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 in the three main European countries. To identify changes in weather patterns, we use a novel composite European Extreme Events Climate Index, summarizing information about the main climatic hazards: cold and heat stresses, droughts, heavy precipitations and intense winds. A series of country-specific Bayesian SVAR models is estimated to assess the different impact of various weather events on sectors of production, namely manufacturing, construction, energy and services. We find clear evidence of a significant impact of weather shocks on European economic activity, each weather component impacting heterogeneously across various countries and production sectors. A non-linear Local Projection approach points out some non-linearities in the impact of weather shocks on economic activity.

Keywords: Weather shocks, European production, Bayesian VAR, Non-linear Local Projections.
JEL classification: C32, E23, Q54.

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1 Introduction

Relationships between economic activity, on the one hand, and climate events, on the other hand, have been shown to be strongly intertwined. It is now widely acknowledged among experts that economic activity has long-run negative effects on climate. Empirical evidence of reverse causality from climate shocks to aggregate economic activity is scarcer, at least until recently. Over the recent months, we have seen an increase in the number of papers trying to identify the specific role of extreme climate events on the business cycle (see for example Kim et al., 2021 for the U.S.; Billio et al., 2020 for European countries). In the terminology used in this literature, the word *climate* refers to the joint probability distribution of outcomes describing the state of the atmosphere, oceans and fresh water including ice. In the remaining of this paper, we will refer to a specific outcome of climate, that is weather conditions and their variations overtime. 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. It is noteworthy that other economic sectors, beyond agricultural (Gallic & Vermandel, 2020), are generally neglected when assessing short-run effects.

Weather shocks are often associated to temperature time series as they are available over a long historical sample. This is for example what has been done by Natoli (2022) for the U.S. economy or by Burke et al., 2005 and Acevedo et al. (2020) for a large panel of high- and low-income countries. Some research works also focus on extreme precipitation events and droughts, as for example Billio et al. (2020) for a bunch of European economies. In particular, they study the interplay of weather shocks with the business and financial cycles, and they differentiate between countries and weather shocks. 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. Kim et al. (2021) investigate potential time-varying effects of extreme weather on the U.S. economy over the past 60 years by using the Actuaries Climate Index (ACI, provided by American Academy of Actuaries and Canadian Institute of Actuaries). This monthly ACI summarises physical and meteorological observations of temperatures, rainfall, drought, wind speed and sea level, into a unique measure of extreme weather. By estimating a SVAR model accounting for standard macroeconomic variables, the authors show evidence of adverse aggregate macroeconomic impact of weather shocks that tend to significantly reduce output and increase inflation. Interestingly, they show by estimating a time-varying model that the economic impact of weather shocks has increased over time.

Building on the Kim et al. (2021) paper dealing with U.S. variables, our objective in this paper is to assess the potential macroeconomic effects of weather shocks on the main European countries. In this respect, we use an original database of European Extreme Events Climate Index (E^{3}CI), published by the IFAB (International Foundation Big Data and Artificial Intelligence for Human Development), that aims at replicating the U.S. ACI index for European countries. We get monthly data for this composite index starting in January 1981, as well as the five individual components: cold and heat stresses, droughts, heavy precipitations and intense winds. This rich database allows us to not only focus on temperature shocks, as done in most studies, but also on a variety of weather shocks. In addition, most of the published papers focus on the effects on industrial production (Billio et al., 2020; Kim et al., 2021), as a proxy for monthly economic activity. Here, we add an additional layer by considering various production sectors, namely manufacturing, construction, energy and services for France, Germany and Italy[1]. Our methodology relies on the estimation of a Bayesian VAR (BVAR) model for each country, each production sector and each type of weather shock. For each of the three dimensions, we estimate impulse response functions (IRFs) of sectoral production to a given weather shock. In the BVAR model, we control for inflation, unemployment rate and short-term interest rate for each considered country. In addition, to those main results, we integrate some non-linearities by estimating IRFs through Local Projections (LPs) as proposed by Jorda (2005).

Empirical results show that weather shocks have significant but heterogeneous effects across countries (in line with Billio et al., 2020) and sectors of production. Among the studied countries, France appears as the most resilient, in the sense that responses are relatively muted, while Italy shows large and significant responses to extreme weather shocks. In particular, the Italian production appears extremely responsive to an excess or deficit of rainfall. Among the sectors, manufacturing and construction are the most sensitive to extreme weather conditions. But interestingly, the direction of the response is not always the same. For example in Italy, a clear opposition emerges between the manufacturing and the construction sectors. Indeed, a weather shock clearly generates a surge in manufacturing production lasting about 1.5 year, while, in opposition, the construction sector sees a persistent and significant drop in its activity, up to 2 years after the initial date of the shock. This latter dive is associated with significantly negative response of inflation and a rise in unemployment. As regards the construction sector, results suggest that a positive temperature shock differently impacts a country depending on its latitude. Indeed, a country in the North of Europe, which can be considered as a cool country compared to other European countries, tends to see its construction activity positively affected by a heat stress. In opposition, a Southern European country like Italy, which can be considered as hot country in Europe, negatively reacts to a heat stress. To the best of our knowledge, this is the first study that also considers the effects of extreme weather on the production of services, which tend to respond mildly, but positively, to all weather shocks, although the analysis can only be conducted for France due to limited data availability. In addition, non-linear results highlight evidence of disproportionate effects on production of large shocks, compared to effects of shocks of smaller size, in particular in Germany. Last, we don't get evidence of non-linearity

[1]Unfortunately, monthly service production is only available for France for a sufficiently long period of time.

to business cycle phases in the responses to weather shocks, in opposition to the results obtained by Billio et al., 2020.

The rest of this work is structured as follows. Section 2 presents a selected review of the literature on macroeconomic impact of weather shocks. Section 3 introduces the methodology that we carry out, 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 and on non-linear effects of weather shocks and, finally, Section 6 concludes. Additional figures and tables are presented in the Appendix.

2 Selected literature review

There is a large macroeconometric literature trying to assess the aggregate macroeconomic dynamic effects of structural shocks. For example, seminal papers include Romer and Romer, 2004, for monetary policy shocks, Ramey, 2011, for government spending and fiscal shocks, as well as Bloom, 2009, for uncertainty shocks. However, in recent years, growing attention has been given to the role of weather shocks, as there is empirical evidence that climate hazards are more frequent and more intense and present long-lasting consequences, especially on health, agriculture, the ecosystem and the economy (Tol, 2009, or Dell et al., 2012). 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 on business cycles of weather shocks 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 and, in a 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 devoted 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, but they highlight a strong heterogeneity of effects across countries, especially in Europe (Acevedo et al., 2020, or Billio et al., 2020).

Overall, estimating the effects of extreme weather remains a key open issue, with previous studies finding heterogeneous results, ranging from limited, to no effects, to even sometimes positive effects (Felbermayr and Gröschl, 2014, Tran and Wilson, 2021, or Hsiang and Jina, 2014). In this paper, we provide new evidence by studying the impact of various types of extreme weather events on several production sectors, using data of three of Europe's main economies. To the best of our knowledge, there is no study that considers as many production sectors as we do in this paper.

The research works that are most closely related to ours are the ones by Kim et al., 2021 and Billio et al., 2020. Kim et al., 2021 propose a Smooth-Transition VAR (ST-VAR) model to investigate potential time-varying effects of extreme weather shocks on the U.S. economy over the past 60 years. As weather data, they use the Actuaries Climate Index (ACI) developed by the American Academy of Actuaries and Canadian Institute of Actuaries, which summarises physical and meteorological observations of temperatures, rainfall, drought, wind speed, and sea level, into a unique measure of extreme weather conditions. They introduce this ACI index into a small-scale econometric model that also includes the growth rate of industrial production, unemployment rate, inflation and short-term interest rates. Their main building block is a SVAR model estimated with monthly data and identified by assuming that economic shocks do not have contemporaneous (that is, within the same month) effects on the ACI. The model is then extended by allowing for time-varying parameters, a choice motivated by the clear upward trend of the ACI starting around 1995, to investigate whether the effects of extreme weather have changed over time. The model is estimated using Bayesian techniques (namely informative priors) and impulse response functions (IRFs) to various shocks are computed. Overall, they find that the 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 they differentiate between countries and weather shocks. They consider thirteen European countries and three types of weather shocks: high temperatures, drought and very heavy rainfall. They estimate a Panel Markov-Switching model able to jointly account for the cyclical behaviour of the EU economy at the country-specific and at the aggregate level, and to account for interaction between the financial cycle and weather shocks. 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 summer days, while Central and Northern countries respond asymmetrically over the business cycle (positively during recessions and negatively during expansions). Furthermore, extreme 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 extreme weather events on industrial production, more sensitive to business cycles.

3 Methodology

In this section we present the methodology used in this paper. First, we describe the monthly data involved in the analysis, then the econometric modelling that relies on BVAR models and Local Projections.

