Dynamic effects of weather shocks on production in European economies

Daniele Colombo[1] Laurent Ferrara[2]

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Abstract

This paper evaluates the dynamic impact of weather shocks on economic activity in the three main European countries—Germany, France, and Italy. To capture meaningful variations in weather patterns, we propose a novel monthly Composite Weather Index (CWI). This index incorporates relevant information of five weather-specific shocks: heat, cold, drought, precipitation, and winds. We estimate a series of country-specific Bayesian Structural Vector Autoregressive models to assess the effects of weather shocks on distinct production sectors, including energy, construction, manufacturing, and services, as well as sectoral prices. The findings reveal evidence of both direct and indirect significant impacts 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.

[1]London Business School. Email: *dcolombo@london.edu*
[2]Skema Business School - University Côte d'Azur. Email: *laurent.ferrara@skema.edu*

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1 Introduction

The complex relationship between economic activity and climate events has been widely acknowledged, with a consensus among experts that economic activity contributes to long-term negative effects on climate. However, empirical evidence demonstrating reverse causality—from climate shocks to aggregate economic activity—has been relatively limited. In recent years, there has been a notable increase in research efforts aimed at identifying the impact of climate on the business cycle. Noteworthy examples include the studies by Kim et al. (2021) for the U.S. and Billio et al. (2020) for European countries. In this literature, the term "climate" conventionally refers to the joint probability distribution of outcomes describing the state of the atmosphere, oceans, and freshwater, including ice (Dell et al., 2012). In this paper, we focus on large deviations from seasonal averages of the empirical realization of climate: *abnormal* weather conditions and their variations over time. The literature suggests that weather shocks generally have adverse effects on short-term aggregate economic activity, particularly in industrial manufacturing, with significant country-specific heterogeneity. Other economic sectors, such as energy and construction, have been less frequently studied when assessing short-term effects. Conversely, longer-term effects in agriculture have received more attention in this context (Gallic & Vermandel, 2020). It is important to distinguish this body of research on the macroeconomic effects of weather shocks from studies focusing on the impacts of *extreme* weather events typically classified as natural disasters (e.g., hurricanes or floods). For example, Strobl (2011) and Felbermayr and Gröschl (2014) examine the economic impacts of natural disasters on economic activity, while Kruttli et al. (2023) and Ferriani et al. (2023) investigate their effects on the financial system.

Temperature time series, due to their long historical availability, are frequently utilized in studies aiming to identify economic responses to temperature fluctuations, rather than to other climate aspects. This approach is employed by Natoli (2022) for the U.S. economy, Lucidi et al. (2022) for various European economies, and by Burke et al. (2005) and Acevedo et al. (2020) for a broad panel of high- and low-income countries. Some research also investigates the impacts of severe precipitation events and droughts, as in Billio et al. (2020), who examine these effects for several European economies. Additionally, there are studies examining the effects of comprehensive weather indices, such as Kim et al. (2021), who explore potential time-varying effects of extreme weather on the U.S. economy over the past 60 years using the Actuaries Climate Index.[1]

Our objective in this paper is to evaluate the short- to medium-run effects of various types of weather shocks on output by sector in Germany, France, and Italy—the three largest European economies. We specifically analyze the impacts on energy production, manufacturing production, and construction, comparing the effects across these sectors. Furthermore, we investigate contagion effects between sectors and dif-

[1]ACI, provided by the American Academy of Actuaries and Canadian Institute of Actuaries

ferentiate between the direct and indirect consequences of weather shocks. To study these effects, we also incorporate sectoral producer and consumer prices. A key innovation of our study lies in the construction of the weather shocks. We utilize granular data that we aggregate, weighting by proxies of economic activity, to construct five distinct country-level weather indices, which can be interpreted as "shocks": cold and heat, drought, precipitation, and wind. We then integrate these series to obtain the Composite Weather Index (CWI). This comprehensive index enables us to contribute to the literature by examining the economic impacts of multiple weather dimensions—not limited to temperature. Our empirical analysis is based on impulse response functions estimated through a series of Bayesian VAR models, which allows us to identify the impact of weather shocks. This methodology provides a coherent framework for directly comparing the responses of different sectors and countries to these shocks.

Our empirical analysis reveals several key findings that shed light on the macroeconomic effects of weather shocks on European economic activity, highlighting notable sectoral and geographical differences. First, weather shocks have a significant direct impact on the construction sector. Cold weather exerts a substantial negative effect, while wind also has negative consequences, albeit to a lesser extent. Notably, a latitude effect is observed with heat shocks: these have a negative impact in Italy (a warmer country) but a positive impact in Germany (a colder country), indicating that geographic location plays a crucial role in the sector's response to weather changes. Second, the energy sector is influenced through both demand and supply channels. Temperature fluctuations affect the demand for heating, while wind impacts the supply side by influencing the cost of electricity production. This demonstrates that weather conditions can alter the sector's dynamics from multiple angles. Third, the manufacturing sector is less directly impacted by weather shocks. However, it experiences indirect effects primarily through changes in input costs, particularly energy prices, suggesting that weather-related disruptions in the energy market can ripple through to manufacturing. Additionally, our findings indicate significant heterogeneity across countries. France demonstrates greater resilience to weather shocks, with manufacturing largely unaffected except by heat through the energy costs channel. In contrast, Italy appears particularly vulnerable, consistent with previous findings such as those by Olper et al. (2021). Our study is, to the best of our knowledge, the first to explicitly examine the effects of weather shocks on services. We find that these exhibit demand complementarities with construction, as output and prices tend to move in tandem. However, due to data constraints, we can only analyze output for France. Finally, our analysis does not reveal significant non-linearities with respect to the business cycle or seasonal variations in response to weather shocks. Additionally, cross-country spillovers from weather shocks do not appear to be a significant issue in this study. These findings contribute to the literature by providing a nuanced understanding of how different economic sectors and countries respond to weather shocks, with implications for policy and risk management in the face of climatic variability.

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. Section 6 concludes. Additional figures, robustness checks, and technical details are presented in the Appendix.

2 Selected literature review

There is a substantial macroeconometric literature aimed at assessing the aggregate macroeconomic dynamic effects of structural shocks. Seminal papers include Romer and Romer (2004) on monetary policy shocks, V. Ramey (2011) on government spending and fiscal shocks, and Bloom (2009) on uncertainty shocks. In recent years, increasing attention has been given to the role of weather shocks, driven by empirical evidence that climate hazards are becoming more frequent, more intense, and have long-lasting consequences. These impacts have been documented as significant in areas such as health, agriculture, tourism, employment, sales, and overall macroeconomic activity (see, e.g., Bigano et al., 2005, Tol, 2009, Dell et al., 2012, Wilson, 2019, Roth Tran, 2020, Vicedo-Cabrera et al., 2021, and Ballester et al., 2023).

Several theoretical models have been proposed to analyze the impact of climate on economic activities, such as integrated assessment models (Nordhaus, 1993; Hassler and Krusell, 2018), which focus primarily on long-term effects. Recent reviews on the economic effects of weather-related shocks include Hsiang (2016) and Giglio et al. (2021). Empirically, econometric models allow for a quantitative assessment of the effects of weather shocks on business cycles and their transmission channels (Kamber et al., 2013; Mumtaz and Alessandri, 2021). Two main types of econometric modeling approaches have been considered.

On the one hand, panel regressions offer the advantage of allowing for a high geographical resolution and a larger number of observations. This approach allows for the integration of a significant amount of regional data into the analysis. For instance, Wilson (2019) employs a dynamic panel approach to estimate the effects of temperature, precipitation, and snowfall on monthly employment growth in the U.S. Starr (2000) utilizes Heating Degree Days (HDD) and Cooling Degree Days (CDD) in a panel regression to demonstrate that U.S. monthly consumer spending is partially influenced by temperature fluctuations. Bloesch and Gourio (2015) also use temperatures and snowfall in a panel regression setting to study the impact of anomalous weather deviations on various non-farm employment sectors in the U.S. Bigano et al. (2005) adopt a panel approach to examine the relationship between temperature and tourism in Italy, with the panel dimension corresponding to Italian regions. Additionally, Kotz et al. (2022) employ a precipitation index in a fixedeffects panel regression at a yearly frequency to estimate the impacts on regional economic growth, finding that economic growth rates decline with increases in the number of wet days and extreme daily rainfall. Billio et al. (2020) investigate the interplay of weather shocks with business and financial cycles, differentiating between countries and types of 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.

