[1] we construct five different weather series, which can be interpreted as "shocks": cold and heat shocks, droughts, heavy precipitation and intense wind. We combine all five weather series to obtain the Composite Weather Index (CWI hereafter). This rich database allows us to contribute to the literature by studying the impact of several aspects of weather on the economy, beyond temperatures. Using daily weather data, we can identify large deviations from historical calendar-specific averages. In addition, while most papers focus on the effects on industrial production as a proxy for monthly economic activity (Billio et al., 2020; Kim et al., 2021), we add an additional layer by considering various production sectors: energy, construction, manufacturing, and services. Our methodology relies on the estimation of a Bayesian SVAR model for each country, each production sector and each of weather shock. Across each of these three dimensions, we estimate impulse response functions (IRFs) of sectoral production to a given weather shock. Finally, we explore some non-linearities by estimating IRFs through non-linear Local Projections (Jordà, 2005).

The results of our study unveil that weather shocks have significant yet varied impacts across both countries and production sectors. Notably, France emerges as the most resilient among the studied countries, with relatively muted responses, while Italy shows significant reactions to weather shocks. Specifically, Italian production appears to be responsive to variations in rainfall, exhibiting notable sensitivity to both excess and deficit conditions. Our findings for energy production indicate a commonality across all countries, specifically related to a demand-for-heating channel. A heat shock results in a substantial reduction in energy production, whereas the opposite holds true in response to a cold shock. Regarding construction, an outdoor activity, our results suggest that the impact of a positive temperature shock varies based on a country's latitude, and consequently, its temperature. For example, in a Northern European country like Germany, characterized by colder climates compared to other European nations, a heat shock tends to positively affect construction activity. In contrast, Southern European countries such as Italy react negatively to such heat shocks. To the best of our knowledge, this is the first study that also considers the effects of weather conditions on the production of services. Although the analysis is limited to France due to data constraints, our results suggest that services generally respond positively and modestly to heat and drought shocks while exhibiting a negative reaction to cold and precipitation shocks. Finally, we obtain only mixed evidence regarding non-linearity in responses to weather shocks across

[1]The E^3CI is published by the International Foundation Big Data and Artificial Intelligence for Human Development (IFAB), and aims at creating for a panel of European and Mediterranean countries an index similar to the Actuaries Climate Index (ACI) available for North America.

business cycle phases, which contrasts with the results obtained by Billio et al. (2020).

The rest of this paper is structured as follows. Section 2 presents a selected review of the literature on the macroeconomic impacts of weather shocks. Section 3 introduces our empirical strategy, by describing the data and the econometric methods. Section 4 presents the main results expressed in terms of impulse response functions to various weather shocks. Section 5 contains additional results on service production, non-linear effects of weather shocks and cross-country spillovers. Finally, Section 6 concludes. Additional figures and technical details are presented in the Appendix.

2 Selected literature review

There is a large macroeconometric literature trying to assess the aggregate macroeconomic dynamic effects of various structural shocks. Seminal papers include Romer and Romer (2004) for monetary policy shocks, V. Ramey (2011) for government spending and fiscal shocks, as well as Bloom (2009) for uncertainty shocks. However, in recent years, growing attention has been devoted to the role of weather shocks, as there is empirical evidence that climate hazards are more frequent, more intense, and present long-lasting consequences, especially on health, agriculture and aggregate macroeconomic activity (see e.g. Tol, 2009, Dell et al., 2012, Vicedo-Cabrera et al., 2021, or Ballester et al., 2023). Several theoretical models have been proposed to analyse the impact of climate events on economic activities, such as integrated assessment models (Nordhaus, 1993, or Hassler and Krusell, 2018), which focus mostly on long-term effects. Recent reviews on the economic effects of weather and climate-related shocks include Hsiang (2016) and Giglio et al. (2021).

Empirically, econometric models allow to quantitatively assess the effects of weather shocks on business cycles as well as their transmission channels (Kamber et al., 2013, or Mumtaz and Alessandri, 2021). However, most of these studies have focused on agriculture. For example, Ciscar et al. (2011), quantify the potential consequences of weather change in Europe's agricultural sector. In a more recent paper, Gallic and Vermandel (2020), study the effects of droughts on agricultural production and macroeconomic fluctuations in New Zealand, finding that drought shocks explain more than a third of GDP and agricultural output fluctuations. Beyond the agricultural sector, less attention has so far been given to other sectors of the economy, such as production (Arent et al., 2015, offer a review of the implications of weather change on key economic sectors and services). Only few comparative studies are available and they highlight a strong heterogeneity of effects across countries, especially in Europe (Acevedo et al., 2020, or Billio et al., 2020).

In this paper, we provide new evidence by studying the impact of various types of severe weather events on several production sectors, namely energy, construction, manufacturing and services. In this respect, we focus on European countries and use data on the three main European economies: Germany, France and Italy. To the best of our knowledge, there is no study that considers as many production sectors for European countries. Importantly, our paper is situated within the literature on business cycle effects of weather shocks, which differs from research focusing on the economic impact of natural disasters. The latter typically focus on *extreme* weather events such as hurricanes, cyclones or very large earthquakes with significant adverse local consequences on impact. We refer for example to Strobl (2011), Hsiang and Jina (2014) or Felbermayr and Gröschl (2014) for economic impact of natural disasters on economic activity or to Kruttli et al. (2023) on the financial system. Interestingly, some results sometimes point to positive economic effects in the long-run, in particular for income per capita and wages (see Roth Tran and Wilson, 2021).

A topic that has been highly debated among economists relates to the possible transmission channels of severe weather conditions to the business cycle. On the one hand, many papers tend to emphasize that factors of production are adversely affected by weather shocks. For example, using a standard SVAR model, Donadelli et al. (2017) show that a temperature shock has a sizable, negative and statistically significant impact on TFP, output and labor productivity. Negative effects of increases in temperature on labour productivity have been found in various empirical studies, such as Burke et al. (2005), Graff Zivin and Neidell (2014) or Deryugina and Hsiang (2014), among others. Kim et al. (2021) document a simultaneous drop in industrial production and an increase in inflation following a composite weather shock, suggesting that the latter acts as a negative supply shock. Supply drivers also tend to impact some sectors largely exposed to weather conditions, such as construction (Graff Zivin & Neidell, 2014). On the other hand, demand factors have been highlighted in some papers trying to identify channels of transmission. For example Ciccarelli and Marotta (2021) consider a panel of 24 OECD countries and estimate that climate events have a significant, albeit not sizeable, macroeconomic effect over the business cycle. They point out that physical risks work as negative demand shock by depressing both output and inflation. As far as energy production, Lucidi et al. (2022) show that energy demand is the main transmission channel of temperature shocks. In some specific sectors, as retail trade, it seems that weather shocks are transmitted through shifts in consumer demand. (Roth Tran, 2022). In the present paper, we do not provide a structural model able to disentangle supply and demand factors. However, whenever possible, we explore the economic channels for each production sector considered, based on our empirical results and recent published works.

The recent papers by Kim et al. (2021) and Billio et al. (2020) are strongly related to our work. Kim et al. (2021) propose a Smooth-Transition VAR (ST-VAR) model with standard macroeconomic variables to investigate potential time-varying effects of severe weather shocks on the U.S. economy over the past 60 years. Their weather data stem from the Actuaries Climate Index (ACI) developed by the American Academy of Actuaries and Canadian Institute of Actuaries, which consolidates observations of temperatures, rainfall, drought, wind speed, and sea level. By estimating impulse response functions (IRFs) to various shocks, they find that an increase in the ACI causes adverse long-lasting effects on industrial production, an increase in the unemployment rate, as well as upward inflationary pressures. Instead of exploring the heterogeneity of effects across the time dimension, Billio et al. (2020) focus on the interplay of weather shocks with the business and financial cycles, and differentiate between countries and weather shocks. They estimate a panel Markov-Switching model for thirteen European countries and three types of weather shocks: high temperatures, drought and very heavy rainfall. They mainly focus on the effects of weather shocks on industrial production growth and find evidence of an uneven impact across the different phases of the business cycle and across the considered countries. Most of the economies of Southern Europe are found to be negatively impacted by exposure to a lengthy spell of high temperatures, while Central and Northern countries respond asymmetrically over the business cycle (positively during recessions and negatively during expansions). Furthermore, severe drought seems to negatively impact most of the countries in Northern Europe, while, overall, France is found to be the most resilient economy to all weather shocks, in particular during recessions. Finally, they find that the impact of weather shocks on the economy is mostly felt through the manufacturing sector, which also contributes to explain the asymmetric impact of severe weather events on industrial production, more sensitive to business cycles.

3 Methodology

In this section we present the methodology used in this paper. We first describe the monthly data involved in the analysis, then discuss our approach to econometric modelling that relies on Bayesian SVAR models and Local Projections.

3.1 Data

To carry out the empirical analysis, we construct monthly weather indexes for France, Germany and Italy by using daily data. We then add data on production by sector, as well as macro aggregate variables (unemployment, inflation and short-term ECB interest rates). The dataset covers the period from January 1990 to December 2019.[2]

3.1.1 Weather data

We use daily weather data to construct five different monthly weather shocks: cold and heat stress, droughts, precipitation and wind. The daily weather data are taken from ERA5's single levels dataset, the fifth-generation atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts. It covers

[2] All data are available after 2019, but given the large volatility of macroeconomic data during the Covid pandemic, we decided not to include this period in the sample.

the entire globe on regular latitude-longitude grids at 0.25 x 0.25 degree resolution from 1940 to the present, and is conveniently updated at daily frequency with a latency of about 5 days allowing for a constant update of the components (Hersbach et al., 2020). To aggregate the grid-level data to the country level we use the GADM dataset (Database of Global Administrative Areas).

The computation of the monthly shocks differs slightly for each weather component, but broadly speaking they can be thought of as large deviations from historical climate realizations. For illustration, we provide an example of our approach for precipitation. For each calendar day (across all years), we compute the 95^{th} percentile of daily precipitation $P_{95,i,j}$ (day i, month j), which we use as threshold to calculate the monthly exceedance value:

$$PS_{j,k} = \sum_{i=1}^{n_j} \max\left[0;\ P_{i,j,k} - P_{95,i,j}\right]$$

where $P_{i,j,k}$ is total daily precipitation (year k) and n_j is the number of days in the month. Then, for each month j, we standardize the series via month-specific means and standard deviations:

$$PS^{std}_{j,k} = \frac{PS_{j,k} - \mu^{PS}_j}{\sigma^{PS}_j}$$

All the technical details for precipitation and the other components are given in Appendix 1. We then average the five components to obtain an aggregated index that we label the Composite Weather Index (CWI).

Constructing weather shocks in this way has several advantages. First, seasonal adjustment, a key aspect when working with weather variables, is obtained by construction. Second, we obtain series that are effectively standardized and hence easier to interpret.[3] Furthermore, the components do not exhibit strong auto-correlations, and unit-root tests do not reveal changes in trends, making them close to white noise processes. On the economic side, we argue that measuring deviations from calendar-specific historical averages is an advantage since it allows to look at impacts of "abnormal" weather conditions (in many ways similar to the notion of deviations from a "steady state"). Furthermore, looking at *large* deviations is important since it makes it more unlikely for economic agents to be able to forecast these events and to incorporate them in their economic decisions *before* the actual climate realization.[4] The monthly frequency at which we construct our shocks is crucial in this respect, and also allows us to claim exogeneity of the weather components with respect to the aggregate economic variables that we consider (see Section 3.2). We can thus interpret our weather indexes, both composite and components, as "shocks" (V. A. Ramey, 2016). Furthermore, these components have the desirable feature highlighted in Natoli (2022) that they not only measure isolated large weather events but also

[3] Note that performing such a month-specific standardization delivers a series that is 0-mean and 1-standard deviation, in the same way as a traditional standardization would.