3.1 Data

To carry out our empirical analysis, we collect monthly data for France, Germany and Italy on the E^3CI index, on production by sector, as well as three 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

To measure extreme weather we take advantage of the European Extreme Events Climate Index (E^3CI), which is a new dataset of indexes aiming at providing information about the areas affected by various types of weather-induced hazards and the severity of such events. This data set is produced by the International Foundation Big Data and Artificial Intelligence for Human Development (IFAB[3]) and is based on the corresponding index developed for North America (Actuaries Climate Index, ACI[4]), which has been used recently by (Kim et al., 2021). The E^3CI index is available at the country level and is the combination of five components collecting information about the main weather hazards: cold and heat stresses, droughts, extreme precipitations, and extreme winds. The estimation of those components exploits ERA5, the fifth-generation atmospheric reanalysis produced by European Centre for Medium-Range Weather Forecasts. ERA5 covers the entire Globe on regular latitude-longitude grids at 0.25 x 0.25 degree resolution from January 1950 to present. Interestingly, ERA5 is updated daily with a latency of about 5 days permitting a constant update of the components. Note that the reference values are computed on the 1981-2010 time span. So overall, those components can be seen as deviation to average over 1981-2010, the exact computation is presented in the Appendix. Components of the E^3CI index for Germany, France and Italy are presented in the Appendix in Figures 18, 19 and 20, respectively. The components do not exhibit any strong auto-correlation, and are thus close to white noise processes, and they do not present significant cross-correlations if we except the negative correlation of about -0.40 between precipitations and droughts. *In fine*, these components are summarized into a unique extreme weather index, computed as the average of the five components and referred to as the E^3CI index, and presented in Figure 1 in addition to its smoothed version, a simple asymmetric moving-average over 5 years.

[2] All data are available after 2019 but given the large volatility of macroeconomic data during the Covid period, we decided to not integrate for the moment this period into the sample.

[3] `www.ifabfoundation.org`

[4] `actuariesclimateindex.org`

We don't observe any clear changes in trends, in spite of a slight upward trending common movement starting around 2015.

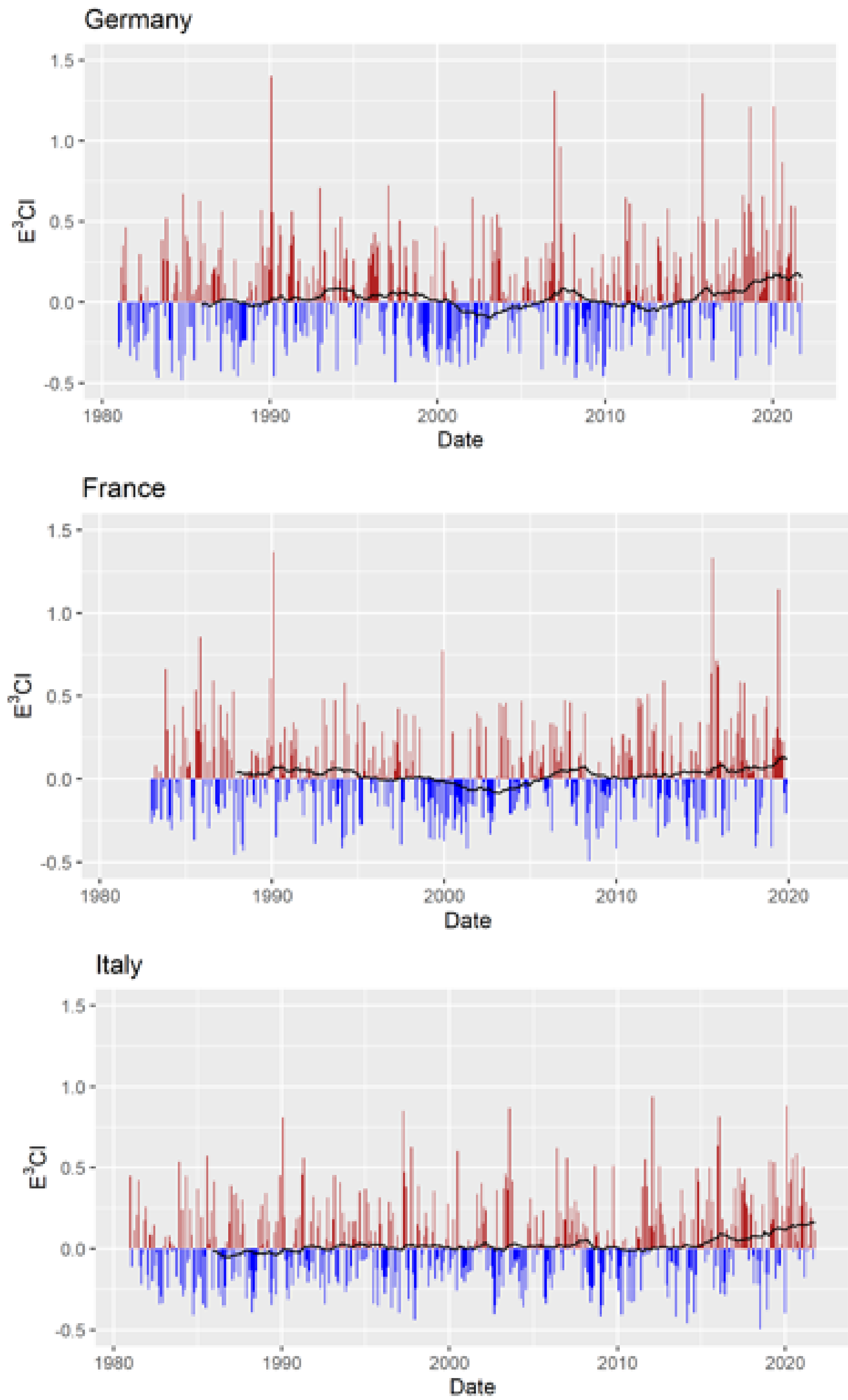

Figure 1: *Composite E^3CI indexes for Germany, France and Italy*

3.1.2 Aggregate and sectoral macro data

The aggregate macroeconomic data that we integrate into our analysis are similar to those from Kim et al., 2021, namely unemployment rate (in level), inflation (annual growth rate of harmonized consumer price index) and ECB main refinancing interest rate (3-month Euribor, in level). Those series are standard macroeconomic variables and are often integrated into small-scale SVAR models to assess the dynamic impact of shocks of aggregate macroeconomic activity.

Instead of proxying output by industrial production as in Kim et al., 2021, we are using various sectoral production series for each country. The sectoral classification is NACE Rev.2 proposed by Eurostat. We consider sectors from section B to section N (with the exception of section K, financial and insurance activities). The considered sections, reported in Table 1, are: Mining and quarrying (B); Manufacturing (C); Electricity , gas, steam and air conditioning supply (D); Water supply, sewerage, waste management and remediation activities (E); 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); Professional, scientific and technical activities (M); 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 as being one of the most impacted by weather shocks and has been extensively studied by previous literature), because most of the series are aggregated at the yearly frequency and very few data are available on a monthly frequency. Also note that there are likely to be large seasonal effects in this sector.

Section	Division
B	*MINING AND QUARRYING*
C	*MANUFACTURING*
D	*ELECTRICITY, GAS, STEAM AND AIR CONDITIONING SUPPLY*
E	*WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT AND REMEDIATION ACTIVITIES*
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*
M	*PROFESSIONAL, SCIENTIFIC AND TECHNICAL ACTIVITIES*
N	*ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES*

Table 1: *Sections from NACE Rev.2*

3.2 Econometric modelling

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

3.2.1 SVAR modelling

In this respect, we estimate small-scale SVAR model for each of the 3 countries of the following reduced form:

$$\mathbf{y}_t = A_0 + A_1\mathbf{y}_{t-1} + \cdots + A_p\mathbf{y}_{t-p} + u_t \tag{3.2.1}$$

where y_t contains all the variables of the system in the following order: weather shock, production, unemployment rate, inflation and short-term interest rate. Thus matrices A_j for $j = 1, \ldots, p$ are 5×5 coefficients matrices. Reduced-form residuals u_t from this model are supposed 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. By imposing this ordering, we thus assume that any unexpected change in economic variables does not have any influence on extreme weather events *within the same month*. But obviously, medium-run evolution of economic variables can in turn influence extreme weather shocks.

Parameter estimation of the SVAR model is carried 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 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 into the model, which is the minimum value that guarantees the existence of the mean of the IW distribution of Σ which in this case is $\frac{\Phi}{d-n-1}$. The matrix Φ is diagonal with the vector ϕ on the main diagonal. We refer to the Appendix 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 great advantage of being simple to implement and extremely flexible to integrate non-linearities, as we do in

Section 5. In addition, recent theoretical research proved that IRFs stemming from a LP approach converge to the ones 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 easier way through this horizon-specific equation, for each horizon h:

$$x_{t+h} = c^h + \beta_h \nu_t + \Gamma_h(B)\mathbf{y}_{t-1} + u^h_{t+h} \qquad \text{for} \quad h = 0, 1, \cdots, H \tag{3.2.2}$$

where ν_t is the structural weather shock, y_t a set of control variables similar to those included into the SVAR model in equation (3.2.1). 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 (3.2.2) can be easily adapted to a non-linear framework by assuming there exists two regimes in the nature for which parameters are not equal. In this respect, we simply interact the right hand side of equation (3.2.2) once with $(1 - F(s))$, 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:

$$x_{t+h} = (1-F(s_{t-1}))[c^h_1+\beta_{1,h}\nu_t+\Gamma_{1,h}(B)\mathbf{y}_{t-1}]+F(s_{t-1})[c^h_2+\beta_{2,h}\nu_t+\Gamma_{2,h}(B)\mathbf{y}_{t-1}]+u^h_{t+h}. \tag{3.2.3}$$

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

$$F(s_t) = \frac{e^{-\gamma \hat{s}_t}}{1 + e^{-\gamma \hat{s}_t}}, \; \hat{s}_t = \frac{s_t - \mu}{\sigma_s} \tag{3.2.4}$$

where s_t is the transition variable taken as indicative of the regime with respect to which potential non-linear effects are estimated. 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 will do to test the hypothesis put forward by Billio et al., 2020. As an output, we get IRFs to various weather shocks in each regime.