On the other hand, panel regressions are not ideal for estimating the dynamic effects of weather shocks over time. It is crucial for economic research to determine whether the effects of such shocks are persistent or transitory. In this respect, Structural Vector Autoregressive (SVAR) models are well-suited for efficiently estimating impulse response functions (IRFs) to various types of exogenous shocks. For instance, Ciccarelli et al. (2023) use an SVAR strategy to examine the impact of temperatures on inflation in four European countries, finding that temperature increases tend to raise inflation, with a more pronounced effect in warmer countries. Similarly, Kim et al. (2021) employ a Smooth-Transition VAR (ST-VAR) model incorporating standard macroeconomic variables to investigate the potential time-varying effects of severe weather shocks on the U.S. economy over the past 60 years. They rely on the Actuaries Climate Index (ACI), developed by the American Academy of Actuaries and the Canadian Institute of Actuaries, which consolidates observations of temperatures, rainfall, drought, wind speed, and sea level. They find that an increase in the ACI causes adverse long-lasting effects on industrial production, an increase in the unemployment rate, and upward inflationary pressures.

Many empirical studies have studied the agricultural sector. For instance, Ciscar et al. (2011) quantify the potential consequences of climate change on Europe's agricultural sector. Similarly, Gallic and Vermandel (2020) examine the effects of droughts on agricultural production and macroeconomic fluctuations in New Zealand, finding that drought shocks account for more than a third of GDP and agricultural output fluctuations. These findings indicate a direct impact of weather conditions on harvests, where adverse weather conditions result in reduced production and increased prices. However, recent literature has begun to explore other sectors of the economy that might be sensitive to such shocks, aiming to identify the potential transmission channels of severe weather conditions to the business cycle.

Some studies emphasize the *supply channels*, where factors of production are adversely affected by weather shocks. For instance, using a SVAR model, Donadelli et al. (2017) demonstrate that temperature shocks have a sizable, negative, and statistically significant impact on TFP, output, and labor productivity. Several other empirical studies, including Burke et al. (2005), Graff Zivin and Neidell (2014), Deryugina and Hsiang (2014), and Kalkuhl and Wenz (2020), also find negative effects of temperature increases on labor productivity. Similarly, Kim et al. (2021) document a simultaneous drop in industrial production and an increase in inflation following a composite weather shock, suggesting that such shocks act as negative supply shocks. Moreover, other works have explored the effects on employment. Wilson (2019) shows that, at the country level, contemporaneous local monthly employment growth increases with temperature, decreases with precipitation, and decreases with snowfall. Temperature and snowfall are estimated to have only temporary impacts, whereas precipitation is estimated to have both an immediate negative effect and a positive cumulative effect over time. Bloesch and Gourio (2015) use temperatures and snowfall to study the impact of anomalous deviations in weather on various non-farm employment sectors in the U.S., finding that weather has a significant but short-lived effect on most economic sectors studied, except for utilities, construction, and hospitality, where the effect is more persistent. Similarly, Graff Zivin and Neidell (2014) highlight the sustained supply-driven impacts in sectors heavily exposed to weather conditions, such as construction. Downey et al. (2023) examine the implications of increasing precipitation volatility on construction and employment in the U.S., finding that employment falls in response to forecasted rainfall. The suggested mechanism is that firms adjust production when precipitation is anticipated.

Other studies have highlighted the role of *demand factors* in the impact of weather shocks. For instance, Ciccarelli and Marotta (2021) examine a panel of 24 OECD countries and estimate that climate events have a significant, albeit not substantial, macroeconomic effect over the business cycle. They argue that physical risks act as negative demand shocks by depressing both output and inflation. Auffhammer and Mansur (2014) provides a comprehensive review of the empirical relationships between climate conditions and energy consumption. In specific sectors, such as retail trade, weather shocks appear to be transmitted through shifts in consumer demand (Roth Tran, 2022). Roth Tran (2020) investigates the role of short- and long-run adaptation to climate in the apparel and sporting goods sectors using data from large US firms. The study finds minimal inter-temporal substitution and indicates that weather shocks can induce large and persistent fluctuations in retail sales, only partially mitigated by short-term adaptation measures. Arent et al. (2015) offer a broader review of the implications of weather changes on key economic sectors and services. Additionally, external demand can be influenced by weather conditions. Bigano et al. (2005) utilize raw monthly temperatures at the regional level in Italy and find that tourism is positively correlated with temperatures, with weather expectations also playing a significant explanatory role.

Considerable heterogeneity across sectors has been documented, indicating that weather conditions can exert divergent effects on different economic sectors. For instance, Parnaudeau and Bertrand (2018) examine the impact of weather on sales across various French sectors and find that a single weather shock can produce varied effects on sales depending on the sector. This sectoral heterogeneity is also apparent at the country level, particularly within Europe (Acevedo et al., 2020). Moreover, Billio et al. (2020) investigate the effects of weather shocks on industrial production growth and uncover evidence of uneven impacts across different phases of the business cycle and among the countries studied. Specifically, Southern European economies tend to suffer from prolonged high temperatures, while Central and Northern European countries exhibit asymmetric responses throughout the business cycle—benefiting during recessions and experiencing negative effects during expansions. Additionally, severe droughts generally have a detrimental impact on most

Northern European countries. Consistent with our findings, France is identified as the most resilient economy to weather shocks.

The literature on the macroeconomic impact of weather shocks is extensive. Our work contributes significantly to this field by introducing a framework that enables a coherent assessment of the dynamic effects of various weather shocks on output across different economic sectors. We construct new weather indices that can be updated to study multiple weather shocks over time. Our analysis reveals that different sectors can be impacted in diverse ways: immediately due to weather conditions, or through demand and supply channels, or indirectly via changes in costs. Additionally, we provide a comparative analysis of the responses of the three largest European economies, offering new insights into the sector-specific and cross-country variations in the impact of weather shocks.

3 Methodology

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

3.1 Data

To measure abnormal deviations in climate realizations we construct a novel index which we call the "Composite Weather Index" (CWI), which we will argue can be interpreted as a macroeconomic shock. We then study the propagation of these shocks on production in three key sectors of the economy: manufacturing, energy and construction. We complement these with producer price indices and consumer prices to enrich our understanding of the underlying mechanisms. Finally, we also use standard macro aggregate variables (unemployment and short-term ECB interest rates) as controls. We use data from January 1990 to December 2019.[2]

3.1.1 Weather data

We construct indices for abnormal deviations in five weather variables: cold and heat, drought, precipitation, and wind. We then consolidate these into a single index that measures abnormal weather deviations. This composite index allows for a comprehensive assessment of the overall impact of weather anomalies on economic activity by integrating the diverse effects of different weather conditions into a unified metric. This aligns with the increasing recognition of the need to consider additional weather variables impacting economic activity beyond temperatures, which have historically been the primary focus of the empirical literature (see for example Acevedo

[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.

et al. (2020), Burke et al. (2005), Lucidi et al. (2022), and Natoli (2022)). Indeed, recent years have seen the introduction of new indices, such as the ACI [3] for North America and the E^3CI[4]for Europe, which incorporate multiple weather indicators and have been used by some recent works in the economics literature, such as Kim et al. (2021).

In constructing a new index to study the impact of weather on the economy, our contribution to the literature is twofold. First, we utilize gridded granular weather data to compute abnormal weather deviations at the grid-cell level before aggregating them at the country level, the spatial resolution required for our analysis. This approach is crucial as it prevents the dilution of effects that can occur when different areas within the same country experience different weather conditions. For example, if Northern Italy experiences unusually cold temperatures in a given month while Southern Italy experiences unusually hot temperatures, the economic impact of these deviations is the sum of the effects of the cold weather in the North and the hot weather in the South, not the effect of the average weather at the country level. Although such situations are uncommon, given the spatially correlated nature of weather realizations, accounting for them is essential.

Furthermore, when aggregating grid-cell level weather data to the country level, we weight the data by proxies of economic activity, following the approach of Gortan et al. (2024). This method ensures a more accurate representation of the economic impact of weather deviations. When examining the impact of climatic conditions and weather events on the economy, it is crucial to consider the varying exposure of socio-economic activities within an administrative region. For instance, average temperatures in the industrialized North of Italy may differ significantly from those in the less industrialized South, and the magnitude of economic activities in these two regions varies greatly. As a result, economic activity in Italy may be disproportionately influenced by temperatures in the North compared to the South. Therefore, an aggregate analysis of weather data that does not account for the geographical distribution of socio-economic activities may introduce bias in assessing the economic impacts of climate realizations.