[4] Temperature and other weather forecasts typically drop in accuracy as the horizon increases, quickly becoming relatively unreliable, even when the most advanced forecasting methods are employed. See for example Lopez-Gomez et al. (2023).

take into account the accumulation of several smaller abnormal events within the same month. Indeed, while economic agents might be able to workaround isolated large weather events (hence without hinging economic output), this might not be possible when the abnormal events are frequent within a short time span.

The components that make up our CWIs are heavily based on the European Extreme Events Climate Index[5], which is a new dataset of indexes aimed at providing information about the areas affected by different types of weather-induced hazards and the severity of such events (Giugliano et al., 2023)[6]. It also aims to provide an index equivalent to the ACI available for North America, which has been used recently by Kim et al. (2021).[7] The main differences lie in the ERA5 variables that we use, the fact that we compute calendar-day instead of calendar-month thresholds, and, most importantly, that we compute the month-specific means and standard deviations over the effective estimation sample. This way, we obtain variables that are indeed mean-zero and unit-standard deviation. Instead, the E^3CI indices are computed relative to the fixed 1981-2010 reference period, so that the series outside of this interval are not effectively standardized. Moreover, this might introduce time trends and time-varying sample variance in the presence of long-run trends, due for example to climate change. Finally, to measure drought we use the Standardised Precipitation-Evapotranspiration Index (SPEI) (Beguería et al., 2023), which accounts for both precipitation and potential evapotranspiration, while E^3CI uses the Standardised Precipitation Index (SPI), which only accounts for precipitation. As a robustness check, we also run the full analysis using the E^3CI indices "off-the-shelf", and do not find notable differences in the core results.

As we have discussed, weather shocks constructed in this way broadly measure large deviations from historical calendar-specific averages. We believe that we should think of these as capturing weather events that lead to rescheduling of economic activity and have effects via other economic channels such as shifts in sectoral demand and supply. This differs from the impacts of natural disasters leading to destruction of human and physical capital often studied in the literature (see Kruttli et al. (2023) and Ferriani et al. (2023) among others). Note that in the European countries that we study, natural disasters are relatively rare when compared to other areas of the globe. For example, many studies focus on the United States (Kim et al., 2021), where larger and more frequent natural disasters are observed. To further back this argument, we use the EM-DAT International Disaster Database (Guha-Sapir et al., 2016) to identify months when documented natural disasters are observed in Germany, France and Italy and set to zero the relevant weather shock observation corresponding to the month when the natural disaster occurred.[8] When we perform this robustness exercise our results are virtually unchanged, suggesting that natural

[5] This dataset is made available by the International Foundation Big Data and Artificial Intelligence for Human Development (IFAB): www.ifabfoundation.org.

[6] https://e3ci.dataclime.com/.

[7] https://actuariesclimateindex.org.

[8] Using EM-DAT, we classify as natural disasters weather-related events that implied either at least 100 deaths, at least 1000 affected people or at least a total estimated damage of 1000000 US

disasters are not the main force driving our results.

Figure 1 shows the three country-specific CWIs, in addition to their smoothed versions, a 5-year window moving-average. The single weather components of the CWIs for Germany, France and Italy are presented in Appendix 1 in Figures 12, 13 and 14, respectively.

3.1.2 Aggregate and sectoral economic data

The aggregate macroeconomic data that we use in the empirical analysis are unemployment rate (in level), inflation (annual growth rate of harmonized consumer price index) and the ECB main refinancing interest rate (3-month Euribor, in level). These are standard macroeconomic series that are often included in small-scale SVAR models to assess the dynamic impact of shocks on aggregate macroeconomic activity (see for example Caggiano et al., 2014).

Instead of proxying output by industrial production like is often done (Kim et al., 2021), we use various sectoral production series for each country. We use Eurostat's NACE Rev.2 sectoral classification. We consider sectors from section B to section N (with the exception of section K, financial and insurance activities). As reported in Table 1, these are: Manufacturing (C); Electricity , gas, steam and air conditioning supply (D); Construction (F); Wholesale and retail trade, repair of motor vehicles and motorcycles (G); Transportation and storage (H); Accommodation and food service activities (I); Information and communication (J); Real estate activities (L); Administrative and support service activities (N). Unfortunately, the services sections G to N are only available for France on a monthly basis. We do not include section A, Agricultural production (which we could expect to be one of the most impacted by weather shocks and has been extensively studied by previous literature), because most of the series are aggregated at a yearly frequency and very few data are available at a monthly frequency. Also note that large seasonal effects are likely in this sector.

Section	
C	*MANUFACTURING*
D	*ELECTRICITY, GAS, STEAM AND AIR CONDITIONING SUPPLY*
F	*CONSTRUCTION*
G	*WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES*
H	*TRANSPORTATION AND STORAGE*
I	*ACCOMMODATION AND FOOD SERVICE ACTIVITIES*
J	*INFORMATION AND COMMUNICATION*
L	*REAL ESTATE ACTIVITIES*
N	*ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES*

Table 1: *Sections from NACE Rev.2*

dollars. Such events occurred over our 1990-2019 sample during 22 different months in Germany, 42 months in France and 22 months in Italy, and are mostly related to abundant precipitation.

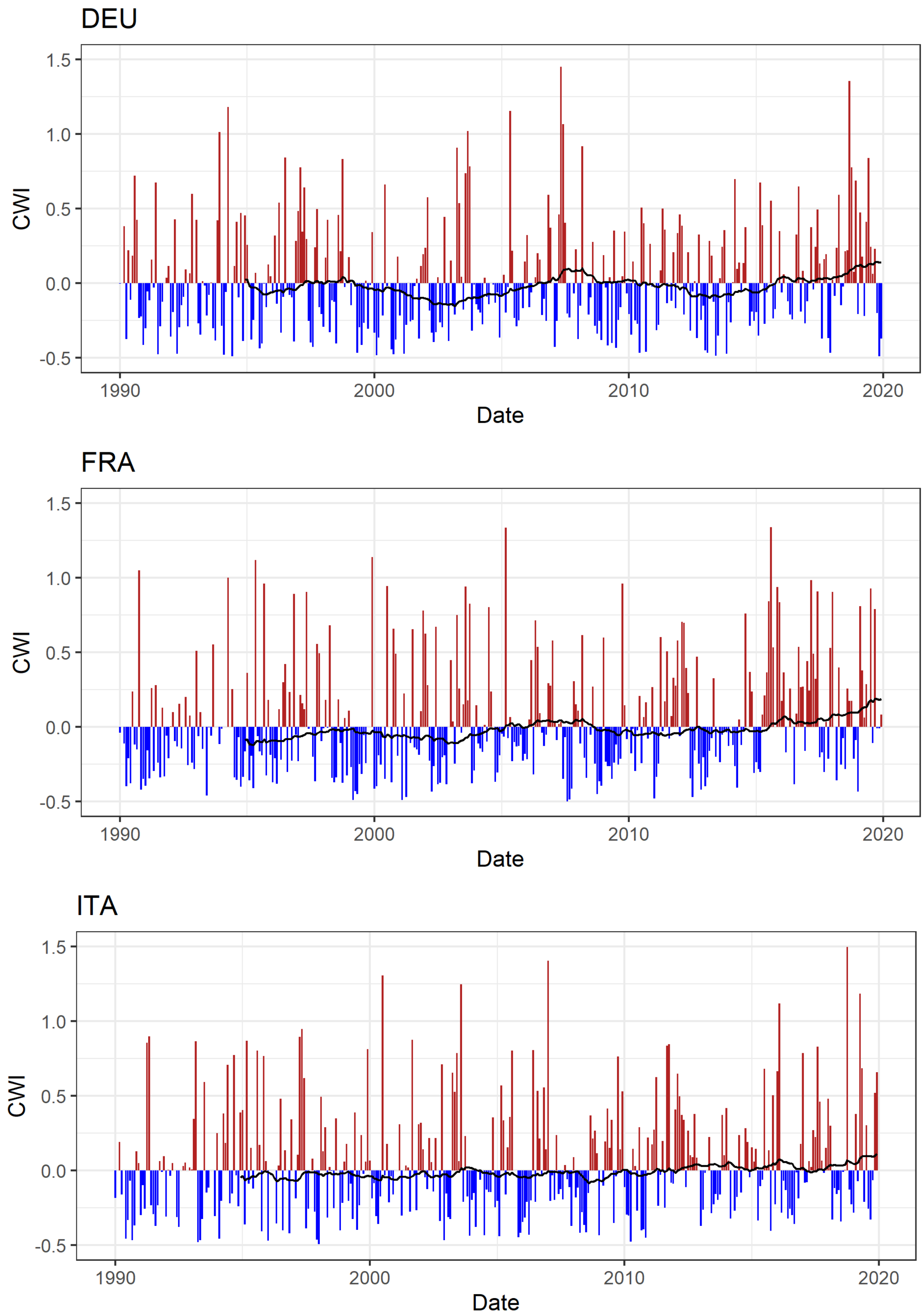


Figure 1: *Composite Weather Indexes for Germany, France and Italy*

3.2 Econometric modelling

The objective of our econometric modelling is to estimate impulse response functions (IRFs) to a given weather shock, in a given country. In this respect, we use two approaches, namely SVAR models and Local Projections (LPs) as put forward by Jordà (2005). Recently, Plagborg-Møller and Wolf (2021) have shown that the two approaches lead to similar results asymptotically when the lag structure is unrestricted.

3.2.1 SVAR modelling

We estimate a small-scale SVAR model for each of the 3 countries. The reduced-form model is summarized by the equation

$$\mathbf{y}_t = A_0 + A_1\mathbf{y}_{t-1} + \cdots + A_p\mathbf{y}_{t-p} + u_t, \tag{1}$$

where y_t contains all the variables of the system in the following order: weather index, production, unemployment rate, inflation and short-term interest rates. As regards weather indexes, both the CWI and its components, they are sequentially introduced into the SVAR model. Thus, matrices A_j for $j = 1, \ldots, p$ are 5×5 coefficients matrices. The reduced-form residuals u_t from this model are assumed to be such that $u_t \sim \mathrm{N}(0, \Sigma)$ where Σ is the covariance matrix. In order to get the underlying structural shocks ε_t of the system, we impose a linear relationship between ε_t and u_t such that $\varepsilon_t = \Gamma u_t$ where Γ is the matrix of contemporaneous relationships, that is within the month. Identification of Γ is obtained via the Cholesky decomposition of Σ, using the predefined ordering, and we adopt the customary unit standard deviation normalization. By imposing this ordering, we assume that any unexpected change in economic variables does not have any influence on severe weather events *within the same month*. However, medium-run evolution of economic variables can in turn influence severe weather realizations.