4 Main empirical results

This section presents the main results from our empirical analysis. We start by assessing the macroeconomic effects of a composite weather shock, then we will consider the specific-weather shocks. Additional results are presented in the next section.

4.1 Macro effects of a composite weather shock

Let's first have a look at the global effects of the composite E^3CI index on all sectors for the three countries involved in the analysis (Germany, France, Italy). For a given country we assess the sectoral impact of the composite weather shock by considering production in three sectors: manufacturing, energy and construction. To get dynamic responses to shocks in each country, we sequentially employ in this section the SVAR model described in equation (3.2.1) by always keeping the following standard ordering of variables: weather shock, sectoral production, unemployment rate, inflation and short-term interest rates. Recursive identification and estimation steps are described in section 3.

IRFs for all the economic variables included in the SVAR model to a one standard error shock on the composite weather index, as well as the 68% confidence bounds, are presented in Figures 2 to 4 for Germany, Figures 5 to 7 for France and Figures 8 to 10 for Italy[5]

In Germany, a weather-induced shock leads to similar expected reaction of manufacturing and energy sectors as the production initially significantly drops following the initial extreme weather shock then rapidly converges to zero after the the first few months (3 to 5 months). This shock tends to push inflation higher, though not significantly, and unemployment slightly decreases by about -0.02 percentage points (pp) after one year, but in a statistically significant way. In opposition, a weather shock tends to increase activity in the construction sector, over the 12 months after the shock. The response of unemployment is still positive as we observe a significant decline. In general, the interest rate tends to significantly increase by few pp (maximum of 0.03pp after one year). Overall, a weather shock in Germany could be characterized as being close to a positive aggregate demand shock as unemployment decreases and inflation increases.

In France, a composite weather shock first leads to a decline in production for all sectors following the initial impact, with heterogeneous degrees of persistence. While the shock rapidly vanishes for the manufacturing and energy sector, it tends to be much more persistent for construction, the effects being still visible 20 months after the impact date. An extreme weather shock in France acts as an aggregate negative demand shock in the medium run as it steers a drop in inflation and central bank rate, as well as a surge in unemployment rate. Interest rates react negatively in all cases, reflecting a more accomodative monetary policy reaction. When construction

[5]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.

is considered, macroeconomic effects are larger than in other sectors and are highly persistent.

In Italy, a clear opposition emerges between the manufacturing and the construction sectors. Indeed, a weather shock clearly generates a surge in manufacturing production lasting about 1.5 year. On impact, the one standard error shock leads to 0.4pp increase in production of manufactured goods, then progressively vanishes. This movement is however associated to a slight increase in unemployment. In opposition, the construction sector sees a persistent and significant drop in its activity, until 2 years after the initial date of the shock. This dive is associated with significantly negative response of inflation and a rise in unemployment. In particular, the unemployment rates reaches a peak of 0.07pp after two years. Overall, interest rates do not strongly react. As regards the energy sector in Italy, we observe a positive reaction of production one month after the impact, followed by a drop the month after. Then, there is no clear evidence of significant response over the rest of the horizon. Compared to France and Germany, Italy seems to more sharply react to weather shocks, positively and negatively.