Lastly, as opposed to indices such as the E^3CI, which adopt a specific computation for each weather variable, we harmonize the computation across weather variables, ensuring a consistent and comprehensive analysis.

We compute each of our weather indices as follows:

1. We first consider the daily grid-level variable $W_{c,d}$, where c denotes a given grid-cell and d a day. This is for example the average daily temperature or the total precipitation amount registered at a given grid-cell. As suggested in Parnaudeau and Bertrand (2018), we detrend $W_{c,d}$ to avoid negative (positive) deviations being clustered at the start of the sample and positive (negative) deviations at the end of the sample in the presence of climate time trends, such as global warming.

[3] American Academy of Actuaries (2016).

[4] Giugliano et al. (2023).

2. We then compute the calendar-month-specific percentiles $W_{\tilde{t}}$, which we use as thresholds. It is natural to consider month-specific thresholds since weather variables exhibit strong seasonal patterns. We favor month-specific percentiles over day-specific ones to reduce noise. The use of calendar-specific thresholds represents a core difference from works such as Kotz et al. (2022), which utilize percentiles computed on the unconditional full time series. Furthermore, note that the use of calendar specific thresholds achieves seasonal adjustment by construction.

3. For each month, we compute the total in the days that exceed the threshold:

$$WM_{c,m,y} = \sum_{d=1}^{D_m} W_{c,d} \mathbb{1}\{W_{c,d} \geq W_{\tilde{t}}\},$$

   where D_m denotes the number of days in a calendar month m, and $\mathbb{1}\{\}$ is an indicator function that takes on value 1 when the daily observation is above the respective month-specific threshold.

4. These grid-cell level measures are aggregated to the country level using both a grid-cell level proxy for economic activity and administrative areas from the GADM dataset. The aggregation procedure is detailed in Gortan et al. (2024). We prefer using nocturnal light levels (Li et al., 2020) over alternative population weights because they provide a more accurate proxy for economic activity related to production, though the results are similar using either method[5]. The result of this aggregation is denoted as $WM^C_{m,y}$, where C represents the country index.

5. Finally, we standardise the weather index using month-specific means and standard deviations:

$$\frac{WM^C_{m,y} - \bar{W}^C_m}{\sigma^C_m}$$

   This standardization accounts for the inherent seasonal variability in weather conditions, allowing for a more accurate comparison across time as well as across weather variables.

Finally, the cold, heat, drought, precipitation, and wind shocks are averaged to obtain the Composite Weather Index (CWI), displayed in Figure 1, which shows the three country-specific CWIs, in addition to their smoothed versions, a 5-year window moving-average. The individual weather components of the CWIs for Germany, France and Italy are presented in Appendix 1 in Figures 16, 17 and 18, respectively.

Appendix 1 also gives additional details on the computation of these weather shocks and the data used. Our preferred computation of the weather indices is the one that uses the 95$^{\text{th}}$ percentile of the calendar-month-specific distribution as the

[5] This robustness check is not included in the main text for brevity but is available upon request.

threshold. However, in Appendix 3.4 we show that our results are robust to computing the CWI using the 98$^{\text{th}}$ or 99.9$^{\text{th}}$ thresholds.

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.[6] Furthermore, the components do not exhibit strong auto-correlations, and unit-root tests do not reveal changes in trends. 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.[7] 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 indices, both composite and components, as macroeconomic "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 take into account the accumulation of several smaller (but only when these are relevant, that is above the threshold) 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.

We perform several robustness checks on the computation of the Composite Weather Index (CWI). Appendix 3.2 presents the CWI when this is computed by counting the number of days in each month that exceed the specified threshold[8] This approach explicitly accounts for accumulation effects. Appendix 3.3 shows the results when the CWI is computed by first aggregating the weather observations at the country level *and then* constructing the shock by computing the exceedance values and standardizing. This approach yields less precise estimates of the effects, resulting in some responses being more confounded. In Appendix 3.1 we also propose a falsification test, we randomly shuffle the observations of the weather indices, reassigning them to different months rather than their actual month of observation.

[6] 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.

[7] 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).

[8] Formally,

$$\tilde{WM}_{c,m,y} = \sum_{d=1}^{D_m} \mathbb{1}\{W_{c,d} \geq W_{\tilde{t}}\}.$$

The remainder of the analysis is then conducted following the standard procedure. The IRFs that we obtain are non-significant, suggesting that our weather shocks do not exhibit spurious effects and reinforcing the validity of our findings.

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 the three countries we study and set to zero the relevant weather shock observation corresponding to the month when the natural disaster occurred.[9] When we perform this robustness exercise our results are virtually unchanged, suggesting that natural disasters are not the main force driving our results. These are displayed in Appendix 3.5.

Comparison to existing weather indices

Our weather indices bear some similarities to existing works. Here, we highlight the key similarities and differences with the most closely related studies.

Several papers utilize deviations of weather variables, primarily temperatures, from historical averages. For instance, Ciccarelli et al. (2023) examine changes in mean temperature relative to historical means as well as changes in temperature variability. Similarly, Parnaudeau and Bertrand (2018) use monthly deviations from a 30-year average in temperatures, precipitation, humidity, and wind speed. Few studies, however, focus on deviations from seasonal averages. Starr (2000), for example, use Heating Degree Days (HDD) and Cooling Degree Days (CDD), adjusted taking deviations from seasonal averages. Bloesch and Gourio (2015) employ temperatures and snowfall, transformed by taking anomalous deviations from calendar-month averages. As discussed above, this approach is crucial for evaluating the impact of weather anomalies that are not aligned with typical seasonal variations, as such events are likely to become more frequent with global warming. Moreover, this method achieves seasonal adjustment by construction, allowing for a more accurate assessment of weather impacts on economic variables. By accounting for seasonal patterns, it isolates the true effect of unusual weather conditions from reg-

[9] 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 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 (see Table 2).

ular seasonal fluctuations, providing a clearer understanding of how these anomalies influence economic outcomes.

Some papers apply thresholds to weather variables to reduce noise. Additionally, focusing on significant deviations from seasonal averages is important as economic agents are unlikely to anticipate these events and factor them into their economic decisions. This approach is used in Wilson (2019), who compute the number of days above or below a given threshold to estimate accumulation effects, and in Kotz et al. (2022), who construct two measures of yearly rainfall: the number of wet days where precipitation exceeds a given percentile threshold and the total amount of precipitation on those days. This thresholding method is akin to taking deviations from unconditional (not calendar-specific) averages.

The majority of the literature calculates weather deviations at an aggregated level (see, e.g., Billio et al., 2020; Ciccarelli et al., 2023; Giugliano et al., 2023). Few studies compute weather indices at a high spatial resolution. For example, Bloesch and Gourio (2015) calculate anomalous deviations from calendar-month averages at the station level and aggregate them at the state level by simple averaging. Kotz et al. (2022) use grid-cell level time series and then aggregate them to the regional level by taking area-weighted or population-weighted means. Roth Tran (2020), who studies the impact of temperatures, argues that what matters is unusual warm or cold weather, which depends on both location and time of year. This argument underscores the importance of calculating deviations specific to the calendar and at a granular level, as averaging effects across different times and regions can lead to attenuation bias.

Finally, several papers standardize the final weather index using season-specific means and standard deviations (Bloesch & Gourio, 2015) or month-specific means and standard deviations (Kotz et al., 2022). This eases the interpretation of the index by accounting for seasonal variability and ensuring comparability across different countries and weather indices.

To the best of our knowledge, this paper is the first to construct weather shocks across five distinct variables (heat, cold, drought, precipitation, and wind) as anomalous deviations from calendar-month-specific averages at the grid-cell level. These deviations are then aggregated to the country level using economic activity proxies for weighting. Furthermore, we standardize the indices using month-specific means and standard deviations. This methodology provides the most precise computation to evaluate the effects of anomalous weather deviations on economic activity.