Parameter estimation of the SVAR model is performed within a Bayesian framework in the spirit of Giannone et al. (2015). The priors for the SVAR coefficients are taken from the *Normal-Inverse-Wishart* family and are of the following form:

$$\beta|\Sigma \sim N(\mathbf{b}, \Sigma \otimes \Omega),$$

$$\Sigma \sim IW(\Psi, \mathbf{d}),$$

where $\mathbf{b}$, Ω, Ψ and $\mathbf{d}$ can be expressed as function of the lower-dimensional vector of hyper-parameters γ. Here, β is the vector of listed coefficients of the A_j matrices. This class has two advantages: it includes the priors most commonly used in the literature and, since the priors are conjugate with respect to the likelihood function, the marginal likelihood is available in closed form. Giannone et al. (2015) set the degrees of freedom of the inverse-Wishart distribution to $d = n + 2$, where n is the number of variables included in the model, which is the minimum value that guarantees the existence of the mean of the IW distribution of Σ, given by $\frac{\Phi}{d-n-1}$. The matrix Φ is diagonal with the vector ϕ on the main diagonal. We refer to Appendix

2 for additional details.

3.2.2 Local Projections

As an alternative to VAR models, Jordà (2005), introduced the Local Projection (LP) approach to estimate IRFs. This approach has the advantage of being simple to implement and extremely flexible for the integration of non-linearities in the analysis, as we do in Section 5. In addition, recent theoretical research has proved that IRFs stemming from a LP approach converge to those obtained through a SVAR model (Plagborg-Møller and Wolf, 2021). LPs allow to directly estimate IRFs for a given variable of interest x_t in a simple way through the horizon-specific equation

$$x_{t+h} = c^h + \beta_h \nu_t + \Gamma_h(B)\mathbf{y}_{t-1} + u^h_{t+h} \qquad \text{for} \quad h = 0, 1, \cdots, H \tag{2}$$

where ν_t is the weather shock, and y_t a set of control variables similar to those included in the SVAR model in equation (1). It can be shown that β_h is the response of x at $t+h$ after a shock at t and the IRF is estimated by the sequence of β_h.

The LP equation (2) can be easily adapted to a non-linear framework by assuming that there exist two regimes in nature, for which the parameters are not equal. To estimate these different parameters, we simply interact the right hand side of equation (2) once with $(1 - F(s))$, interpreted as the probability of the economy being in the first regime, and once with $F(s)$, the probability of being in the second. This non-linear pattern is integrated into the previous horizon-dependent equation as follows:

$$x_{t+h} = (1-F(s_{t-1}))[c^h_1+\beta_{1,h}\nu_t+\Gamma_{1,h}(B)\mathbf{y}_{t-1}]+F(s_{t-1})[c^h_2+\beta_{2,h}\nu_t+\Gamma_{2,h}(B)\mathbf{y}_{t-1}]+u^h_{t+h}. \tag{3}$$

The $F(.)$ function maps real values to the interval $[0, 1]$ and a customary choice is the logistic function:

$$F(s_t) = \frac{e^{-\gamma \hat{s}_t}}{1 + e^{-\gamma \hat{s}_t}}, \ \hat{s}_t = \frac{s_t - \mu}{\sigma_s} \tag{4}$$

where s_t is the transition variable taken as indicative of the regime with respect to which potential non-linear effects are estimated, and μ and σ_s are its mean and standard deviation. For example, if we take s_t as an indicator of the business cycle, $F(s_t)$ will be close to 0 during the low phases of the business cycle (regime 1) and close to 1 during the high phases of the cycle (regime 2). This is what we do to test the hypothesis put forward by Billio et al. (2020). As output, we get IRFs to various weather shocks in each regime.

4 Main empirical results

This section presents the main results stemming from our empirical analysis. We start by evaluating the macroeconomic impact of various types of weather shocks on energy production, followed by construction and manufacturing. For each sector, we assess the dynamic responses to the composite weather shock, as well as sequentially to weather-specific shocks (heat, cold, drought, heavy precipitation, and intense winds). We compare results across our panel of three European countries—Germany, France, and Italy. Therefore, our results span three dimensions: production sector, weather shock, and country. To obtain dynamic responses to weather shocks in each country, we estimate SVAR models as described by equation (1). We maintain a standard ordering of variables throughout, namely weather index, sectoral production, unemployment rate, inflation and short-term interest rates. The recursive identification scheme and the estimation technique are described in Section 3. Additional results are presented in Section 5, including results related to the production of services in France.

Note that we adopt the one standard deviation normalization so that all the impulses responses presented in the two following sections are relative to an impulse of one standard deviation in the weather variable.[9] All the aggregate and sectoral macroeconomic variables used to assess the dynamic responses are expressed in growth rates (in percentage). Except where explicitly noted, whiskers represent 68% confidence intervals.

4.1 Dynamic effects on the energy production

We first focus on production in the energy sector. For each economic variable included in the SVAR model, IRFs of energy production to a one standard deviation shock on the composite weather index, are presented in Figure 2.[10] Detailed results for all variables are presented in the Appendix 3 in Figure 15 for Germany, Figure 16 for France and Figure 17 for Italy.

We observe that a composite aggregate weather shock initially results in a sig-

[9] To correctly interpret the results presented in this section, it is useful to clarify the meaning of a standard deviation in the weather variable. Indeed, this is not straightforward given the nature of the weather components (see Appendix 1), as the interpretation changes across different months and different countries. For example, a one standard deviation in the heat shock in Germany corresponds to approximately four to five days (depending on the month) in which the maximum daily temperature exceeds the corresponding calendar-day threshold. Such threshold is calendar-day specific and ranges from around 10°C/50°F in January to around 30°C/86°F in July. Similarly, a standard deviation in the cold shock corresponds to three to five days per month in which the minimum daily temperature is below the threshold (around -11°C/12°F in January and 10°C/50°F in July).

[10] Note that by convention, the IRFs start at date $t = 1$ which is the date of the initial impact. Consequently they stop at date $t = 41$, that is 40 months after the impact.

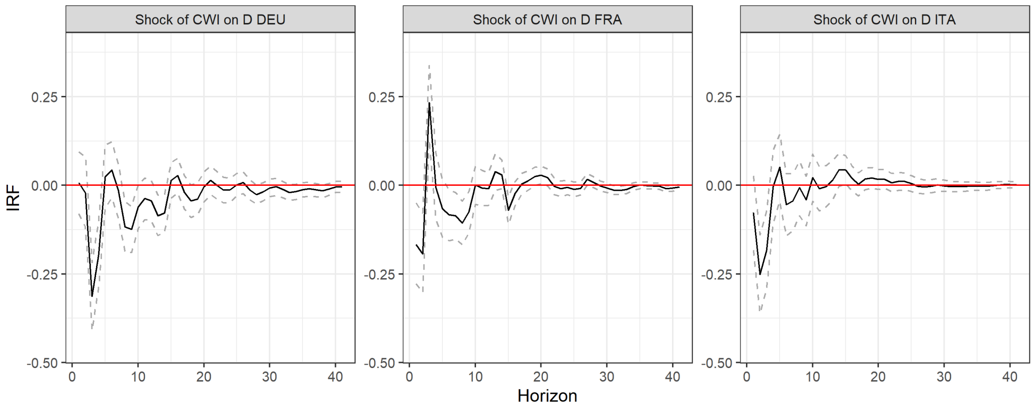


Figure 2: *Impulse responses of energy production to CWI shocks for Germany, France and Italy.*

nificant drop in energy production in all countries, returning to zero after only a few months (3 to 5 months). Notably, France exhibits a short-lived bounce-back following the initial negative impact. In Germany, this shock tends to push inflation slightly higher, although not significantly, and unemployment decreases by about -0.04 percentage points (pp hereafter) after one year in a statistically significant way. Conversely, in France, this composite weather shock leads to an increase in the unemployment rate, while inflation significantly decreases. In Italy, the same shock generates a persistent and significant rise in unemployment.

A concern that might arise when using the composite CWI is its consolidation of all types of severe weather events into a single index. Indeed, different types of weather events may impact production differently and potentially offset each other, contributing to the observed heterogeneity across countries. To address this, we now examine the impact of the individual components of the CWI on energy production. For each of the three countries, we sequentially assess the dynamic effects of the five weather-specific shocks—heat, cold, drought, heavy precipitation, and intense winds—on the energy production sector.

To efficiently summarize the results in graphs, we only consider cumulated IRFs to individual weather shocks at 6 months (red bars) and 12 months (green bars). Results are presented in Figure 3. We initially observe that energy production exhibits some comovement across countries. Specifically, a cold shock generates a positive cumulated response of energy production in all countries, while a heat shock leads to a significant decline in production across the board. This finding aligns with the results presented by Lucidi et al. (2022), which provide evidence suggesting energy demand as a major transmission channel for temperature shocks. The authors argue that a positive temperature shock reduces the demand for heating, subsequently leading to a decline in energy production and energy prices, while the opposite occurs following a negative temperature shock. Extending this perspective, Colombo and Toni (2022) go a step further by demonstrating that the main driver of this channel is the price of gas, which serves as the primary source of heating in Europe as a whole.

For our results to be consistent with the demand for energy channel, we would

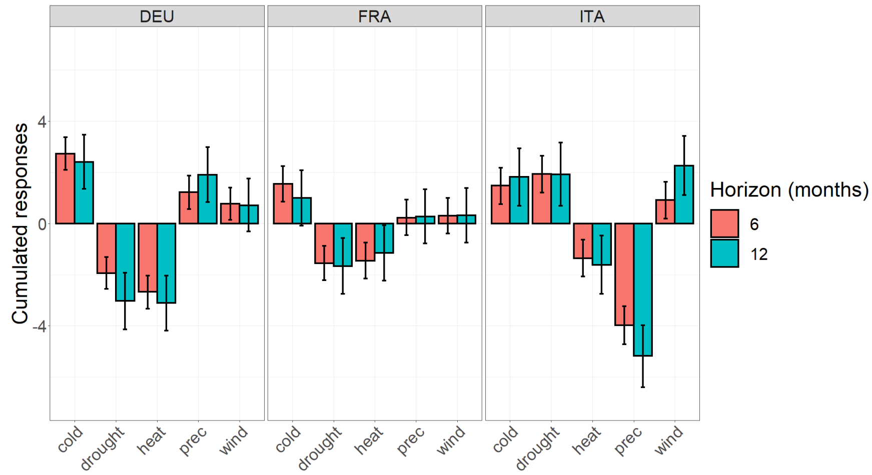


Figure 3: *Cumulated responses of energy production to the five weather-specific shocks.*

expect the effect of temperatures on energy production to be short-lived. This is demonstrated in Figure 4, where we present the full IRFs in response to both cold and heat shocks.[11] Most of the impact occurs within the first two months, with France being the most strongly affected country upon impact (around 1% variation in year-on-year energy production).

When examining responses to other weather-specific shocks in Figure 3, we con-

[11]Note that confidence bands are narrower in this case due to the strong contemporaneous correlation of cold and heat shocks with energy production (around 0.3 and -0.3 respectively). This correlation is much higher than what we observe with the other shocks.