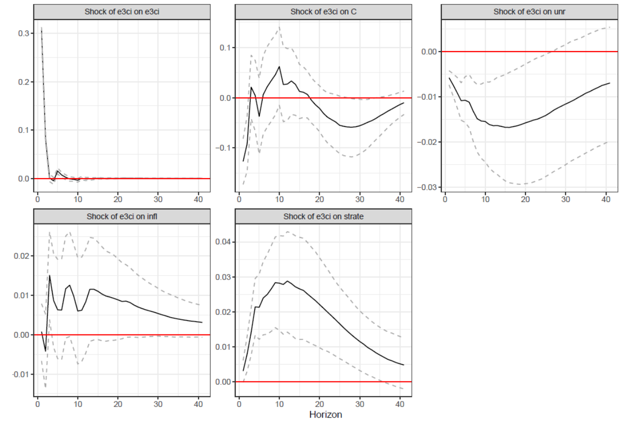

Figure 2: *Germany: IRFs to E^3CI shock for Manufacturing production*

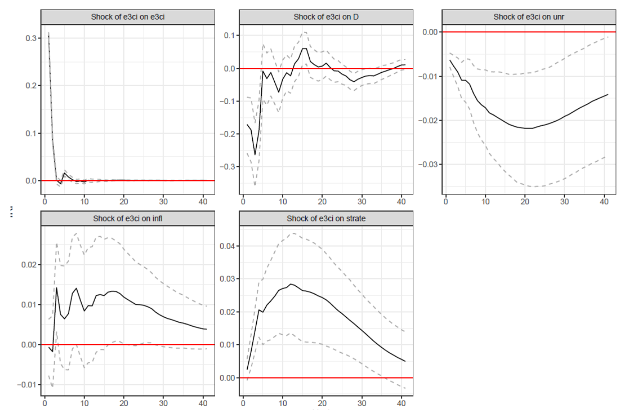

Figure 3: *Germany: IRFs to E^3CI shock for Energy production*

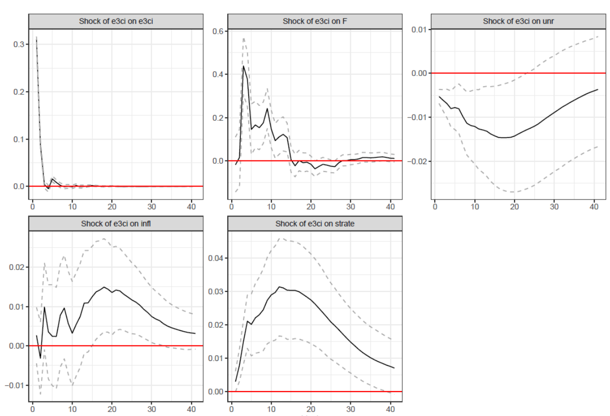

Figure 4: *Germany: IRFs to E^3CI shock for Construction production*

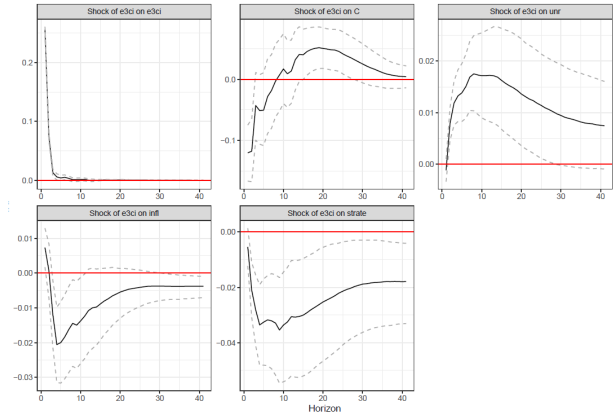

Figure 5: *France: IRFs to E^3CI shock for Manufacturing production*

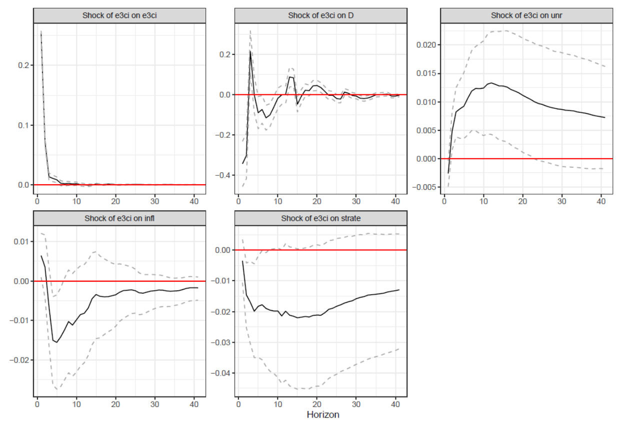

Figure 6: *France: IRFs to E^3CI shock for Energy production*

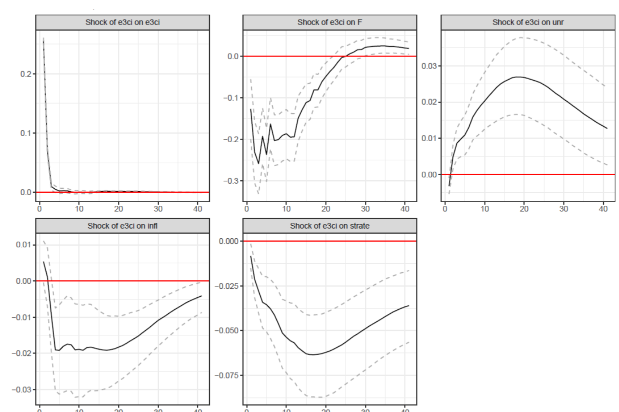

Figure 7: *France: IRFs to E^3CI shock for Construction production*

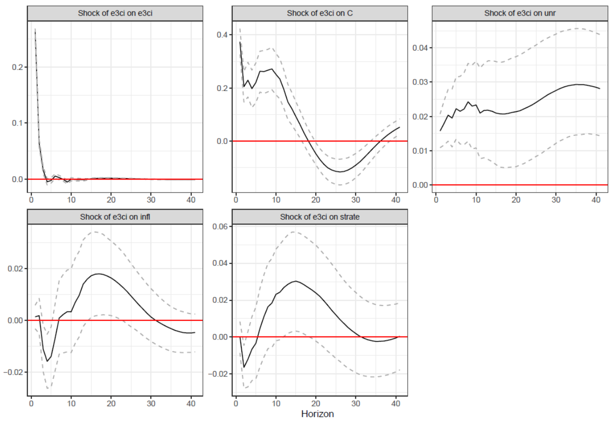

Figure 8: *Italy: IRFs to E^3CI shock for Manufacturing production*

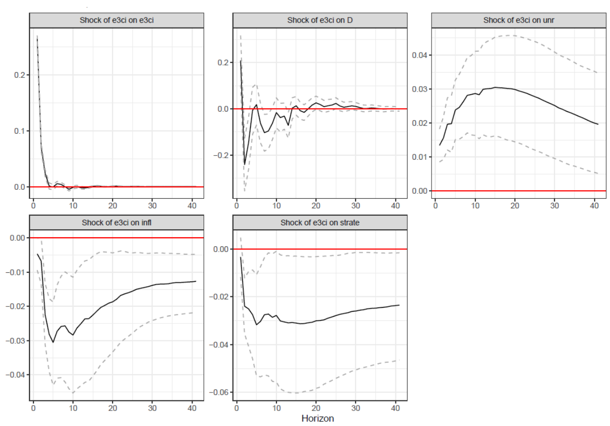

Figure 9: *Italy: IRFs to E^3CI shock for Energy production*

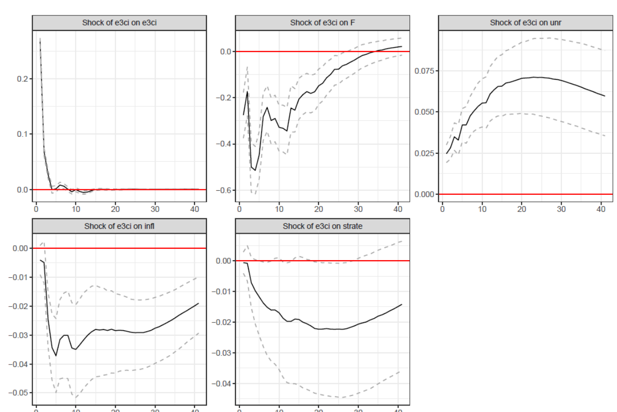

Figure 10: *Italy: IRFs to E^3CI shock for Construction production*

Previous results show evidence of heterogeneity in the response of countries to composite severe weather shocks, as well as variations among sectors of production, in line with the results from Billio et al., 2020. To compare countries and sectors in an easier way, we put on the same graph the cumulated impulse responses after six and twelve months, as well as their confidence bounds at 68% (see Figure 11). Overall, France appears to be the most resilient to weather shocks as the amplitude of responses is lower than the one for Germany and Italy. France has a negative significant response to composite weather shock for *Mining and quarrying* (B) and for *Construction* (F). In both Germany and Italy, it turns out that a weather shock leads to a strong positive response of the *Mining and quarrying* sector. Interestingly, the *Construction* sector (F) is asymmetrically impacted in those countries: positively in Germany but negatively in Italy. As construction is an outdoor activity, it is likely that some specific weather conditions have a strong impact (see below). Note also that Italy is the only country to see a significantly positive response of the *Manufacturing* sector to the composite weather shock.

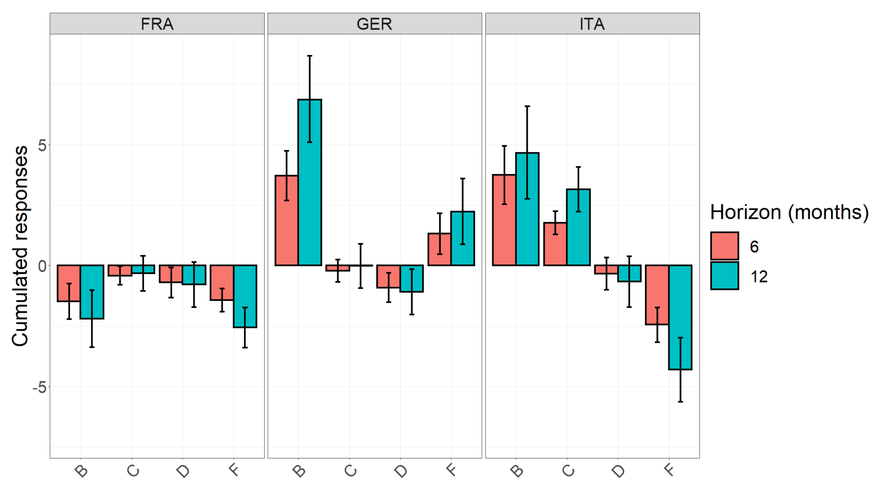

Figure 11: *Cumulated responses to a shock in the E^3CI for the main Sections. The whiskers represent 68% confidence intervals.*

4.2 Macro effects of weather-specific shocks

A major concern when using the composite E^{3}CI index is that it summarizes all kinds of extreme weather events into a single index, while different types of extreme weather shocks might impact production in different ways, and potentially offset each other. This might also help explain why we find such heterogeneity across countries and across sectors. In this respect, we now look at the impact of the individual components of the E^{3}CI index on sectoral production of countries.

For each of the three countries, we assess the impact of the five weather-specific shocks, namely heat stress, cold stress, drought, heavy precipitation and intense winds, on the three various production sectors (manufacturing, construction and energy). So we now have three dimensions in our results: country, weather shocks and production sectors. To summarize the results in graphs, we only consider IRFs to specific weather shocks at 6 months (red bars) and 12 months (red bars). Cumulated responses are shown along with their 68% confidence bounds.

Figure 12 reports the cumulated responses of the manufacturing production. We point out the usefulness of disagregating the composite index, as responses to some shocks appear now 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 2 and 5). 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 significantly positive, except for the response to a drought shock which turns out to be largely negative. In opposition, a drought shock tends to generate a cumulated positive response of the Italian manufacturing production of about 5% after one year. Symmetrically, an excess of precipitation generates a large drop in manufacturing production of about 3% after one year. This high sensitivity

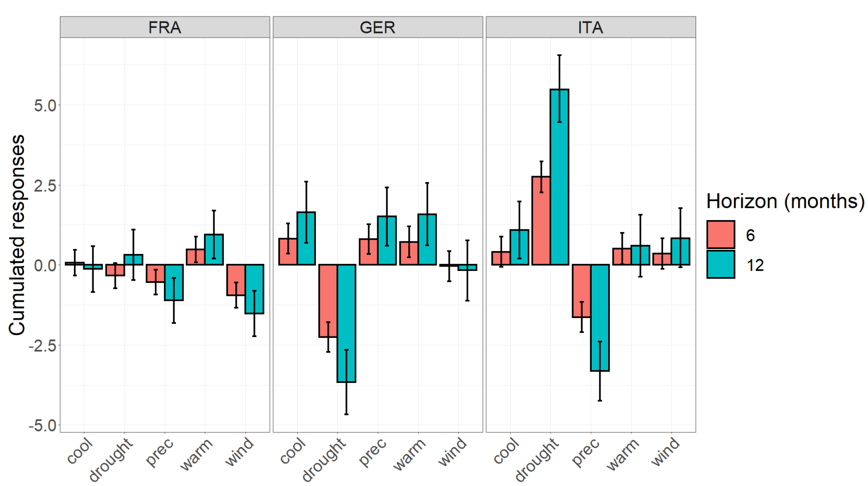

Figure 12: *Cumulated responses of manufaturing production to the 5 weather shocks. The whiskers represent 68% confidence intervals.*

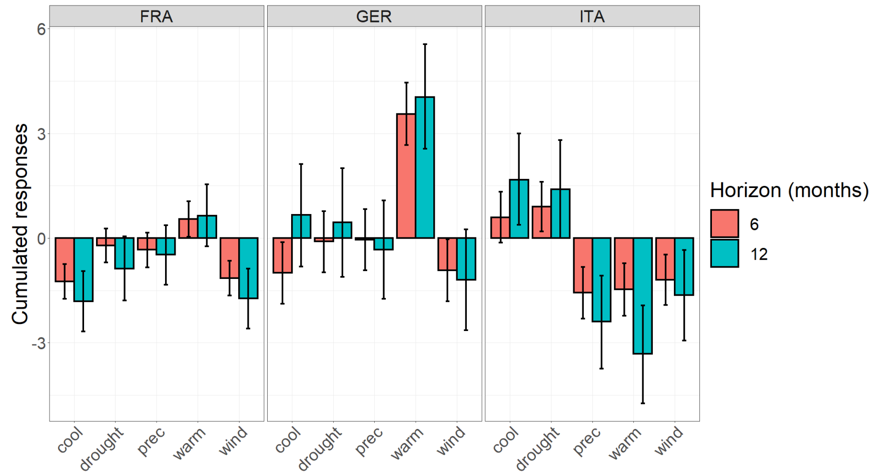

Figure 13: *Cumulated responses of construction production to the 5 weather shocks. The whiskers represent 68% confidence intervals.*

of the Italian manufacturing sector to an excess or a deficit of rainfall is a salient fact of our results. Overall, this largely contributes to the strong positive response of the sector to a composite shock, as can be seen in Figure 8.