3.1.2 Aggregate and sectoral economic data

The aggregate macroeconomic data that we use in the empirical analysis are unemployment rate (in level), 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.,

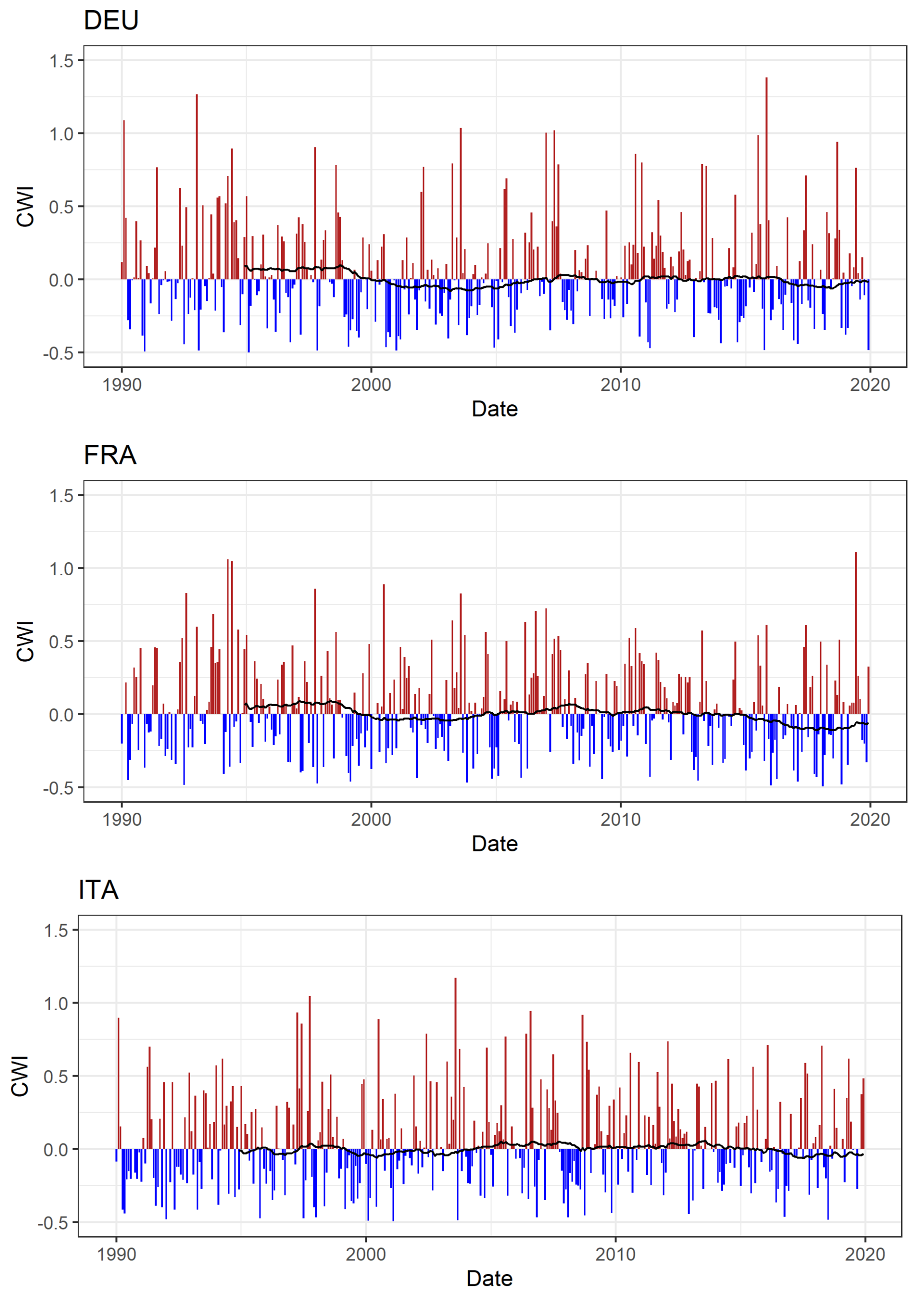


Figure 1: *Composite Weather Indices for Germany, France and Italy.*

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*

From Eurostat we also collect producer price indices for sectors C (Manufacturing) and D (Electricity, gas, steam and air conditioning supply)[10] and consumer prices for energy and services.[11]

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.

[10]Note that for sector F (Construction) the ppi is only available at the yearly frequency.

[11]SERV: Services (overall index excluding goods) and NRG: Energy in the Eurostat *prc_hicp_midx* dataset.

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, sectoral production variables, producer prices, consumer prices, unemployment rate, and short-term interest rates, for a total of 10 variables. As regards weather indices, both the CWI and its components are sequentially introduced into the SVAR model. Thus, matrices A_j for $j = 1, \ldots, p$ are 10×10 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, the 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 a 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 & 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 different regimes, 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), see section 5.2. As output, we get IRFs to various weather shocks in each regime.

4 Main empirical results

This section presents the main results of our empirical analysis using the previously described data and models. We start by evaluating the dynamic impact of the Composite Weather Index on sectoral production in European countries, focusing on three sectors: manufacturing, energy, and construction. We then examine the effects of individual weather shocks—heat, cold, drought, precipitation, and wind. The results are compared across three European countries: Germany, France, and Italy. Thus, our findings encompass three dimensions: type of weather shock, production sector, and country.

To capture the dynamic responses to weather shocks in each country, we estimate Structural Vector Autoregressive (SVAR) models as specified in equation (1), basing our empirical analysis on impulse response functions (IRFs). As explained in the previous section, we maintain a consistent ordering of variables for each country, with the weather variable always ordered first. The variables included in each SVAR model are one of the weather indices, production in the three sectors, sectoral inflation, consumer price indices (HICP), the unemployment rate, and short-term interest rates. Additional empirical results are presented in Section 5, including results related to the production of services in France.

4.1 CWI shock

We first focus on the effects of a composite weather shock on sectoral production. For each country, the IRFs of sectoral production to a one standard deviation shock are presented in Figure 2.[12]

The construction sector is the most uniformly affected by a CWI shock. A standard deviation shock induces a significant decline in the construction sector across all countries (Figure 2, right column). The effect on impact is similar across countries, with a decrease of approximately 0.3 percentage points (pp) in construction output growth. However, the post-shock dynamics differ. In Italy, the construction sector experiences a persistent negative effect lasting about 15 months. In contrast, in both France and Germany, the initial negative impact is less persistent, with production returning to the steady state after 3 to 4 months. Notably, in Germany, construction output rebounds between two and three months after the impact, ultimately compensating for the initial decline. A detailed analysis of the drivers of these effects will be provided in the next sections.

From Figure 2 (middle column), we alse see that a composite aggregate weather shock results in an increase in energy production, which reverts to baseline levels within a few months. However, this increase is significant only in Italy, where a one standard deviation shock leads to an approximate 0.4 percentage point (pp) increase in the growth rate of energy production. Italy experiences a brief decline following the initial positive impact. In the following sections, we show that this

[12]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.