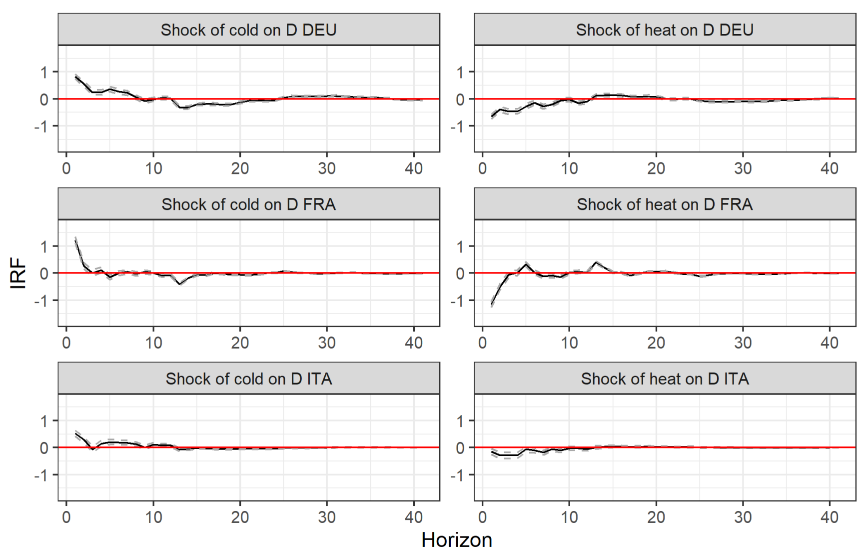


Figure 4: *Impulse responses of energy production to cold and heat shocks. The whiskers represent 90% confidence intervals.*

firm that Italy is the most sensitive country, exhibiting a strongly significant reaction to drought and precipitation shocks on energy production. Indeed, an excess of precipitation leads to a substantial decline in energy production, while, in contrast, a sequence of days of drought results in an increase in energy production. Therefore, we find that the overall rather weak response to the composite weather shock hides large positive and negative responses to various weather-specific shocks (positive for cold shock and droughts, negative for heat shock and precipitation).

4.2 Dynamic effects on the construction sector

This sub-section presents results related to the construction sector. For each economic variable included in the SVAR model, IRFs of production in the construction sector to a one standard error shock on the composite weather index are presented in Figure 5. Detailed results for all variables are available in Appendix 3, with Figure 18 for Germany, Figure 19 for France, and Figure 20 for Italy. By eyeballing these figures, we note that the dynamic effects of weather shocks are more pronounced on the construction sector than on other sectors and also exhibit much more persistence.

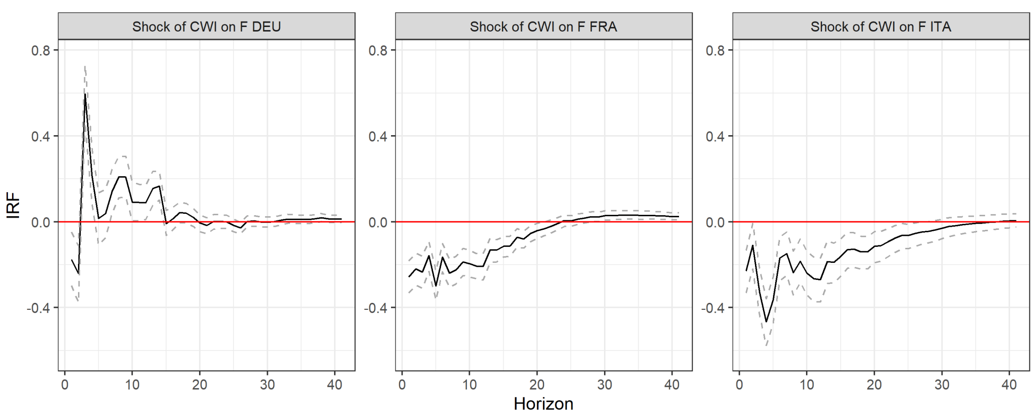


Figure 5: *Impulse responses of construction production to CWI shocks for Germany, France and Italy.*

When comparing countries, the dynamic responses of production in the construction sector reveal a dichotomy between Germany, on the one hand, and France/Italy on the other. Following an initial drop upon impact, a composite weather shock tends to increase activity in the German construction sector over the 15 months after the shock, leading to a significant drop of -0.025pp in the unemployment rate about 2 years after the impact.In contrast, both French and Italian construction sectors show a persistent and significant drop in activity, up to 2 years after the initial month of the shock. This decline is associated with a significantly negative response of inflation and a rise in unemployment. In particular, the unemployment rate in Italy reaches a peak at 0.05pp after 20 months.

Figure 6 reports the cumulated IRFs of production in the construction sector to the five weather-specific shocks. Those results provide some insights on the divergence between Germany and France / Italy. We find that that the positive reaction of the German construction sector is mostly driven by a heat shock that generates a cumulated response of more than 2% after 6 and 12 months. Interestingly, a similar shock leads to a large dive in production in Italy, while France does not show any significant reaction to this shock.

Regarding possible channels of transmission to the construction sector, it is evident that weather shocks are known to primarily affect the labor supply of workers exposed to outdoor conditions. For instance, using U.S. data, Graff Zivin and Neidell (2014) demonstrate that high daily temperatures reduce labor supply among workers exposed to outdoor temperatures, a significant factor for those in the construction industry. They suggest that higher temperatures can lead to changes in the time allocated to work by altering the marginal productivity of labor or the marginal cost of supplying labor. They find that at daily maximum temperatures above 85°F, workers in industries with high exposure to climate reduce their daily time allocated to labor by as much as one hour.

Our results suggest that a positive temperature shock is likely to have a differentiated impact on a country, depending on its latitude. For instance, a country located in the North of Europe, such as Germany, with colder temperatures relative to other European countries, tends to see its construction activity positively affected by a heat shock. Conversely, a Southern European country like Italy, considered a hot country in Europe, negatively reacts to a heat shock. Construction is indeed an outdoor economic activity with strong sensitivity to high temperatures, positively or negatively depending on the latitude. We also note that almost all the climate-specific shocks in Italy contribute significantly to the construction sector, either positively or negatively, making the country the most responsive to the diversity of severe weather shocks in this specific sector.

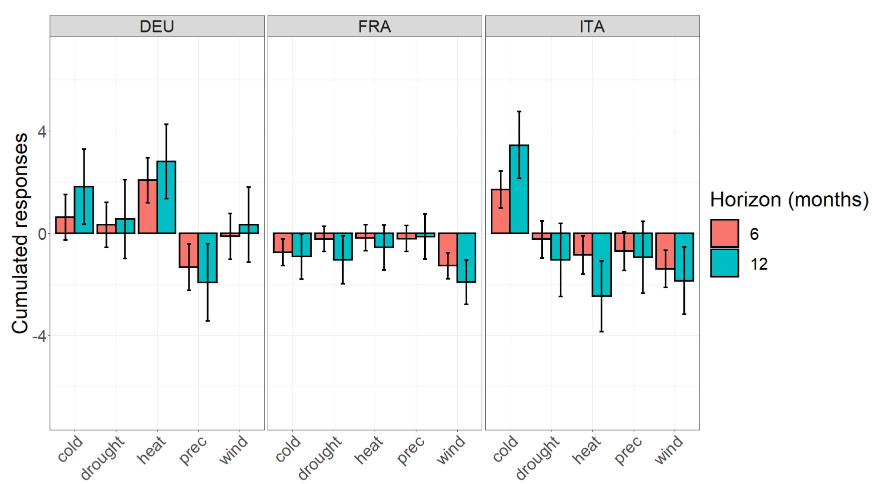


Figure 6: *Cumulated responses of construction production to the five weather shocks.*

4.3 Dynamic effects on the manufacturing production

We now shift our focus to the overall effects of the composite CWI on manufacturing production in the three countries involved in the analysis. For each economic variable included in the SVAR model, IRFs of manufacturing production to a one standard deviation shock on the composite weather index, are presented in Figure 7. Detailed results for all variables are presented in the Appendix 3 in Figure 21 for Germany, Figure 22 for France and Figure 23 for Italy.

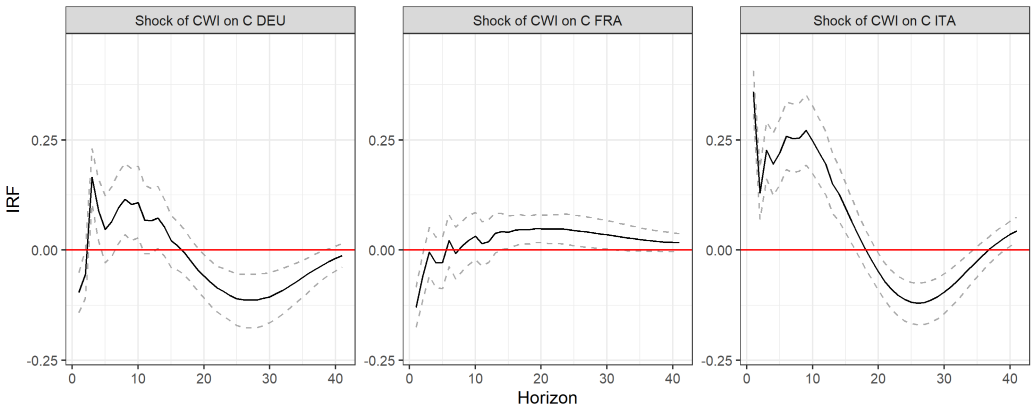


Figure 7: *Impulse responses of manufaturing production to CWI shocks for Germany, France and Italy.*

We find that a composite weather shock leads to a similar reaction in Germany and France, as initially manufacturing production drops following the impact. However, inflation and unemployment react in opposite ways in both countries. In France, after a short-lived increase upon impact, inflation tends to drop before rapidly returning to zero, while there is a persistent increase in the unemployment rate. Conversely, inflation is significantly pushed upward in Germany, while the unemployment rate is significantly reduced by 0.04pp after 20 months. Overall, it turns out that a composite weather shock in France appears to resemble an aggregate negative demand shock in the medium run, while a similar shock in Germany translates into a positive demand shock in the short run.

Manufacturing production reacts in a different way in Italy as an aggregate weather shock generates a surge in manufacturing production lasting about 1.5 years. On impact, the one standard error shock leads to a 0.30pp increase in production of manufactured goods, which then progressively vanishes. Cumulated responses are shown in Figure 8. This highlights the usefulness of splitting the composite index, as responses to some specific weather shocks now appear significant for France and Germany, while the manufacturing impact of the composite index was weak and non-significant for $h = 6$ and $h = 12$ months (see Figures 21 and 22). Again, we note the overall resilience of France to the various weather shocks compared to the other two countries. In Germany, responses to shocks are slightly and significantly positive, except for the response to a drought shock, which we find to be largely negative. In contrast, a drought shock tends to generate a cumulated positive response in Italian manufacturing production of about 4% after one year. Symmetrically, an excess of precipitation results in a significant drop in manufacturing production of about 3% after one year. This high sensitivity of the Italian manufacturing sector to an excess or deficit of rainfall is a salient finding in our results. Overall, this significantly contributes to the strong positive response of the manufacturing sector to a composite weather shock, as illustrated in Figure 23.

From our empirical results, it is not clear whether a weather shock to manufacturing production constitutes a demand or a supply shock. The literature also tends to provide mixed results. For example, Ciccarelli and Marotta (2021) argue that weather shocks leading to physical consequences work as negative demand shocks by depressing both output and inflation in a panel of countries. Kim et al. (2021) show evidence that U.S. industrial production and inflation go in opposite directions in the wake of a composite weather shock, thus suggesting that it acts as a supply shock. Similarly, Deryugina and Hsiang (2014) present evidence that temperature matters as it reduces the productivity of workers, thus highlighting a supply channel.