Figure 13 reports the cumulated IRFs of the construction sector to various weather shocks. The dynamic effect of the composite weather shock points out a divergence between, on the one hand, France and Italy showing a drop in production (Figures 7 and 10), and Germany, on the other hand (Figure 4). It turns out that the positive reaction of the German construction sector is mostly driven by a heat stress that generates a cumulated response of more than 3% after 6 and 12 months. At the same time, other shocks do not generate significant responses in this country. Interestingly, a similar shock leads to a large dive in Italy, while France doesn't show any significant reaction to this shock. These results suggest that a positive temperature shock differently impacts a country depending on its latitude. Indeed, a country in the North of Europe, which can be considered as a cool country compared to other European countries, tends to see its construction activity positively affected by a heat stress. In opposition, a Southern European country like Italy, which can be considered as hot country in Europe, negatively reacts to a heat stress. Construction is an outdoor economic activity that seems to be sensitive to high temperatures, positively or negatively depending on the latitude. We also note that 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.

The production in energy is the sector that shows the lowest heterogeneity among countries. Indeed, as expected, a cool stress generates a positive cumulated response of energy production in all countries, while a heat stress leads to a significant fall in production across the board. Again, Italy is the most sensitive country as we also

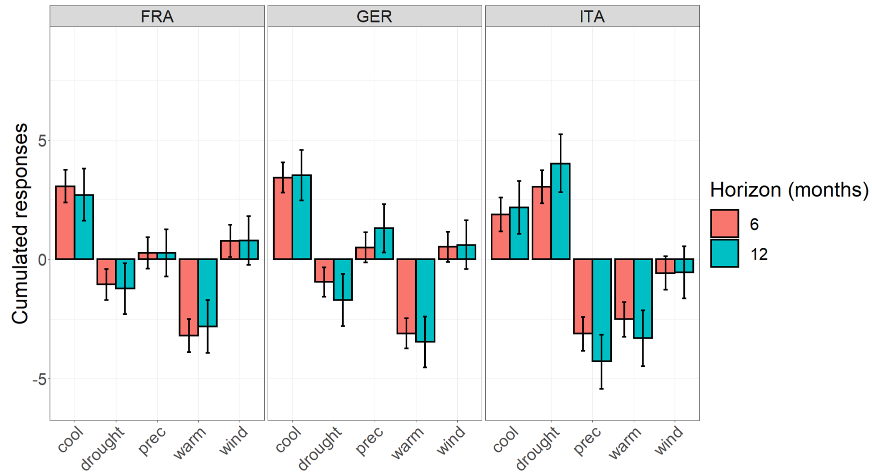

Figure 14: *Cumulated responses of energy production to the 5 weather shocks. The whiskers represent 68% confidence intervals.*

get a strongly significant reaction to drought and precipitation shocks on the sector. Indeed, an excess of precipitation steers a large fall in energy production, while in opposition a sequence of days of droughts conducts to an increase. Therefore, it turns out that the overall rather weak response to the composite weather shock hinders large positive and negative responses to various weather-specific shocks (positive for cool stress and droughts, negative for heat stress and precipitation).

5 Additional results

In this section, we present additional empirical results focusing first on service production, then on some non-linear patterns in the response to composite weather shocks. The first type of non-linearity that we consider is an asymmetric response of production to the size of the shock as pointed out by Burke et al., 2005. The second type of non-linearity that we check is a sensitivity to business cycle phases, as responses to weather shocks can differ whether the economy is in recession or expansion as highlighted in Billio et al., 2020. To assess evidence of non-linearities, we focus on the composite E^3CI shock that we integrate into a non-linear Local Projection approach as described in equation (3.2.3) in order to estimate IRFs.

5.1 Impact on the service sector

As far as the production of services is concerned, we unfortunately have only access to French data on a monthly basis.[6] We compute IRFs from various weather-specific shocks by integrating service production into a SVAR model, as we did in

[6] According to Eurostat, data for most German services are only available from 2016 onwards and are not available for Italian services.

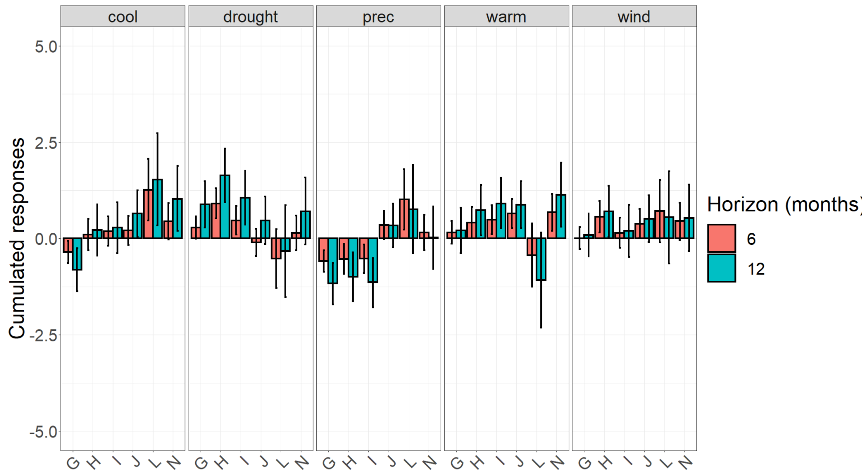

Figure 15: *Cumulated responses of services production in France to the 5 weather shocks. The whiskers represent 68% confidence intervals.*

the previous section. We only focus on responses after 6 and 12 months. Figure 15 contains the cumulated responses of the various sub-sectors in production of services, ranging from G (*Wholesale and retail trade*) to N (*Administrative and support service activities*) (see Table 1). Overall, compared to other sectors considered in the previous section, the response of service production to the various weather-specific shocks is relatively muted, though generally positive. Periods of heat and cool stresses tend to be associated with slightly positive responses of service production, though most of them are not significant. An excess of precipitations leads to negative responses of production in three sub-sectors: *Wholesale and retail trade*, *Transportation and storage* and *Accommodation and food services*. It is also noteworthy that a drought shock implies a positive response after 12 months of production in the *Transportation and storage* activity. Finally, we note that a wind shock does not seem to affect service production as all the IRFs lie within the confidence bounds after 6 and 12 months. We should be careful with the interpretation of results for services, as we already noted that France is overall less responsive than the other two countries to weather shocks.

5.2 Non-linearity to the size of the shock

It seems quite intuitive to assume that a major weather event, of unusual amplitude, is likely to have a disproportionate impact of production compared to a shock of more standard size. This hypothesis has been confirmed by Burke et al., 2005, who show that global productivity around the world is non-linear in temperature, with productivity peaking at a temperature of 13 degrees Celsius and then declining strongly for higher temperature. Their analysis is however limited to temperatures and it would be interesting to generalize to other weather-specific shocks. This is our objective here, through the estimation of IRFs obtained via non-linear LPs (see section 3.2.2). We use the lagged (at $t-1$) composite E^{3}CI index as transition variable. This corresponds to checking for potential non-linear effects to the size of the shock. Therefore, we are implicitly assuming that there are two regimes: a regime of large weather shocks and a regime of small shocks.

Figure 16 shows the IRFs of manufacturing production in Germany to a composite weather shock when the amplitude of the shock is small (low regime, black lines) and when it is large (high regime, blue lines), as well as 68% confidence bounds. Similar graphs for France and Italy are presented in the Appendix in Figures 21 and 22, respectively. We first note that the IRFs of manufacturing production go in opposite directions: while a small shock tends to generate a significant positive response, a large shock clearly leads to a persistent drop in production. This differential between the two types of weather shock is interesting to underline as the total impact the composite index on manufacturing production was rather muted, excepted one month after impact (Figure 2). Similar differences in the evolution of the IRF overtime can be seen for inflation: a large shock leads to persistent disinflationary pressures, while a small shock steers inflation tensions. As regards unemployment rate and the short-term interest rate, they show differentiation in regimes but only after a certain horizon of about two years. In France, results are more mixed. However, we see a differentiation in the response of unemployment rate that strongly increase after a large weather shock. Last, Italy does not show any clear non-linear patterns in the response of manufacturing production to the size of the composite weather shock.

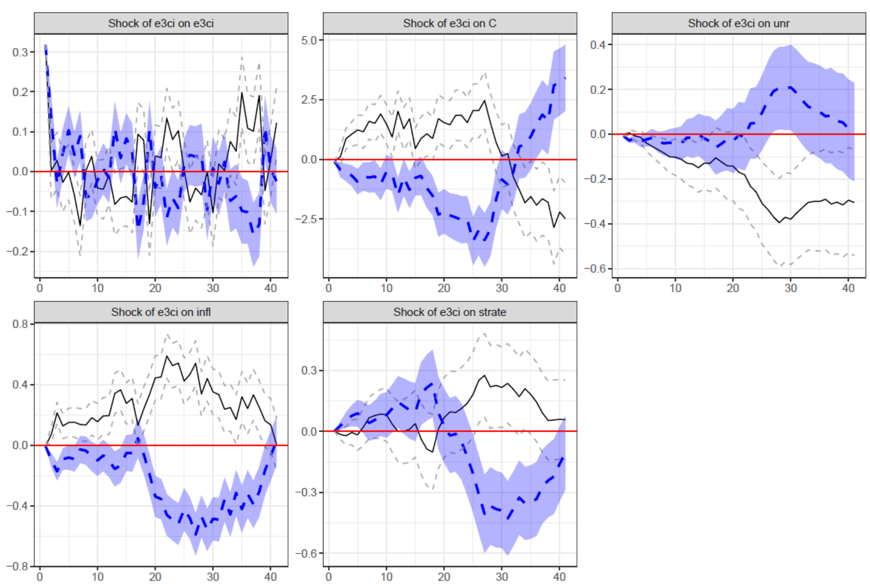

Figure 16: *Germany: Non-linear IRFs of manufacturing production and macro variables with respect to the size of the composite weather shock E^3CI, as well as 68% confidence intervals.*

5.3 Non-linearity to the business cycle

Lastly, we would like to check a result put forward by Billio et al., 2020, according to which there is evidence of non-linearity with respect to the business cycle, namely there is a stronger impact on production of weather shocks during recessions than during expansions. In this respect, we estimate IRFs to a composite weather shock E^3CI on the manufacturing production for the three countries. The approach relies on a non-linear LP framework as above. We allow for two regimes of economic growth using as transition variable the European Sentiment Index (ESI), a composite sentiment index of various surveys released by the European Commission. The ESI reflects business cycle conditions in the sense that the ESI reaches low values during phases of low economic growth and reaches high values during phases of high economic growth. This index is widely used by practitioners to track euro area business cycles in real-time. IRFs of manufaturing production in both regimes of growth are presented in Figure 17 for France, Figure 23 for Germany and Figure 24 for Italy (the two latter figures can be found in the Appendix). Blue lines correspond to IRFs within the low growth regime and dark lines to IRFs within the high growth regime.