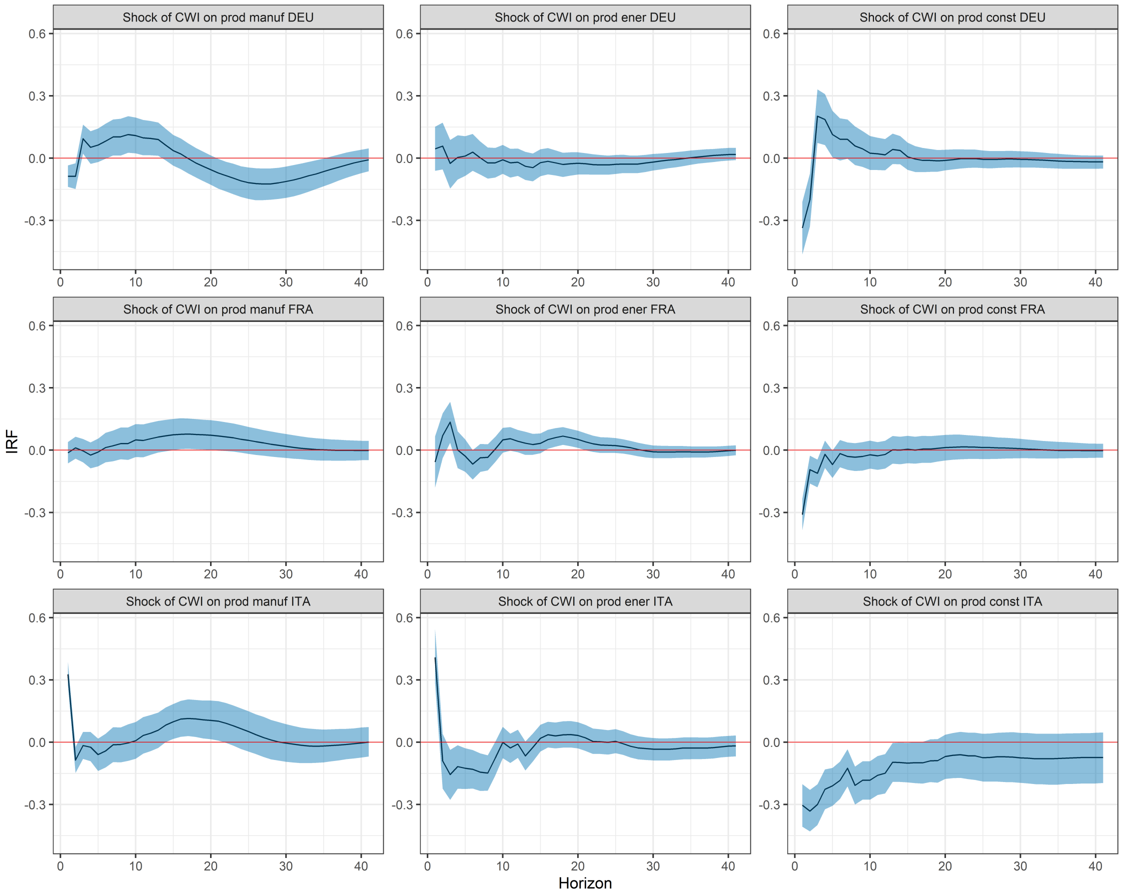


Figure 2: *IRFs of production by sectors to the CWI shock, as well as 68% confidence bands.*

effect is primarily driven by colder weather, which increases energy demand from both households and firms (see section 4.2.1).

The effects of a CWI shock on manufacturing production (left panel) exhibit considerable heterogeneity. The response of the French manufacturing sector to an aggregate weather shock is relatively muted. In Italy, there is a strong initial increase of about 0.3 percentage points (pp), consistent with the observed increase in energy production. However, this is followed by a quick return to equilibrium. Conversely, the initial impact in Germany is slightly negative, around 0.1 pp, though less pronounced, followed by a slight rebound.

Determining the precise sign and magnitude of a composite weather shock's impact on the manufacturing sector, as well as whether it should be classified as a demand or supply shock, is challenging. The existing literature shows mixed results. For example, Ciccarelli and Marotta (2021) suggest that weather shocks with physical consequences act as negative demand shocks, leading to declines in both output and inflation across a panel of countries. In contrast, Kim et al. (2021) provide evidence that U.S. industrial production and inflation tend to move in opposite directions following a composite weather shock, indicating that these act as supply shocks. Similarly, Deryugina and Hsiang (2014) find that temperature affects worker productivity, suggesting a supply-side channel.

Consistent with Billio et al. (2020) and Olper et al. (2021), we find that France is the most resilient country to weather shocks, while Italy is the most affected in our analysis. These initial results suggest that composite weather shocks lead to heterogeneous effects on sectoral production, despite an overall trend of greater co-movement across countries.

4.2 Weather-specific shocks

Using the CWI is beneficial as it provides an overall sense of how sectors are exposed to general weather conditions. However, it is crucial to examine specific weather shocks to distinguish their individual effects on sectoral production. A concern that might arise when using the composite CWI is its consolidation of all types of severe weather events into a single index. Different types of weather events may impact production differently, contributing to the observed heterogeneity across sectors. To address this, we now examine the impact of the individual components of the CWI on sectoral production. For each country involved in the analysis, we sequentially assess the dynamic effects of the five weather-specific shocks—heat, cold, drought, precipitation, and winds—on the production sectors.

To efficiently summarize the results, we present cumulative IRFs for each affected macro variable at six (red bars) and twelve months (green bars), along with their 68% confidence bands. The analysis focuses on the responses of the three sectoral outputs and sectoral prices (manufacturing and energy producer prices (PPIs), as well as the energy component of consumer prices). Where necessary to highlight key aspects of the propagation of weather shocks, we also provide selected IRFs in their extended form.

4.2.1 Cold shock

Cumulated responses to a cold shock are presented in Figure 3 at the 6 and 12 months horizons (red and green bars respectively), for all countries. The first salient result is that energy production (second pair of bars from the left) exhibits a clear comovement across countries. Indeed, a cold shock generates a significantly positive cumulated response of energy production in all countries at both horizons, highlighting the persistence of this dynamic effect in the medium run. We also find that producer price indices and consumer prices of energy increase. A second regularity that emerges is that production in the construction sector is negatively affected by a cold shock, at both horizons (except 12 months in Germany, which is not significant).

While the impact on construction can be attributed directly to adverse weather conditions that hinder construction activities, the impact on energy production is less straightforward to interpret. Therefore, we examine some selected extended IRFs,

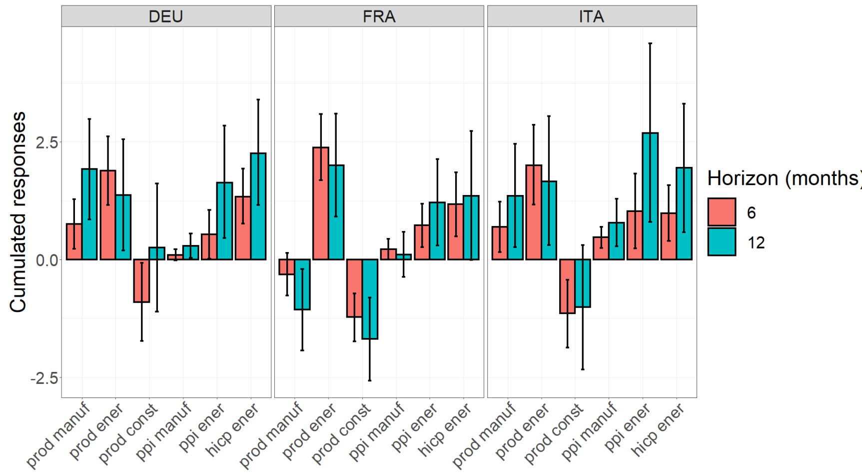


Figure 3: *Cumulated IRFs at 6 and 12 months to a cold shock, as well as 68% confidence bands.*

which offer valuable insights into the propagation of this shock through the economy via the energy sector (see Figure 4). Following a one standard deviation cold shock, energy production in France experiences the most significant initial increase, rising by approximately 1.5 percentage points (pp). In comparison, Italy sees an increase of about 1 pp, while Germany experiences a rise of 0.8 pp. Despite these differences in impact, the dynamics are similar across all three countries, with the impulse response functions (IRFs) returning to the steady state within 4 to 8 months.

Interestingly, a substantial lagged increase in energy prices is observed in all countries following a cold shock (second and third columns of Figure 4). There is a distinct sequence in the reaction of energy prices: consumer prices react first, peaking approximately one to two months after the shock. This is followed by producer prices, which reach their peak between 6 and 11 months later, varying by country (6 months in France, 10 months in Italy, and 11 months in Germany).