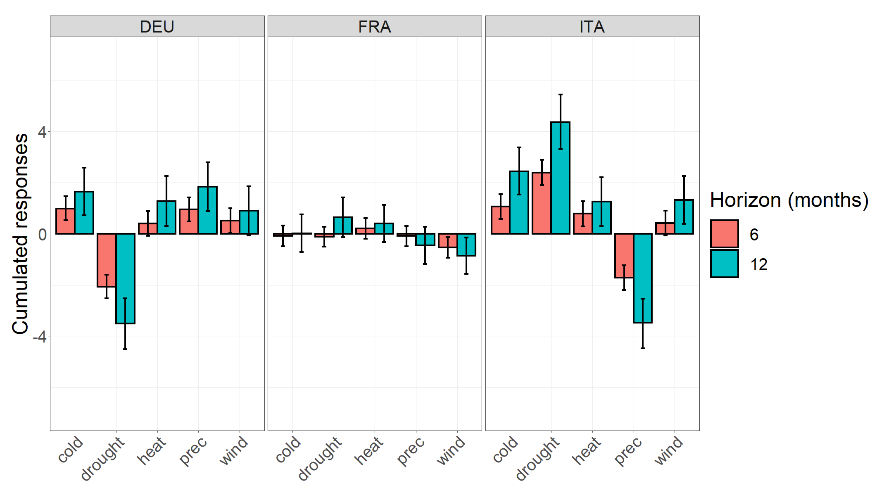


Figure 8: *Cumulated responses of manufaturing production to the five weather shocks.*

5 Additional results

In this section, we present additional empirical results, focusing first on service production, then on non-linear patterns in the responses to composite weather shocks, and finally on the potential presence of cross-country spillovers.

5.1 Dynamic effects of weather shocks on services

As for the production of services, unfortunately, we only have access to French data on a monthly basis.[12] We compute IRFs from various weather-specific shocks by integrating service production into a Structural Vector Autoregressive (SVAR) model, following the same approach as used for the other sectors in the previous section. Figure 9 presents the cumulated responses of various sub-sectors in the production of services, ranging from G (*Wholesale and retail trade*) to N (*Administrative and support service activities*) (refer to Table 1).

Compared to other sectors considered previously, the response of service production to various weather-specific shocks is relatively muted, though generally positive. Periods of heat and cold temperatures tend to be associated with slightly positive responses of service production, though most of them are not statistically significant. Excessive rainfall leads to negative responses in three sub-sectors: *Wholesale and retail trade*, *Transportation and storage*, and *Accommodation and food services.* Notably, a drought shock implies a positive response after 12 months of production in the *Transportation and storage* activity. Finally, it is observed that a wind intensity shock does not seem to significantly affect service production, as all the IRFs lie within the confidence bands after 6 and 12 months.

[12]According to Eurostat, detailed data on production in services are only available from 2016 onwards for Germany and are not available for Italy.

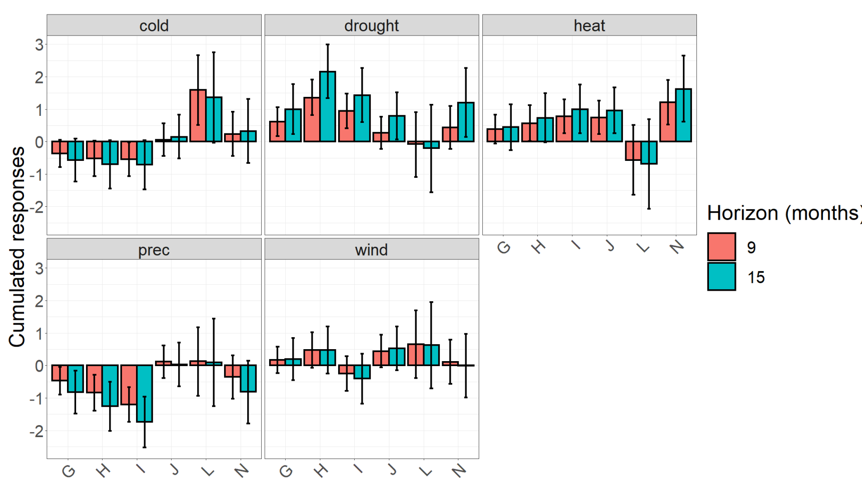


Figure 9: *Cumulated responses of services production in France to the five weather shocks.*

Overall, caution is warranted when interpreting these results for services, given our earlier observation that France exhibits a generally lower responsiveness to weather shocks compared to the other two countries. For some countries, existing literature has identified significant effects of weather shocks on certain services. Notably, Roth Tran (2022) found significant and persistent effects of weather on retail sales in the U.S. Interestingly, the paper also observed that the immediate effects of weather are only minimally offset by sales shifting between store types (indoor vs. outdoor) or over time. Shifts in demand are likely the primary drivers of the persistent response of sales to weather shocks. Highlighting the psychological channel, she suggests that weather can have psychological impacts on mood, subsequently influencing purchasing behavior.

5.2 Non-linearity to the business cycle

We address a result presented by Billio et al. (2020), which suggests evidence of non-linearity with respect to the business cycle. This implies a stronger impact of weather shocks on production during recessions than during expansions. To test this, we estimate non-linear IRFs to a composite weather shock on manufacturing production for the three countries. Our approach relies on the estimation of non-linear Local Projections given by equation (3). We allow for two regimes of economic growth using the European Sentiment Index (ESI) - a composite sentiment index of various surveys released by the European Commission - as the transition variable. The ESI reflects business cycle conditions, reaching low values during phases of low economic growth and high values during phases of high economic growth. Widely used by practitioners, this index tracks euro area business cycles in real-time. IRFs of manufacturing production in both regimes of growth for the three countries are presented in Figure 10. Blue lines correspond to IRFs within the high-growth regime, and black lines to IRFs within the low-growth regime.

Overall, we do not find large differences for any country between the IRFs of manufacturing production in the two alternative regimes of growth, suggesting that the hypothesis from Billio et al. (2020) does not hold against our background. This discrepancy could possibly be due to differences in the definition of business cycle phases. France is the country for which a short-run significant difference exists in the two phases of the cycle. Indeed, manufacturing production appears to be enhanced after a composite weather shock when the economy is in the low-growth regime. In contrast, this shock depresses manufacturing production in the high-growth regime. In comparison to France, the reaction of manufacturing production and macroeconomic variables to a composite weather shock in Italy and Germany appears to be less sensitive to the business cycle.

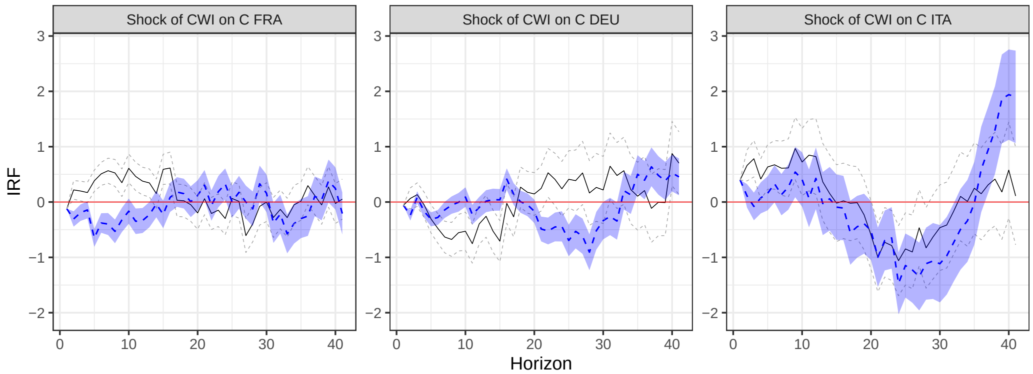
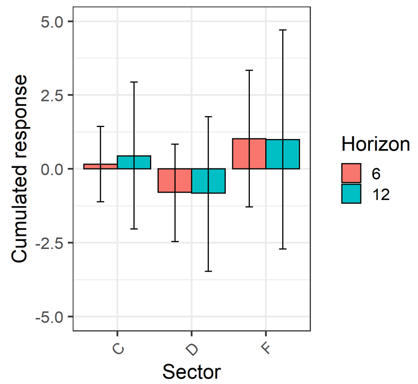


Figure 10: *Non-linear responses with respect to the business cycle of manufacturing production to the composite weather shock CWI. Blue lines correspond to the high-growth regime and black lines to the low-growth regime.*

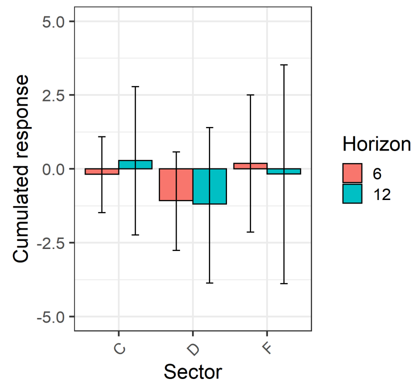
5.3 Cross-country spillovers

A concern that could be raised when estimating separate SVAR models for each country is the potential presence of cross-country spillovers, in particular when the shocks are correlated across countries. Indeed, the contemporaneous correlation between CWI indexes is equal to 0.43 for Germany and France, 0.22 for Germany and Italy, and 0.38. for France and Italy.

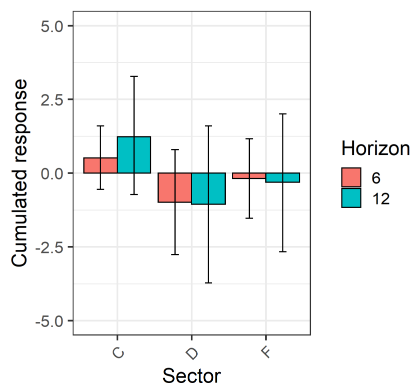
To check for the presence of potential spillovers, we run the same analysis as in the previous section, but substitute the domestic CWI shock with the residual part of the foreign CWI shock *not* explained by the domestic shock. In practice, we first estimate a regression of the foreign CWI on the domestic CWI and then use the residuals stemming from this regression in our benchmark SVAR model to compute IRFs. Results are presented in Figure 11, where we show that cumulated impulse responses are non-significant at both the 6 and 12 months horizons. This result suggests that cross-country spillovers are not a concern in our application.