We do not find any significant differences between the IRFs of manufacturing production in the two alternative regimes of growth, for all the countries, suggesting thus that the hypothesis from Billio et al., 2020 does not hold against our background[7]. Interestingly, if we focus on France (Figure 17), we note that other aggregate macro variables do respond differently in the two regimes. In particular, unemployment rate shows a clear rise after a weather shock during the low growth regime, while

[7] This wedge could possibly be due to differences in the definition of business cycle phases.

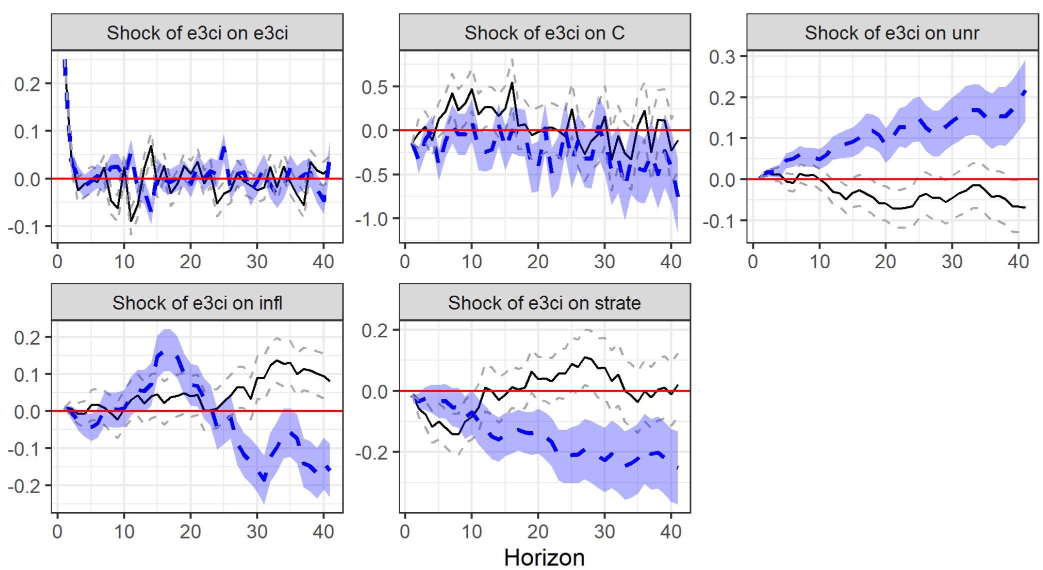

Figure 17: *France: Non-linear responses with respect to the business cycle of manufacturing production and macro variables to the composite weather shock E^3CI, as well as 68% confidence intervals.*

the reaction is muted during the high growth regime. Similarly, we observe the same pattern in the response of central bank interest rates, moving significantly downward after a weather shock during the low growth regime. In comparison to France, Italy and Germany appear to be less sensitive to the business cycle in the reaction of macroeconomic variables to extreme weather conditions.

6 Conclusions

This paper presents an assessment of the dynamic impact of extreme weather events on aggregate macroeconomic variables in the three largest European countries, namely Germany, France and Italy. For each country we carry out an econometric modelling analysis based on SVAR modelling to compute impulse response functions (IRFs) to weather shocks. Weather data come from the IFAB Foundation and contain a composite index summarizing information about the main climatic hazards, as well as its five components, that is cold and heat stresses, droughts, heavy precipitations and intense winds. In addition, we also disentangle the responses according to production sectors of the economy, namely manufacturing, energy, construction and services.

Empirical results show an overall significant impact of weather shocks on sectoral production, as well as on other macroeconomic variables, with a strong heterogeneity among countries and sectors. In particular, France appears as the most resilient to weather shocks, while, on the contrary, Italy strongly reacts. Among the sectors, manufacturing and construction are the most sensitive to extreme weather conditions. But interestingly, the direction of the response is not always the same. For example in Italy, a clear opposition emerges between the manufacturing and the construction sectors. Indeed, a weather shock clearly generates a surge in manufacturing production lasting about 1.5 year, while, in opposition, the construction sector sees a persistent and significant drop in its activity, up to 2 years after the initial date of the shock. This latter dive is associated with significantly negative response of inflation and a rise in unemployment. As regards the construction sector, results suggest that a positive temperature shock differently impacts a country depending on its latitude. Indeed, a country in the North of Europe, which can be considered as a cool country compared to other European countries, tends to see its construction activity positively affected by a heat stress. In opposition, a Southern European country like Italy, which can be considered as hot country in Europe, negatively reacts to a heat stress.

In addition, we also check for evidence of non-linear patterns in the results. We first find that the size of the weather shock matters in the sense that a large shock leads to disproportionate IRFs. This is especially true in Germany where manufacturing production and inflation sharply fall following a large weather shock. There is less evidence of non-linearity to the business cycle phases as regards sectoral production, but macro variables do show a clear non-linear response depending on the phase of the business cycle, especially in France.

This paper builds on previous results obtained for the U.S. economy by Kim et al., 2021 and contributes to point out that, nowadays, extreme weather hazards do not only affect low income countries and the agricultural sector, but also advanced economies and other sectors of production such as manufacturing and construction. This obviously supports a global solution to climate change issues and a strong involvement of advanced countries.

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Appendix

Appendix 1: Weather data

To measure extreme weather we take advantage of the The European Extreme Events Climate Index (E^{3}CI), which is a new dataset of indexes aiming at providing information about the areas affected by different types of weather-induced hazards and the severity of such events. The E^{3}CI, which is available at the country level, includes five components collecting information about the main weather hazards: cold and heat stresses, droughts, extreme precipitations, and extreme winds. Each component uses an indicator as proxy for several hazards. The reference value is computed on the 1981-2010 time span while, at monthly basis, the E^{3}CI shows a standardized anomaly with respect to this reference value. Components are defined as follows:

1. **Heat stress:** on the reference period 1981-2010, for each calendar day, the maximum temperature of the surrounding five days is considered. The 95^{th} percentile among the 150 values (5 days times 30 years) is computed and assumed as threshold. For each month j, the mean value $\mu(j,\ T_{max})$ and the standard deviation $\sigma(j,\ T_{max})$ of the number of days exceeding the corresponding threshold are calculated. Finally, the index is obtained by standardizing the number of days exceeding the corresponding threshold $HS_{j,k}$ for each month j and year k, according to the formula:

$$HS_{std,j,k} = \frac{HS_{j,k} - \mu(j,\ T_{max})}{\sigma(j,\ T_{max})}$$

2. **Cold stress:** on the reference period 1981-2010, for each calendar day, the minimum temperature of the surrounding five days is considered. The 5^{th} percentile among the 150 values (5 days times 30 years) is computed and assumed as threshold. For each month j, the mean value $\mu(j,\ T_{min})$ and the standard deviation $\sigma(j,\ T_{min})$ of the number of days lower than the corresponding threshold are calculated. Finally, the index is obtained by standardizing the number of days exceeding the corresponding threshold $CS_{j,k}$ for each month j and year k, according to the formula:

$$CS_{std,j,k} = \frac{CS_{j,k} - \mu(j,\ T_{min})}{\sigma(j,\ T_{min})}$$

3. **Drought:** the Standard Precipitation Index (SPI) is assumed as reference indicator considering 3 months as accumulation period of interest (SPI-3). Over 1981-2010, for each month j, the 30 cumulated values are fitted to a gamma probability distribution which is then transformed into a normal distribution. For each month j and year k, the $SPI-3_{j,k}$ value represents units of standard deviation from the long-term reference mean. According to the canonical approach, positive SPI indicate values greater than median precipitation and

negative values indicate less than median precipitation. In E^{3}CI, to maintain the consistency with the other components, the opposite of $SPI - 3_{j,k}$ is considered.