These results can be explained by the fact that that a cold temperature shock increases the demand for heating, subsequently leading to a surge in energy production to meet demand, as well as in energy prices. 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. Colombo and Toni (2024) show 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. The authors show that a cold temperature shock increases the demand for heating, subsequently leading to a surge in gas demand, as well as energy production and energy prices. The lagged reaction in producer prices that we observe could reflects the nature of long-term contracts between companies and energy suppliers, making companies less sensitive to sharp movements in prices compared to households. Indeed, these contracts often fix prices for a set period, shielding companies from immediate fluctuations in energy costs. This reduced sensitivity to price changes, compared to households, is a result of

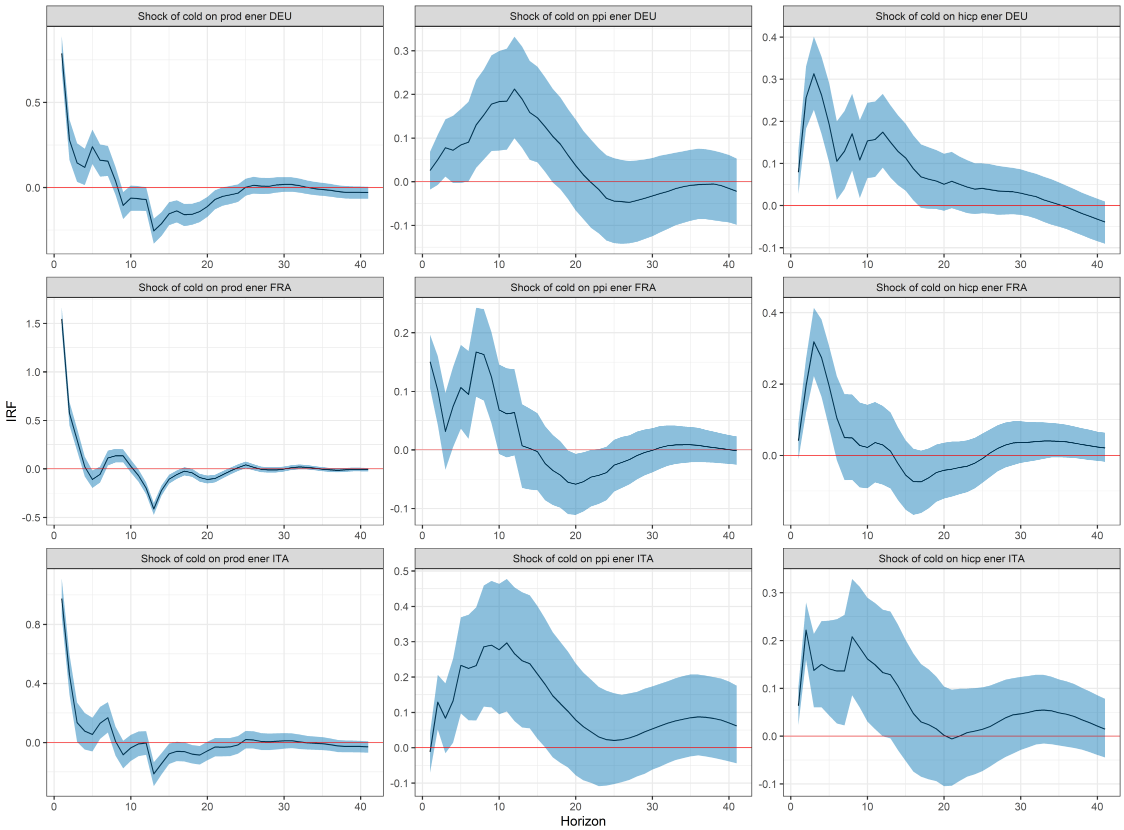


Figure 4: *IRFs of output and prices of the energy sector to a cold shock, as well as 68% confidence bands.*

contractual agreements that typically lock in rates, thus insulating companies from market volatility (see, e.g., McKinsey, 2021). Additionally, the simultaneous upward movement of both output and prices suggests that the primary transmission channel is indeed a demand shock.

4.2.2 Heat shock

The cumulated responses to a heat shock are presented in Figure 5. Compared to a cold shock, we get that the overall dynamics tend to be opposite, with few exceptions. Energy production again exhibits a comovement (opposite to a cold shock) across countries. Energy prices for both producers and consumers are adversely affected, with the exception of Germany, where the response is not significant.

This pattern can be attributed to the same demand channel, where a heat shock leads to reduced demand for heating energy. While one might anticipate that air conditioning could increase energy demand during a heat shock, it is important to note that air conditioning is not as widely used or as significant in Europe compared to heating, resulting in a limited impact on energy consumption.[13] Finally, this

[13]Note that air conditioning represents only roughly 1.2% of household electricity consumption in the EU (Source: Odyssee-Mure, figure for 2021). Furthermore, the heating degree days are much

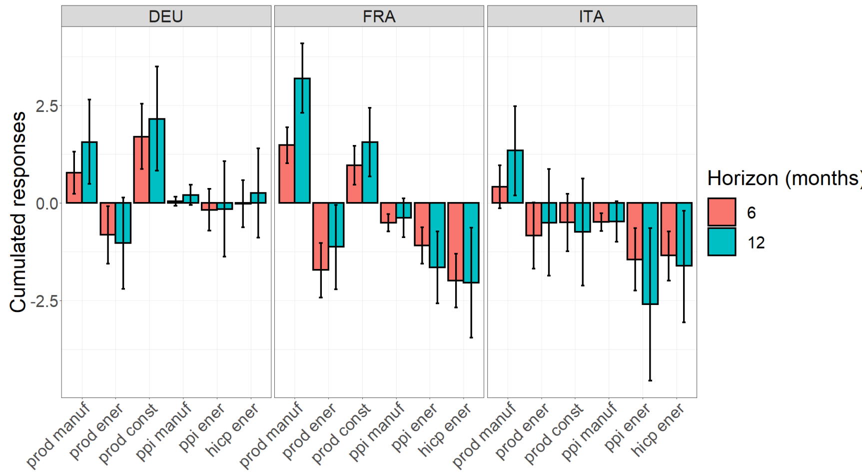


Figure 5: *Cumulated IRFs at 6 and 12 months to a heat shock, as well as 68% confidence bands.*

decrease in energy costs can lead to an increase in manufacturing production-for which energy is a major input (see section 4.3). In this respect, the role of gas is particularly important as it constitutes both a major input to industrial production processes and it is a major source of heating for households (Colombo & Toni, 2024).

A notable aspect of the results from the cumulative IRFs is that a heat shock leads to a substantial medium-term increase in construction production in Germany, a smaller yet still significant rise in France, and no significant effect in Italy. Figure 9 further illustrates the full dynamic response to various shocks in the construction sector. The fourth column distinctly highlights the contrast in short-term dynamics between Germany, which experiences a significant increase, and Italy, which shows a significant decrease in construction output immediately after the shock.

This outcome reflects the nature of the construction sector, which, as an outdoor activity, is directly influenced by weather conditions. We find that a heat shock tends to be beneficial for production in Northern European countries like Germany, while it is more detrimental in Southern European countries like Italy. This contrast between northern and southern regions is consistently supported by empirical literature. The impact of a temperature shock varies by latitude, resulting in different effects across regions. Similar findings are presented by Kalkuhl and Wenz (2020), who demonstrate strong evidence that changes in annual mean temperatures affect economic output at the regional level in a non-linear manner. Specifically, increases in temperature tend to enhance gross regional product (GRP) in colder regions (defined as areas with an annual mean temperature below 5°C) and reduce GRP in hotter regions (see also Billio et al., 2020 on this point).

In examining the potential transmission channels of temperature shocks to the construction sector, the literature has evidenced that these shocks predominantly impact the labor supply of workers engaged in outdoor activities. For example,

higher than the cooling degree days in Europe (Eurostat, 2023).

Graff Zivin and Neidell (2014), using data from the U.S., demonstrate that high daily temperatures reduce labor supply among workers who work outdoors, which is particularly relevant for the construction industry. They argue that higher temperatures can alter the marginal productivity of labor or the marginal cost of supplying labor, thereby affecting the amount of time workers allocate to their jobs. Specifically, they find that "at daily maximum temperatures above 85°F (30°C), workers in industries with high exposure to climate reduce their daily time allocated to labor by as much as one hour."

4.2.3 Precipitation and drought shocks

Cumulated responses to precipitation and drought shocks are presented in Figure 6 and in Figure 7, respectively, for all the countries. It is noteworthy that manufacturing production in Germany demonstrates high sensitivity to these weather shocks: it experiences significant gains from precipitation shocks but is adversely affected by drought shocks. This is consistent with the findings documented in Billio et al. (2020). Conversely, in Italy, the manufacturing sector responds oppositely, albeit to a lesser degree: precipitation shocks lead to a decline in production, while drought shocks result in an increase. In France, the manufacturing sector appears less responsive to these shocks.