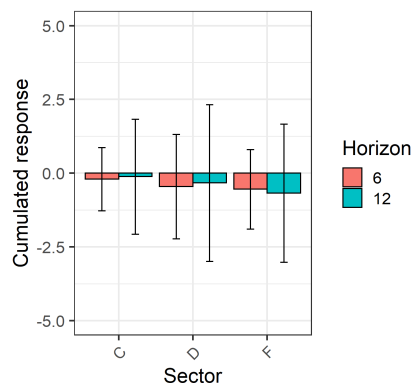
French CWI on German sectors



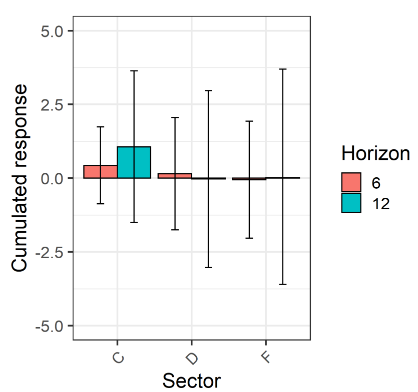
Italian CWI on German sectors



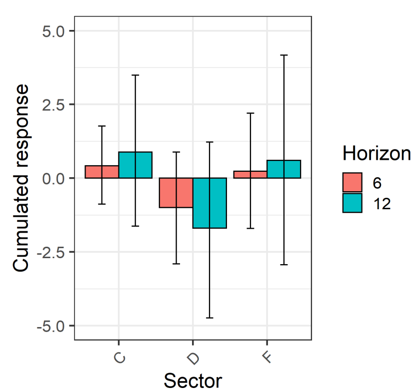
German CWI on French sectors



Italian CWI on French sectors



German CWI on Italian sectors



French CWI on Italian sectors

Figure 11: *Cumulated responses to a shock in the residual foreign CWI on domestic sectors. The whiskers represent 90% confidence intervals.*

6 Conclusions

This paper evaluates the short- to medium-term dynamic impact of weather shocks on sectoral production and aggregate macroeconomic variables within the three largest European countries: Germany, France, and Italy. We introduce a novel monthly composite weather index (CWI), constructed for each country from daily weather data. This index comprehensively encapsulates information on severe cold and heat conditions, drought occurrences, heavy precipitation, and intense winds. Using Structural Vector Autoregression (SVAR) models, we estimate impulse response functions to weather shocks for each country. This study contributes to the existing literature by assessing the distinct responses of various production sectors within the economy, including manufacturing, energy, construction, and services.

The empirical findings collectively demonstrate a significant impact of weather shocks on both sectoral production and broader macroeconomic variables. However, pronounced heterogeneity is evident across countries and sectors. Notably, France emerges as the less responsive country to weather shocks, with amplitude of responses comparatively lower than those observed in Germany or Italy. Conversely, Italy exhibits a more pronounced and varied reaction to weather shocks, showing both positive and negative impacts. These observations align with the empirical findings reported by Olper et al. (2021) for Italy .

The energy sector exhibits a strong comovement across countries, with a heat shock causing a substantial decline in energy production, while the opposite holds for a cold shock. The construction sector, inherently reliant on outdoor conditions, is more vulnerable to the impact of weather variations compared to other sectors. Notably, a heat shock tends to enhance production in Northern European countries such as Germany but has detrimental effects on production in Southern European countries like France and Italy. In Italy, manufacturing production exhibits a positive response to droughts, while an excess of rainfall leads to a significant reduction. Moreover, our findings indicate that weather shocks tend to correspond to demand shocks in the energy sector and supply shocks in the construction sector. The outcomes for manufacturing production, however, display a more nuanced and mixed pattern. Finally, we check for the presence of non-linear patterns with respect to the business cycle. There is weak evidence of non-linearity to the business cycle phases for manufacturing production, except for France.

This paper extends several dimensions of empirical findings from the existing literature on the effects of weather shocks on business cycles. Specifically, our contributions are as follows: (i) we demonstrate that European economies are vulnerable to the effects of weather conditions, broadening the geographical scope of impact beyond regions previously studied; (ii) in contrast to the predominant focus on the agricultural sector in the literature, we show that other sectors of the economy can also be significantly impacted by weather conditions; (iii) by examining a range of weather shocks, not limited solely to temperatures, we show that various meteorological factors play a significant role in shaping the impact on business cycles. This diversified perspective contributes to a more comprehensive understanding of the multifaceted consequences of weather shocks on business cycles.

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Appendices

Appendix 1: Weather data

Weather data from ERA5 (Hersbach et al., 2020) at a regular latitude-longitude grid of 0.25 is taken from the *reanalysis era5 single levels* dataset. In particular, minimum daily temperature corresponds to the *2m temperature* (daily minimum) variable; maximum daily temperature corresponds to *2m temperature* (daily maximum); daily total precipitation corresponds to *total precipitation*; maximum daily wind corresponds to *10m wind gust since previous post processing*. To aggregate the grid-level data to the country level we employ the Database of Global Administrative Areas (GADM), using the first level of resolution GADM0.[13] To measure drought we instead use the SPEIbase dataset v.2.9 (Beguería et al., 2023).[14]

We construct the weather shocks as follows. The composite climate index (CWI) is the average of all five weather shocks:

1. **Cold shock:** over the estimation sample 1990-2019, for each calendar day, the minimum daily temperatures of a five-days centered window are considered. The 5^{th} percentile $T_{05,i,j,k}$ of the 150 values (5 days $\times$ 30 years) is calculated and taken as threshold. For each month j and year k, $CS_{j,k}$ is computed as the monthly exceedance value:

$$CS_{j,k} = \begin{cases} \sum_{i=1}^{n_j} |T_{min,i,j,k} - T_{05,i,j,k}| & \text{if } T_{min,i,j,k} < T_{05,i,j,k} \\ 0 & \text{if } T_{min,i,j,k} \geq T_{05,i,j,k} \end{cases}$$

   Where $T_{min,i,j,k}$ represents the daily minimum temperature (day i, month j, year k). Then, for each month j, the mean value μ_j^{CS} and the standard deviation σ_j^{CS} of $CS_{j,k}$ of the exceedance value are calculated. Finally, the index is obtained by standardizing $CS_{j,k}$ for each month j and year k, via the month-specific means and standard deviations:

$$CS_{j,k}^{std} = \frac{CS_{j,k} - \mu_j^{CS}}{\sigma_j^{CS}}$$

   An alternative definition of the cold shock is given by counting the number of days in which the minimum daily temperature is below the corresponding threshold, instead of computing the monthly exceedance value.

2. **Heat shock:** over the estimation sample, for each calendar day, the maximum daily temperatures of a five-days centered window are considered. The 95^{th} percentile $T_{95,i,j,k}$ among the 150 values (5 days $\times$ 30 years) is calculated and taken as threshold. For each month j and year k, $HS_{j,k}$ is computed as the

[13] `https://gadm.org/`.

[14] `http://hdl.handle.net/10261/332007`.

monthly exceedance value:

$$WS_{j,k} = \sum_{i=1}^{n_j} \max\left[0;\ T_{max,i,j,k} - T_{95,i,j}\right]$$

Where $T_{max,i,j,k}$ represents the daily maximum temperature (day i, month j, year k). For each month j, the mean value μ_j^{WS} and the standard deviation σ_j^{WS} of $WS_{j,k}$ are calculated. Finally, the index is obtained by standardizing $WS_{j,k}$ for each month j and year k, via the month-specific means and standard deviations:

$$WS_{j,k}^{std} = \frac{WS_{j,k} - \mu_j^{WS}}{\sigma_j^{WS}}$$

An alternative definition of the heat shock is given by counting the number of days in which the maximum daily temperature is above the corresponding threshold, instead of computing the monthly exceedance value.

3. **Drought shock:** we consider the monthly Standard Precipitation Index with a 3 months accumulation period $SPEI3_{j,k}$. For each month j, the mean value μ_j^{SPEI3} and the standard deviation σ_j^{SPEI3} are calculated. Then, the index is obtained by standardizing the SPEI3 for each month j and year k, via the month-specific means and standard deviations:

$$SPEI3_{j,k}^{std} = -\frac{SPEI3_{j,k} - \mu_j^{SPEI3}}{\sigma_j^{SPEI3}}$$

According to the canonical approach, positive SPEI values represent large values of precipitation and negative values represent small values of precipitation. To maintain the consistency with the other components, we consider the opposite of the standardized $SPEI3_{j,k}$, as we want large positive values of $SPEI3_{j,k}^{std}$ to represent drought months.

4. **Precipitation shock:** over the sample, for each calendar-day (across all years), the 95^{th} percentile of daily precipitation $P_{95,i,j}$ is computed. Then, the monthly exceedance value is calculated as:

$$PS_{j,k} = \sum_{i=1}^{n_j} \max\left[0;\ P_{i,j,k} - P_{95,i,j}\right]$$

where $P_{i,j,k}$represents the daily total precipitation (day i, month j, year k) and n_j is the number of days in the month. Then, for each month j, the mean value μ_j^{PS} and the standard deviation σ_j^{PS} of the exceedance value are calculated. Finally, the index is obtained by standardizing the exceedance value for each month j and year k, via the month-specific means and standard deviations:

$$PS_{j,k}^{std} = \frac{PS_{j,k} - \mu_j^{PS}}{\sigma_j^{PS}}$$

5. **Wind shock:** over the sample, for each calendar-day (across all years), the 95^{th} percentile of daily maximum wind speed $W_{95,i,j}$ is computed. Then, the monthly Local Loss Index (Donat et al., 2011) is calculated as:

$$LLI_{j,k} = \sum_{i=1}^{n_j} max \left[0; \left(\frac{W_{i,j,k}}{W_{95,j}} - 1 \right)^3 \right]$$

where $W_{i,j,k}$ is maximum daily wind speed. Then, for each month j, the mean value μ_j^{LLI} and the standard deviation σ_j^{LLI} are calculated. Finally, the index is obtained by standardizing the exceedance value for each month j and year k, via the month-specific means and standard deviations:

$$LLI_{j,k}^{std} = \frac{LLI_{j,k} - \mu_j^{LLI}}{\sigma_j^{LLI}}$$

Finally, we get the monthly composite climate index as:

$$CWI = \frac{CS_{j,k}^{std} + WS_{j,k}^{std} + SPEI3_{j,k}^{std} + PS_{j,k}^{std} + LLI_{j,k}^{std}}{5}$$