4. **Heavy precipitation:** on the reference period 1981-2010, for each month j, the 95th percentile of daily precipitation is computed. Then, the exceedance value at monthly basis is computed as: $EP_{j,k} = \sum_{i=1}^{n_j} \max\left[0;\ P_{i,j,k} - P_{95,j}\right]$ where $P_{i,j,k}$ represents the daily precipitation (day i, month j, year k). Over the reference period, for each month j, the mean value $\mu\,(\ EP_j)$ and the standard deviation $\sigma\,(\ EP_j)$ of the exceedance value are calculated. Finally, the index is obtained by standardizing the exceedance value for each month j and year k, according to the formula:

$$EP_{std,j,k} = \frac{EP_{j,k} - \mu\,(EP_j)}{\sigma\,(\ EP_j)}$$

5. **Intense winds:** on the reference period 1981-2010, for each month j, the 95th percentile of daily maximum wind speed $w_{95,j}$ is computed. Then, on a monthly basis, the Local Loss Index (Donat et al., 2011) is calculated as:

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

where $w_{max,i,j,k}$ is the maximum wind speed computed considering mean hourly values. Over the reference period, for each month j, the mean value $\mu\,(\ LLI_j)$ and the standard deviation $\sigma\,(LLI_j)$ are calculated. Finally, the index is obtained by standardizing the exceedance value for each month j and year k, according to the formula:

$$LLI_{std,j,k} = \frac{LLI_{j,k} - \mu\,(\ EP_j)}{\sigma\,(\ EP_j)}$$

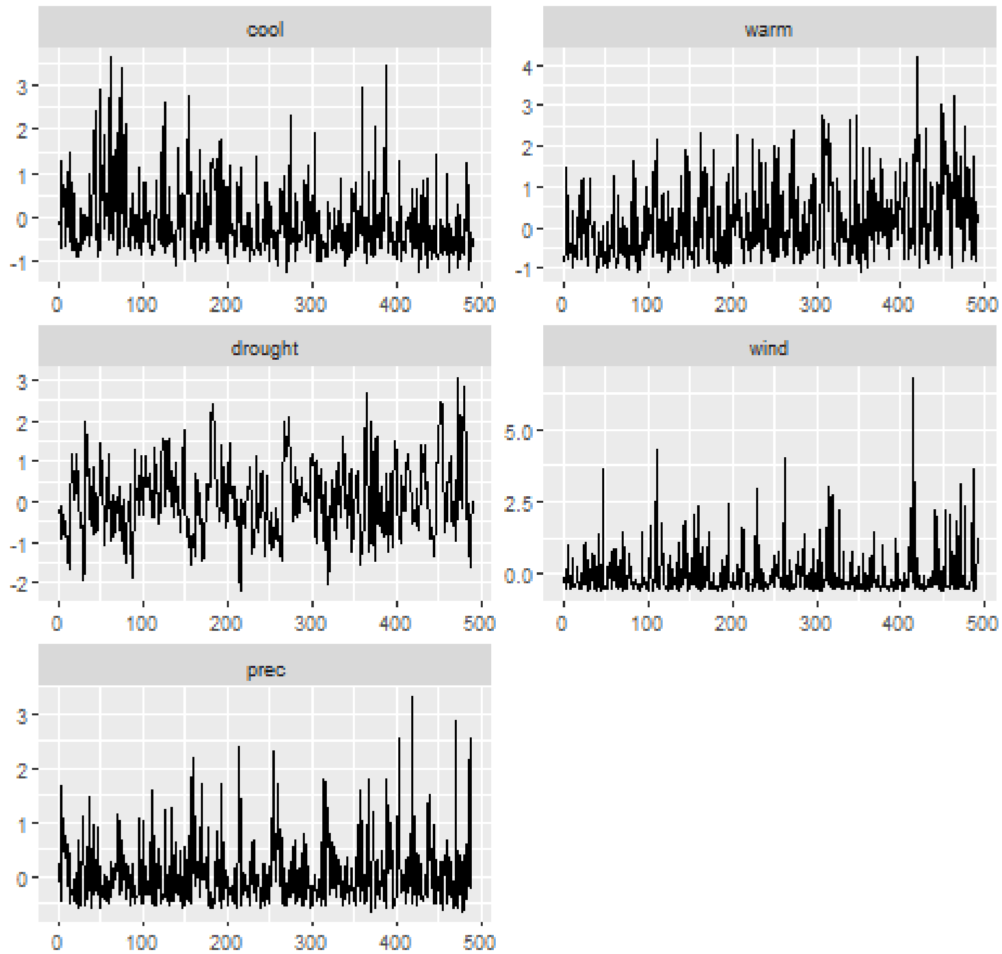

Figure 18: *E^3CI components for Germany*

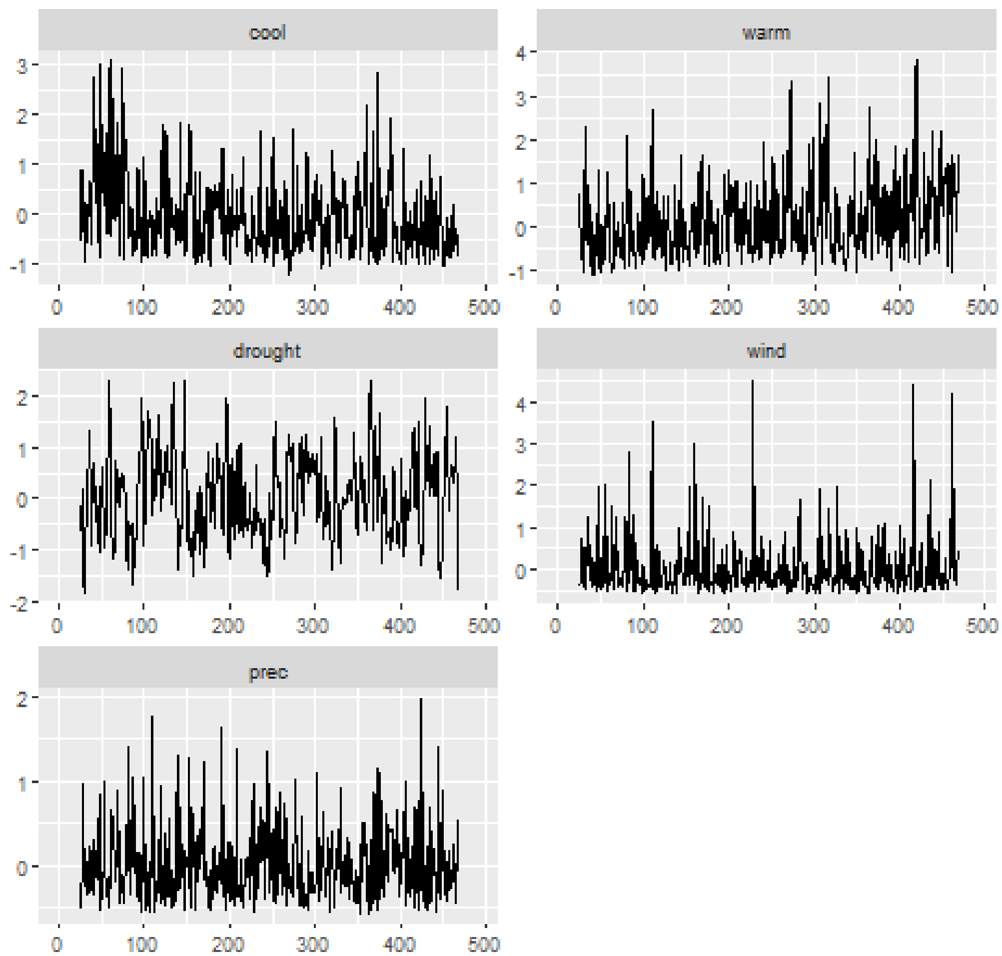

Figure 19: *E^3CI components for France*

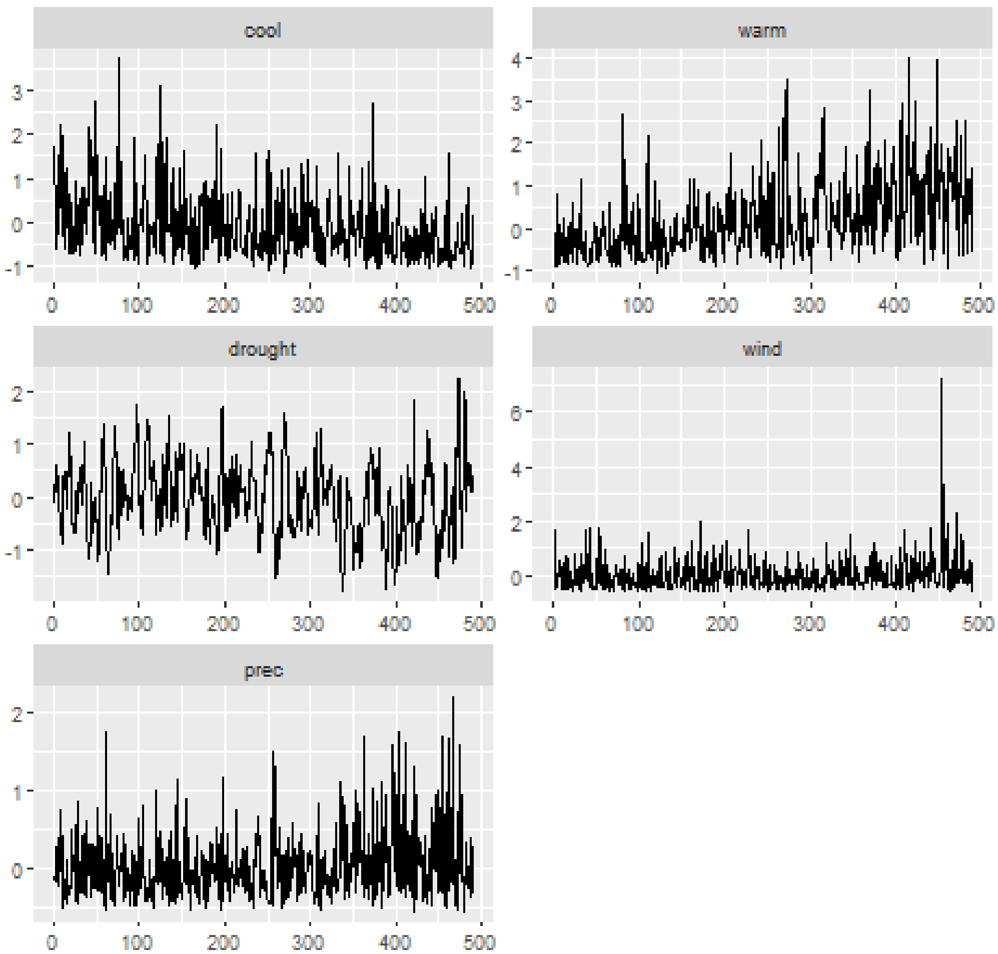

Figure 20: *E^3CI components for Italy*

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: Non-linear IRFs to composite weather shock of manufacturing production and other macro variables, with respect to the business cycle (France and Italy)