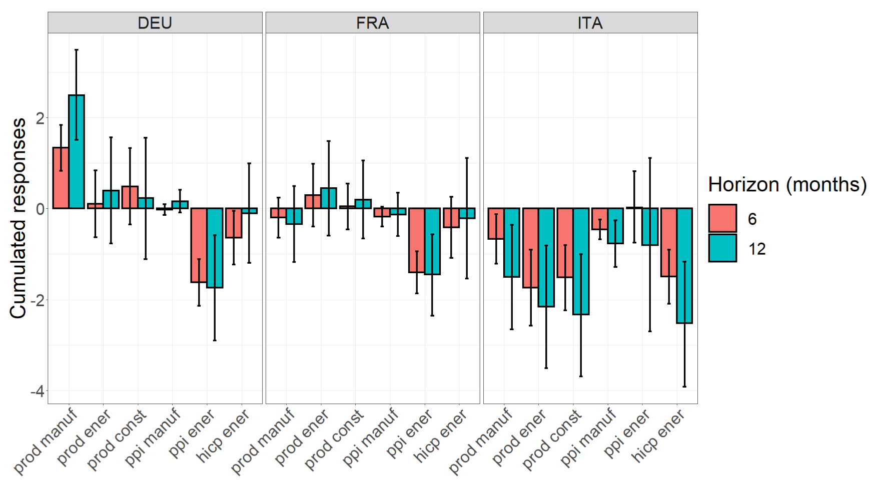


Figure 6: *Cumulated IRFs at 6 and 12 months to a precipitation shock, as well as 68% confidence bands.*

The energy sector generally shows limited responsiveness to these shocks, with the exception of Italy, where energy production decreases following a precipitation shock and increases after a drought shock. The construction sector in Italy is particularly reactive and significantly benefits from drought shocks. As illustrated in Figure 9, a one standard deviation drought shock results in an immediate positive growth of approximately 0.9% in the construction sector. This impact is notably persistent, remaining statistically significant for about a year after the initial impact. Interestingly, there is a symmetrical response observed with precipitation shocks, which lead to a comparable decline in the construction sector. Specifically, a one standard deviation precipitation shock causes an immediate negative growth of about 0.9% in the construction sector. This negative effect is similarly persistent, lasting for approximately the same duration as the impact of a drought shock.

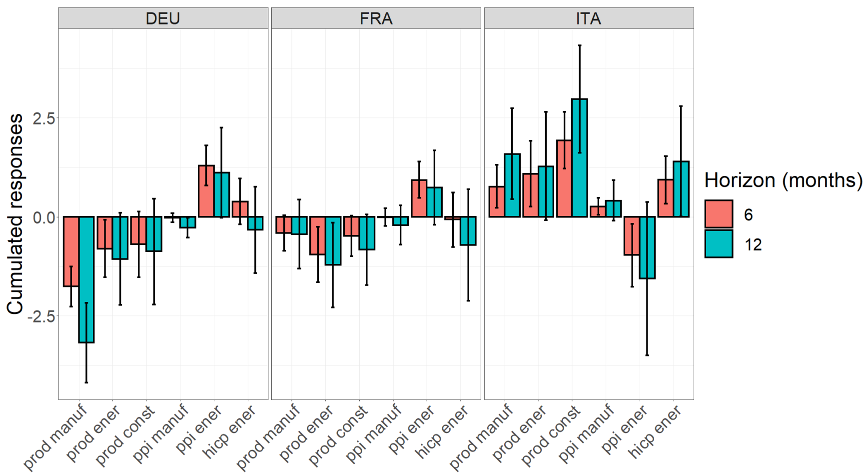


Figure 7: *Cumulated IRFs at 6 and 12 months to a drought shock, as well as 68% confidence bands.*

4.2.4 Wind shock

Cumulative responses to a wind shock are depicted in Figure 8. A first notable finding concerns the dynamic response of the energy sector to a wind shock. Energy prices in all three countries are significantly lowered for both producers and consumers. This widespread impact on energy prices can be attributable to the increase in wind energy production.[14] Despite comparable shares of renewable energy production across Germany, France, and Italy,[15] the proportion of electricity generated from wind power significantly varies among these countries: 21.3% in Germany, 8.0% in France, and 7.2% in Italy (IEA: International Energy Agency, figures for 2022). As illustrated in Figure 8, the impacts on energy prices are comparable in Germany and Italy, and somewhat lower, though still significant, in France. This discrepancy can be attributed to Germany's higher reliance on wind power generation and Italy's

[14]Wind power, being a renewable energy source with zero fuel costs, typically bids into electricity markets at a very low or even negative price. This tendency can lead to lower overall electricity prices, particularly during periods of high wind generation, as these generators are dispatched before more expensive fossil fuel plants. One of the primary mechanisms through which wind power affects electricity prices is through the concept of marginal pricing, where the price of electricity at any location and time is set by the cost of the most expensive generator needed to meet demand at that moment. Since wind power is often among the lowest-cost sources available, its presence can lower the marginal price of electricity, especially during high wind periods (see, e.g., "Regulation (EU) 2024/1747 of the European Parliament and of the Council of 13 June 2024", 2024).

[15]Germany: 20.8%, France: 20.3%, Italy: 19% (source: European Environment Agency, 2022)

overall higher electricity costs. Germany benefits from a more diversified and technologically advanced energy mix, generally resulting in lower electricity generation costs compared to Italy. Italy's higher costs are partly due to a greater dependency on natural gas and less favorable renewable energy resources, leading to increased production expenses. Conversely, France enjoys relatively low generation costs, primarily owing to its substantial reliance on nuclear power, which offers a stable and cost-effective energy source. Consequently, the negative impact of increased wind power generation on energy prices is more pronounced in Italy, causing similar price responses to those observed in Germany, despite the countries' differing reliance on wind power.

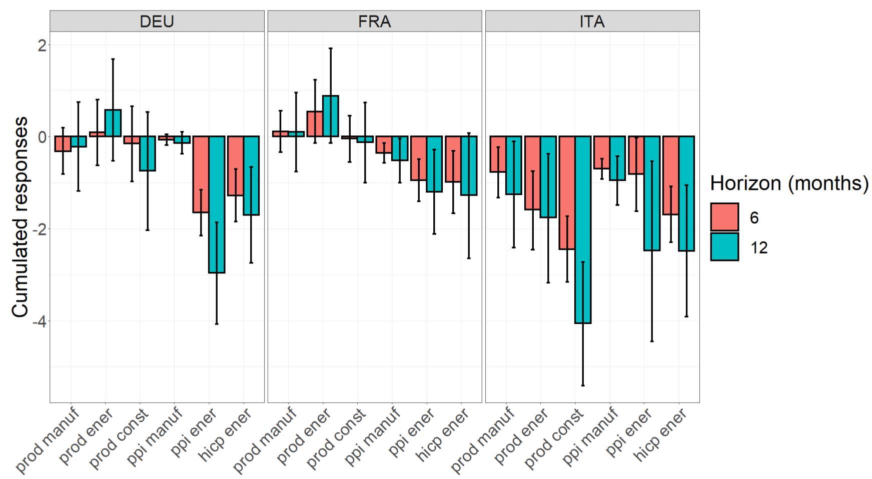


Figure 8: *Cumulated IRFs at 6 and 12 months to a wind shock, as well as 68% confidence bands.*

Our findings also indicate a significant decline in construction activity in Italy, with a reduction of up to 4 percentage points within a year following the shock. In contrast, Germany and France do not exhibit substantial effects. The persistence of this impact is evident in the last column of Figure 9, where an initial drop in construction output growth in Italy by approximately 0.5 percentage points is observed, with the sector returning to its steady state after 20 months. This pronounced impact on construction can be largely attributed to the sector's vulnerability to wind conditions, which can necessitate the suspension of crane operations and disrupt ongoing construction projects. Notably, this adverse effect is not as pronounced in Germany and France.