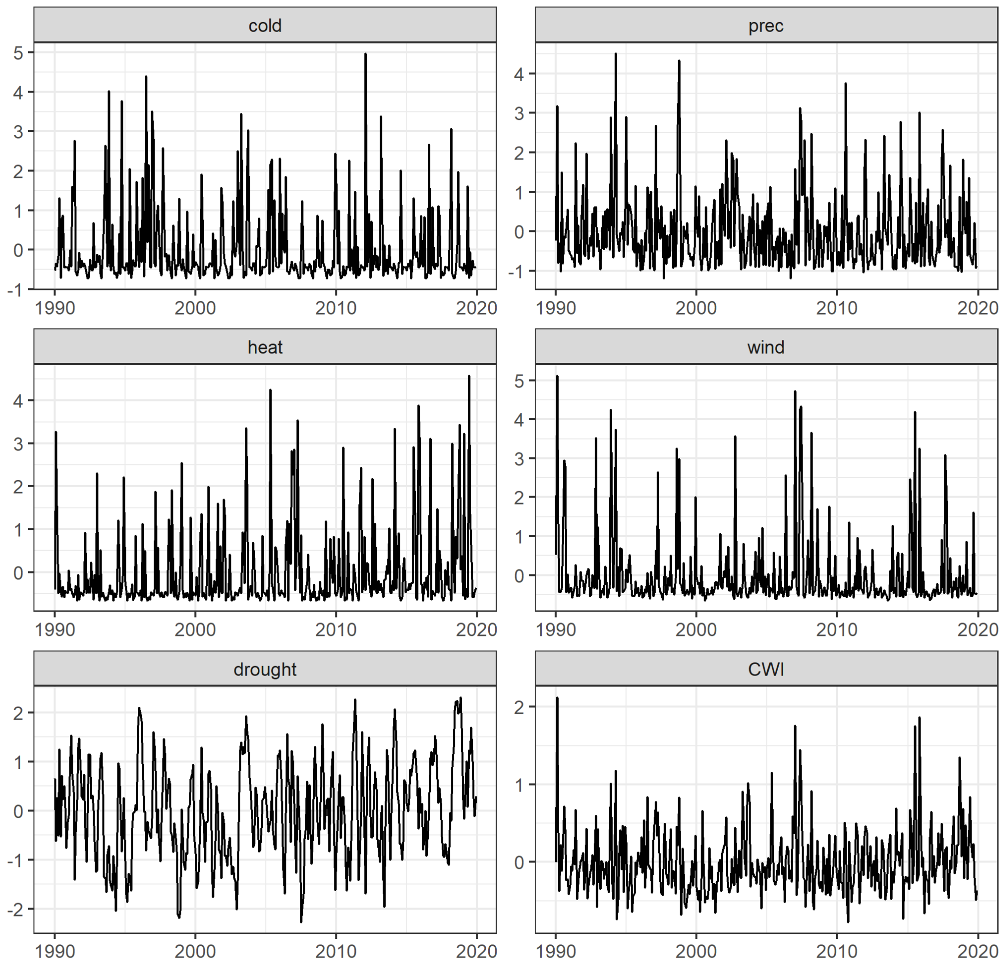

Figure 12: *CWI and its 5 components for Germany*

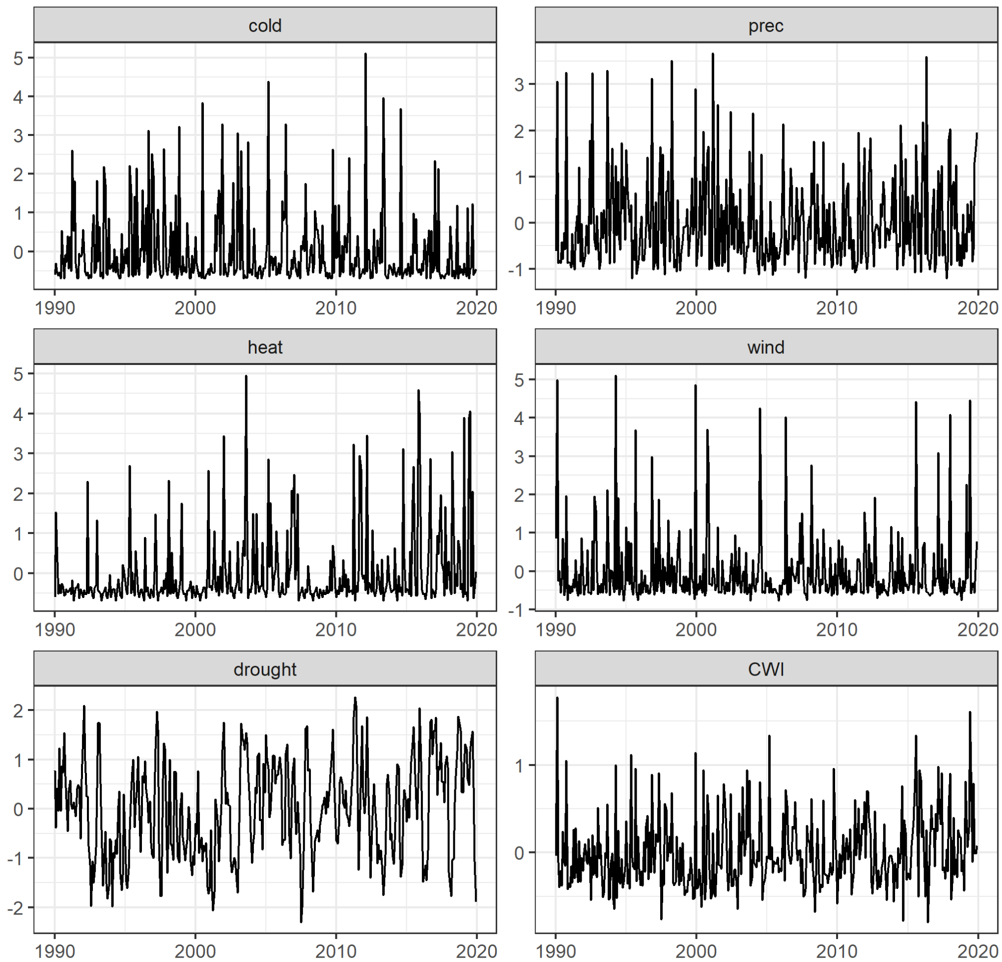

Figure 13: *CWI and its 5 components for France*

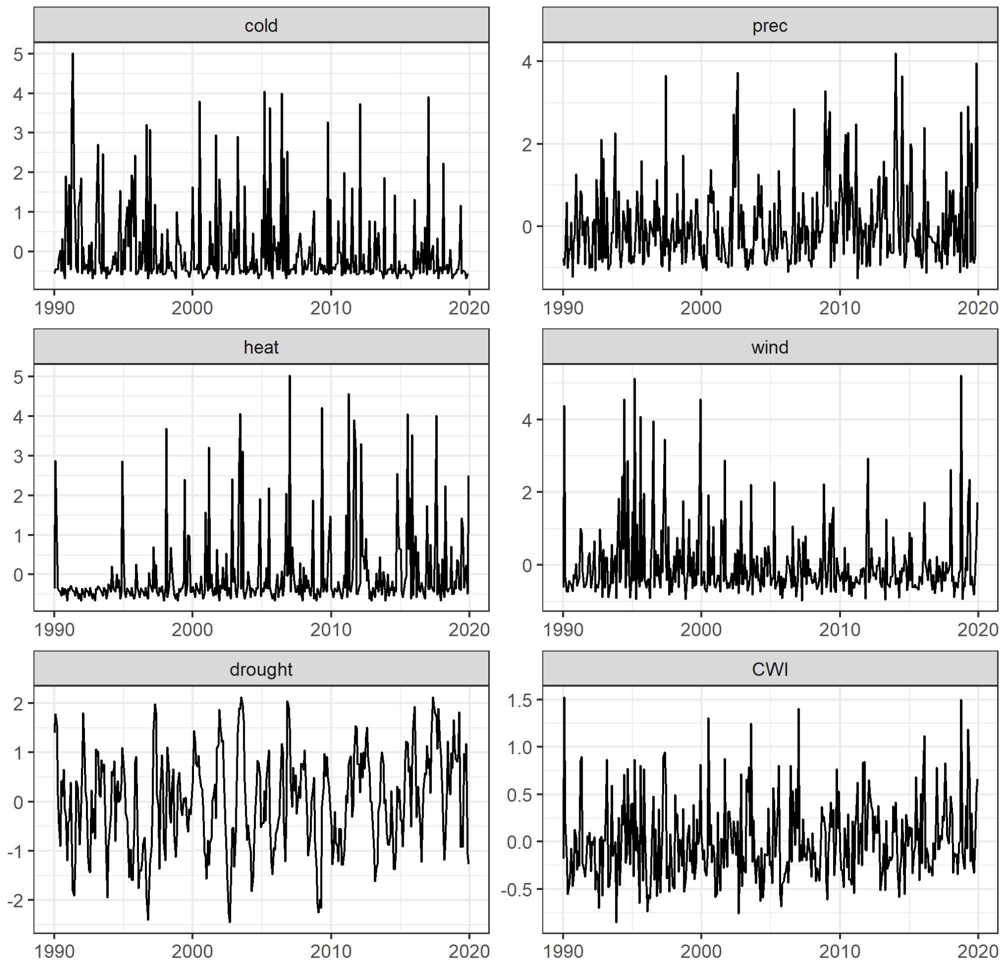

Figure 14: *CWI and its 5 components for Italy*

Appendix 2: Bayesian estimation

Giannone et al. (2015) propose to use three priors pertaining to the normal-inverse-Wishart family. The Minnesota (Doan et al., 1984), formalizes the idea that, ex ante, all the individual variables are expected to follow random walk processes. We specify it as follows. The conditional mean of the prior distribution is given by:

$$E[(\mathbf{A}_s)_{ij}|\Sigma] = \begin{cases} 1 & \text{if } i = j \text{ and } s = 1 \\ 0 & \text{otherwise} \end{cases},$$

so that an impact on a given variable only affects that variable at the next period in time, without affecting any variable at different lags. The conditional covariance of the prior distribution is given by:

$$cov[(\mathbf{A}_s)_{ij}, (\mathbf{A}_r)_{kl}|\Sigma] = \begin{cases} \lambda^2 \frac{1}{s^\alpha} \frac{\Sigma_{ik}}{\psi_j/(d-n-1)} & \text{if } l = j \text{ and } r = s \\ 0 & \text{otherwise} \end{cases},$$

where λ is the main hyperparameter and it controls the relative importance of prior and data (that is, the variance associated to the prior, in other words, the degree of confidence attributed to the prior). When $\lambda \to 0$, no weight is given to the data and vice versa for $\lambda \to \infty$. α is an hyperparameter that controls how fast this covariance should decrease with the number of lags and ψ_j is the j^{th} entry of ψ, which controls the variance associated to each variable. Some refinements of the Minnesota prior have been proposed in order to favour unit roots and cointegration, grounded on the common practices of many applied works. These take the form of additional priors that try to reduce the importance of the deterministic component of the VAR model.

The sum-of-coefficients prior is based on the idea that a "no-change" forecast is a good forecast at the beginning of the period. It is implemented by adding at the beginning of the sample artificial data constructed in the following way:

$$\underset{n\times n}{y^+} = \text{diag}\left(\frac{\bar{y}_0}{\mu}\right) = \begin{bmatrix} \frac{\bar{y}_1}{\mu} & 0 & \cdots & 0 \\ 0 & \frac{\bar{y}_2}{\mu} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \frac{\bar{y}_n}{\mu} \end{bmatrix}$$

$$\underset{n\times(1+np)}{x^+} = \left[\underset{n\times 1}{0}, y^+, \cdots, y^+\right],$$

where $\bar{y}_j$ denotes the average of the first p observations for each variable $j = 1, \cdots, n$. This prior implies that the sum of the coefficients of each variable on its lags is 1 and that the sum of the coefficients of each variable on the other variables' lags is 0. It also introduces correlation among the coefficients of the same variable in that variable's equation. The hyperparameter μ controls the variance of these prior beliefs: as $\mu \to \infty$, the prior becomes uninformative, while $\mu \to 0$ implies the presence of a unit root in each equation and rules out cointegration.

Since in the limit this prior does not allow for cointegration, the single-unit-root (also called dummy initial observation) prior can be implemented to push the variables towards the presence of cointegration. This is designed to remove the bias of the sum-of-coefficients prior against cointegration, while still addressing the overfitting of the deterministic component issue. It is implemented by adding one artificial data point at the beginning of the sample:

$$\underset{1\times n}{y^{++}} = \left(\frac{\bar{y_0}}{\delta}\right)' = \left[\tfrac{\bar{y_1}}{\delta}, \quad \cdots, \quad \tfrac{\bar{y_n}}{\delta}\right]$$

$$\underset{1\times(1+np)}{x^{++}} = \left[\tfrac{1}{\delta}, y^{++}, \cdots, y^{++}\right],$$

The hyperparameter δ controls the tightness of the prior implied by this artificial observation. As $\delta \to \infty$, the prior becomes uninformative. As $\delta \to 0$, the model tends to a form in which either all variables are stationary with means equal to the sample averages of the initial conditions, or there are unit root components without drift terms.