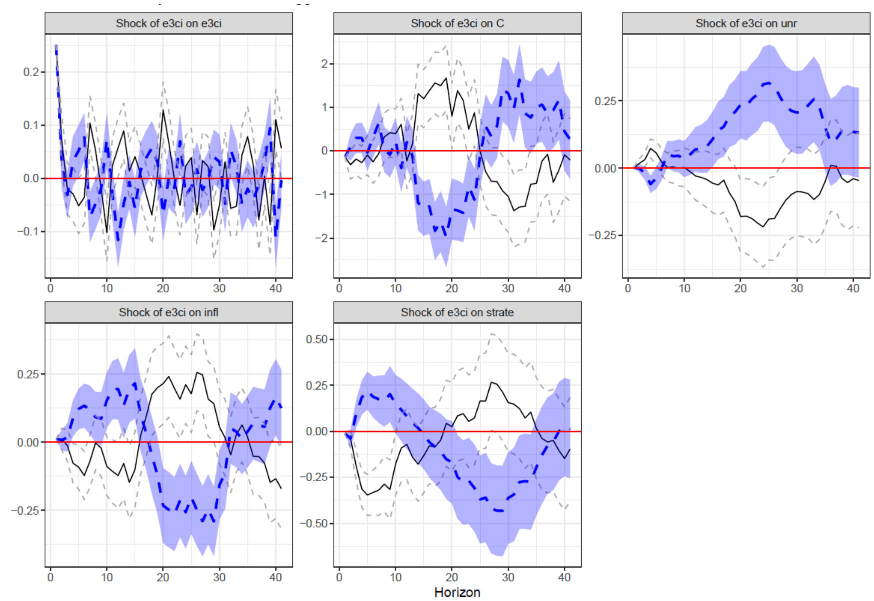

Figure 21: *France: Non-linear IRFs of manufacturing production and macro variables with respect to the size of the composite weather shock E^3CI, as well as 68% confidence intervals.*

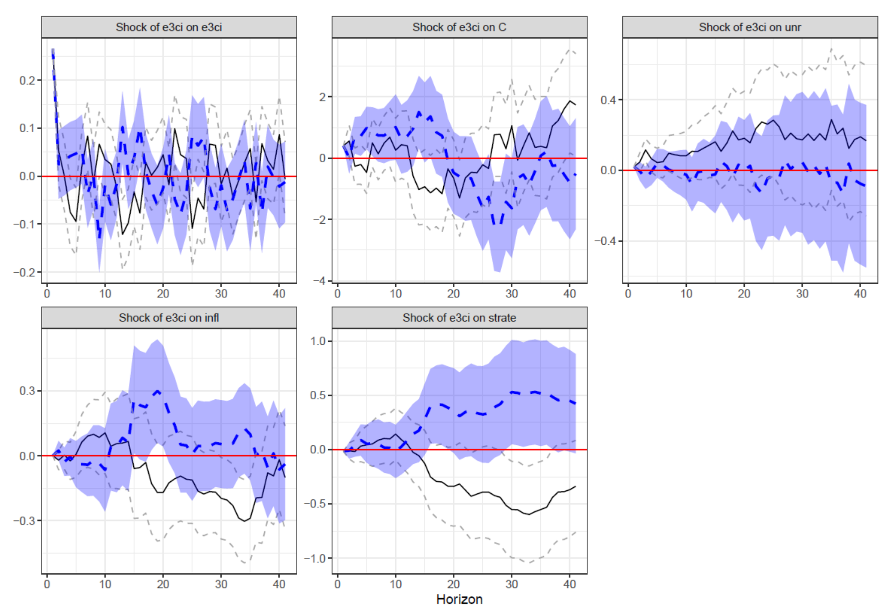

Figure 22: *Italy: Non-linear IRFs of manufacturing production and macro variables with respect to the size of the composite weather shock E^3CI, as well as 68% confidence intervals.*

Appendix 4: Non-linear IRFs to composite weather shock of manufacturing production and other macro variables, with respect to the business cycle (Germany and Italy)

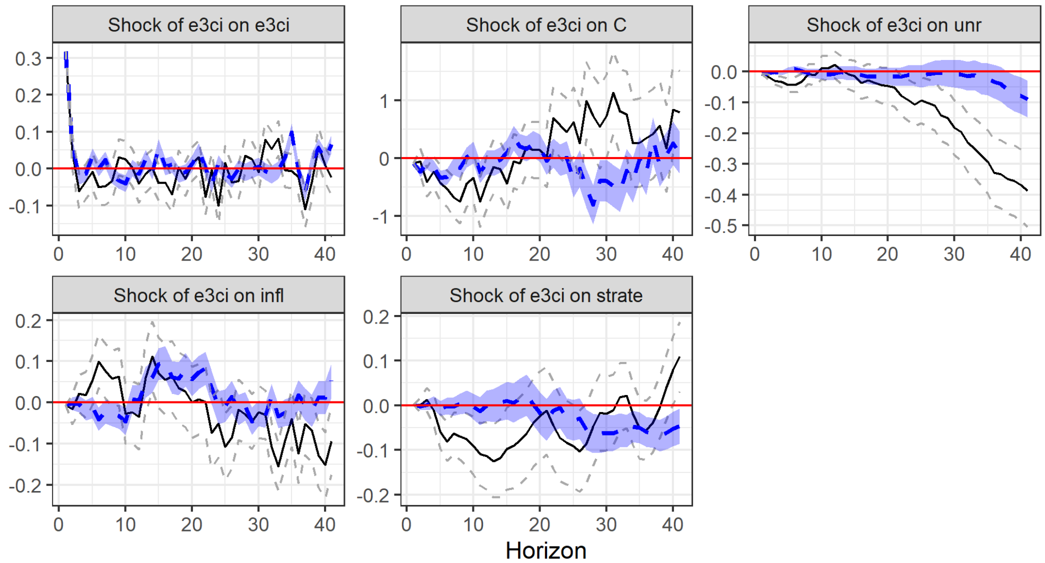

Figure 23: *Germany: Non-linear responses with respect to the business cycle of manufacturing production and macro variables to the composite weather shock E^3CI, as well as 68% confidence intervals.*

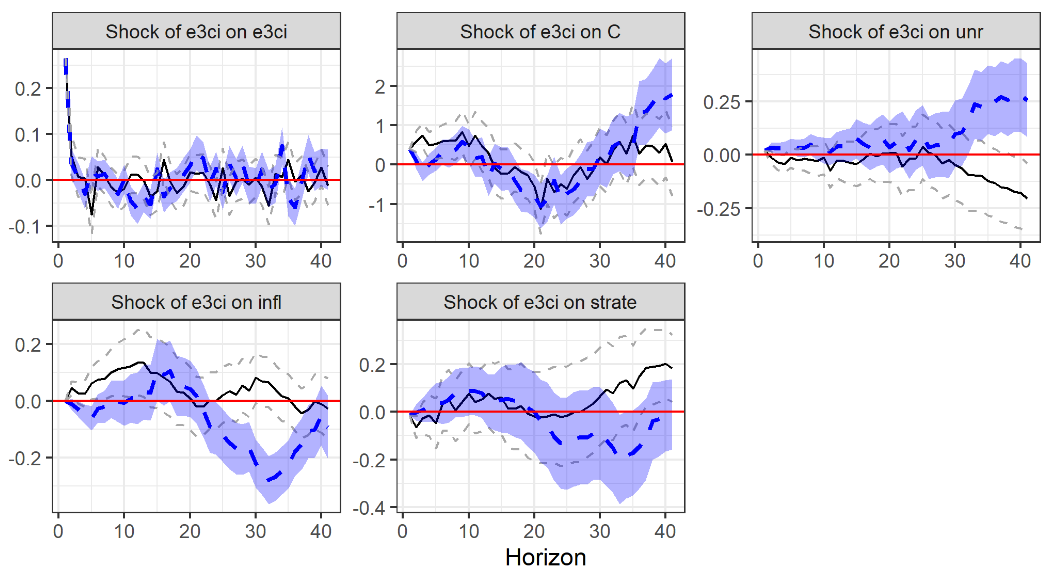

Figure 24: *Italy: Non-linear responses with respect to the business cycle of manufacturing production and macro variables to the composite weather shock E^3CI, as well as 68% confidence intervals.*