The three priors illustrated depend on the hyperparameters λ (the tightness of the Minnesota prior), μ (the tightness of the sum-of-coefficients prior), δ (the tightness of the single-unit root prior) ψ (which specifies the prior variance associated with each variable) and α (which relates to the decay of the covariance of coefficients relative to more lagged variables). We use the following parametrization: $\lambda \sim \Gamma$ with mode equal to 0.2 and standard deviation equal to 0.4; , $\mu \sim \Gamma$ with mode equal to 1 and standard deviation equal to 1; $\delta \sim \Gamma$ with mode equal to 1 and standard deviation equal to 1; $\alpha \sim \Gamma$ with mode equal to 2 and stadard deviation equal to 0.25. The hyperprior for the elements in ψ is set to an inverse-Gamma with scale and shape equal to 0.0004. Note that these are not flat hyperpriors. This guarantees the tractability of the posterior and it helps to stabilize inference when the marginal likelihood happens to show little curvature with respect to some hyperparameters. Please refer to the original paper for additional technical details.

Appendix 3: IRFs to composite weather shock of energy production, construction and manufacturing production, as well as other macro variables, for Germany, France and Italy

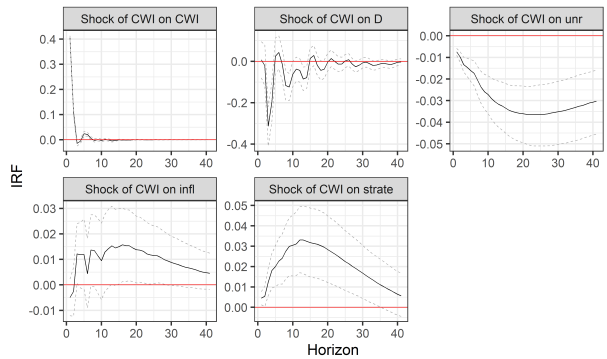

Figure 15: *Germany: IRFs to CWI shock for Energy production*

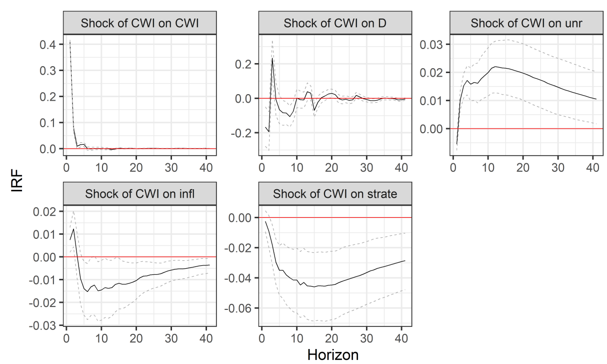

Figure 16: *France: IRFs to CWI shock for Energy production.*

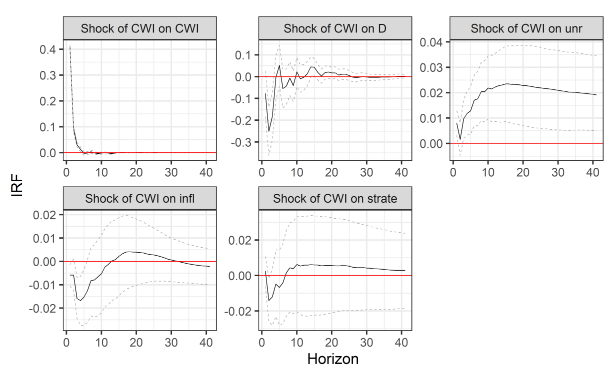

Figure 17: *Italy: IRFs to CWI shock for Energy production.*

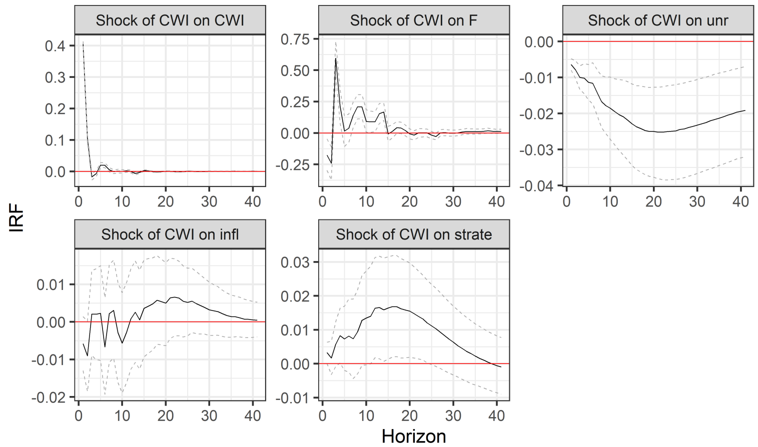

Figure 18: *Germany: IRFs to CWI shock for Construction production.*

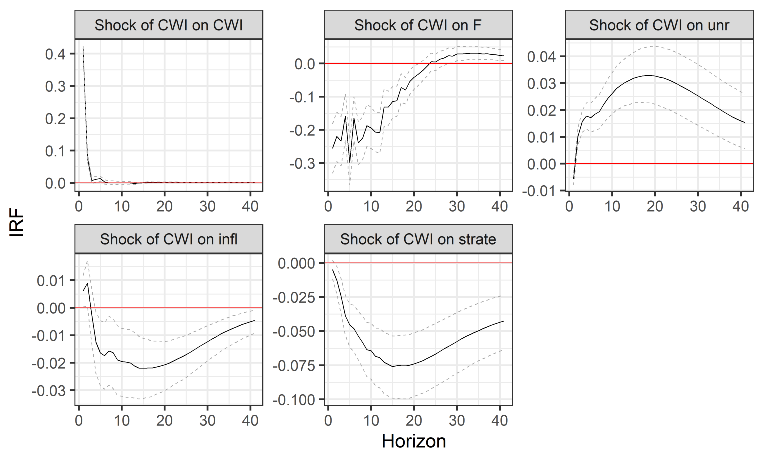

Figure 19: *France: IRFs to CWI shock for Construction production.*

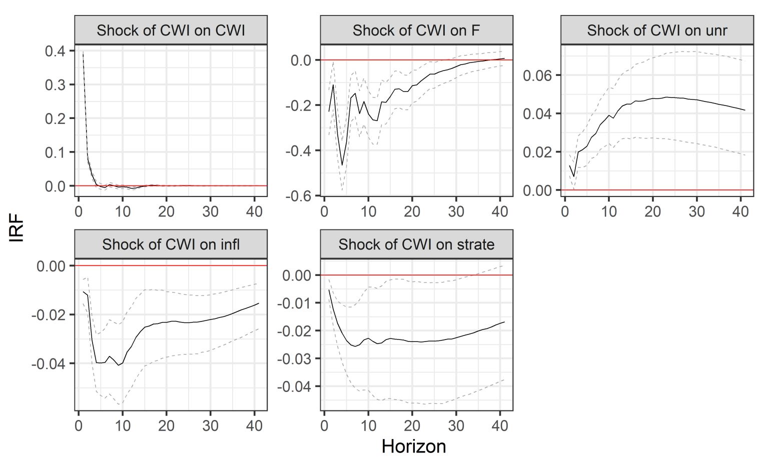

Figure 20: *Italy: IRFs to CWI shock for Construction production.*

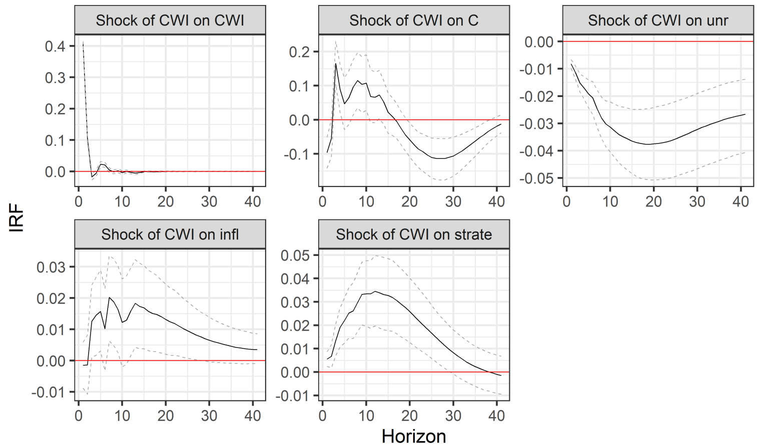

Figure 21: *Germany: IRFs to CWI shock for Manufacturing production.*

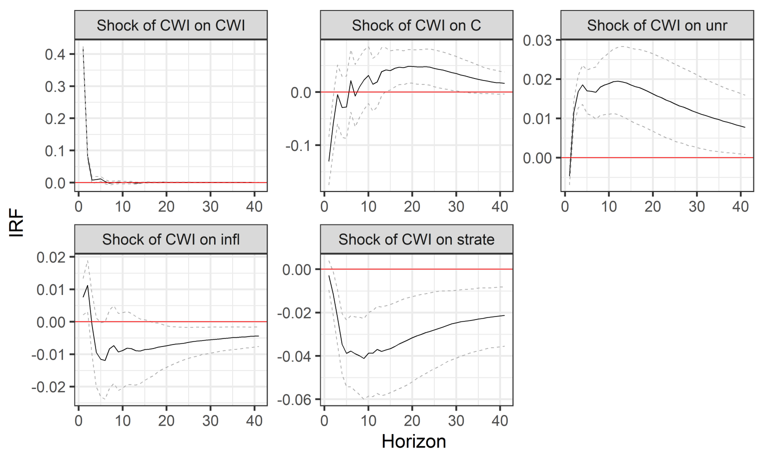

Figure 22: *France: IRFs to CWI shock for Manufacturing production.*

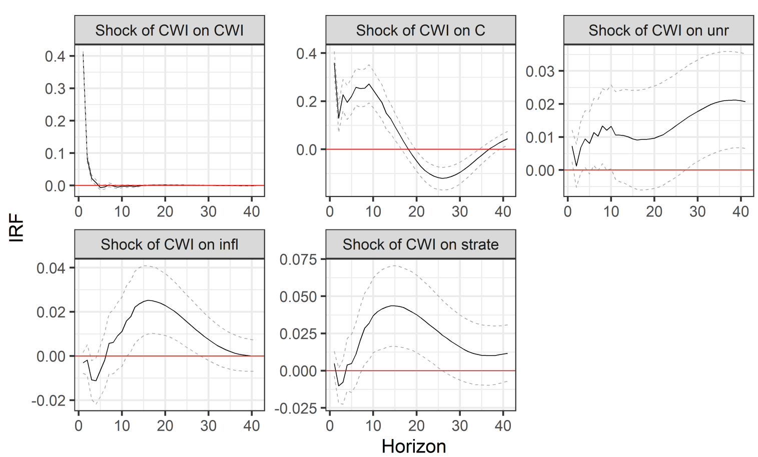

Figure 23: *Italy: IRFs to CWI shock for Manufacturing production.*