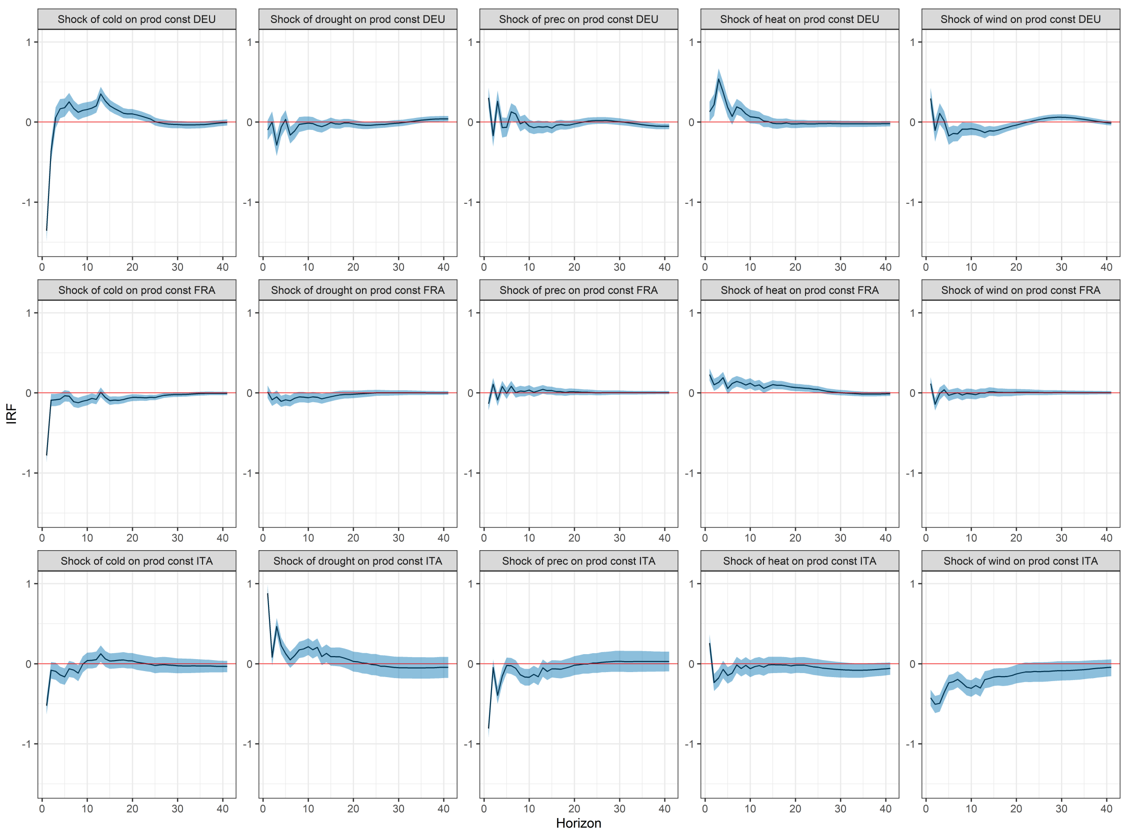


Figure 9: *IRFs of construction production to the various types of weather shocks.*

4.3 Propagation of shocks and policy recommendations

Understanding how the effects of a weather shock propagate across different sectors is crucial. For instance, it's important to investigate how the manufacturing sector might be impacted either directly—through reduced productivity or diminished demand for specific goods—or indirectly—through its interactions with other sectors, such as energy. Although developing a comprehensive structural model with an input-output framework, is beyond the scope of this study (see, e.g., Basu, 1995), our empirical model provides valuable insights into assessing these effects.

We examine the indirect effects of a weather shock on the manufacturing sector through its impact on the energy sector. To this end, we present the complete dynamics of selected impulse response functions (IRFs) in Figure 10. This figure illustrates the dynamics following a heat shock, which reduces energy production across all countries. This shock results in an immediate and significant decrease in energy production due to reduced household heating demand (Colombo & Toni, 2024). Consequently, energy prices for both producers and consumers drop, leading to lower input costs for manufacturing and an increase in manufacturing output. The effect on manufacturing is observed across all countries, with production rising by approximately 0.2 to 0.3 percentage points and showing significant persistence. The peak of the IRFs for manufacturing production is reached approximately 9 to 15 months after the initial shock.

What are the policy implications of these results? As stronger and more frequent weather shocks are expected in the future, it is crucial for policymakers to develop strategies that adapt to, mitigate, and build economic resilience against shocks related to climate change. Our analysis identifies the construction sector as the most exposed to weather shocks due to its outdoor nature and direct dependence on weather conditions. The magnitude and direction of these shocks vary by the latitude of the country, indicating that domestic policy responses should be tailored to support the sector in the event of adverse weather conditions. Notably, the construction sector in Northern countries is likely to benefit from global warming.

The energy sector exhibits a distinct pattern in response to weather shocks. These shocks significantly affect relative prices, particularly energy prices, which in turn can influence manufacturing production through changes in input costs. This underscores the need for coordination among countries within the European Union. One approach could be to assist countries in achieving an optimal energy mix that can help mitigate large fluctuations in energy prices, such as those caused by temperature shocks. To avoid exacerbating climate change, this energy mix should not rely heavily on greenhouse gas (GHG)-emitting energy commodities, such as coal, as is currently the case in Germany. The European Commission could provide strong incentives for countries to transition towards greener energy sources.

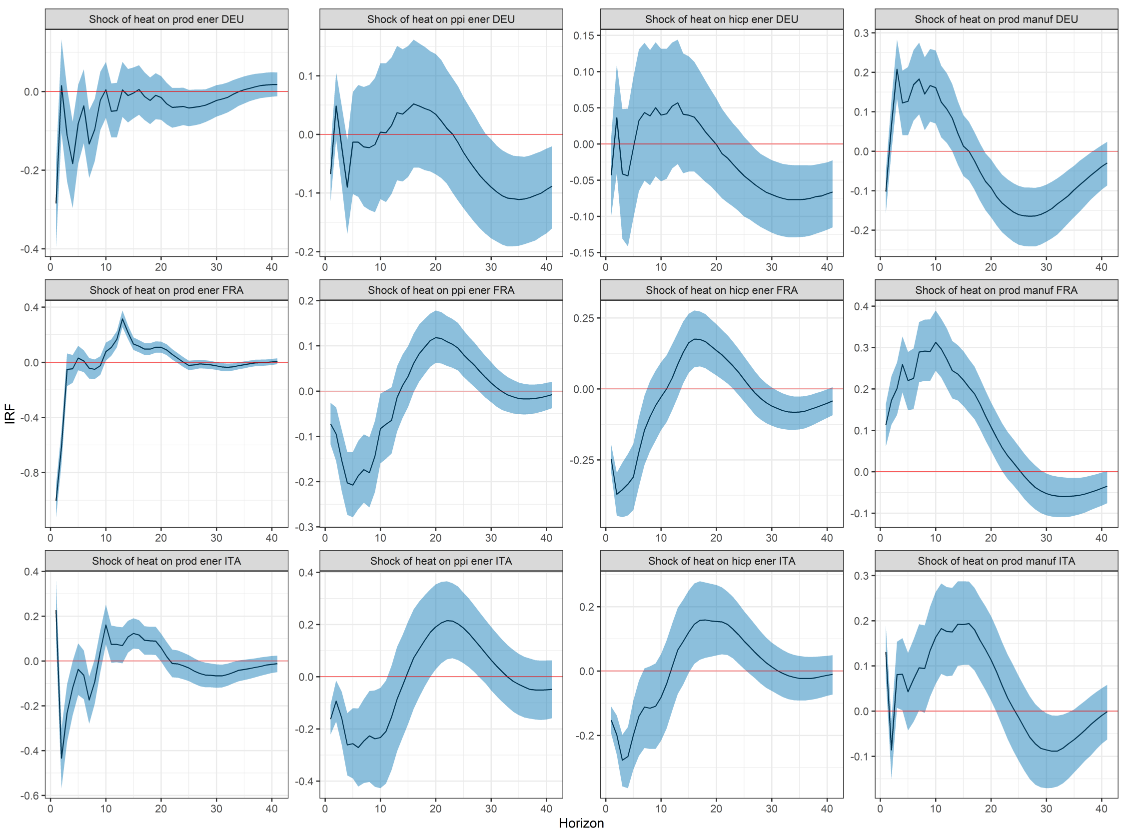


Figure 10: *IRFs of output and prices of the energy sector to a heat shock, as well as 68% confidence bands.*

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.

5.1 Dynamic effects of weather shocks on services

Detailed monthly data on services prices is available for all three countries, whereas data on services output is available only for France.[16] We compute Impulse Response Functions (IRFs) from various weather-specific shocks by incorporating service production into a Structural Vector Autoregressive (SVAR) model, following the same methodology applied to other sectors in the previous section.

Figure 11 displays the cumulative IRFs of inflation in the services sector to various weather-specific shocks across all countries. There is notable heterogeneity in the responses of service prices to weather-specific shocks across different countries, with service prices typically exhibiting limited movements in response to these shocks. However, when significant, the responses of services inflation follow the direction of the impact of production in the construction sector, suggesting demand complementarities between services and the construction sector (see Figures 3, 7 and 8). This is the case for cold shocks, which lead to a significant decrease in service prices in both Germany and Italy, as well as the price movements that follow drought and wind shocks in Italy.

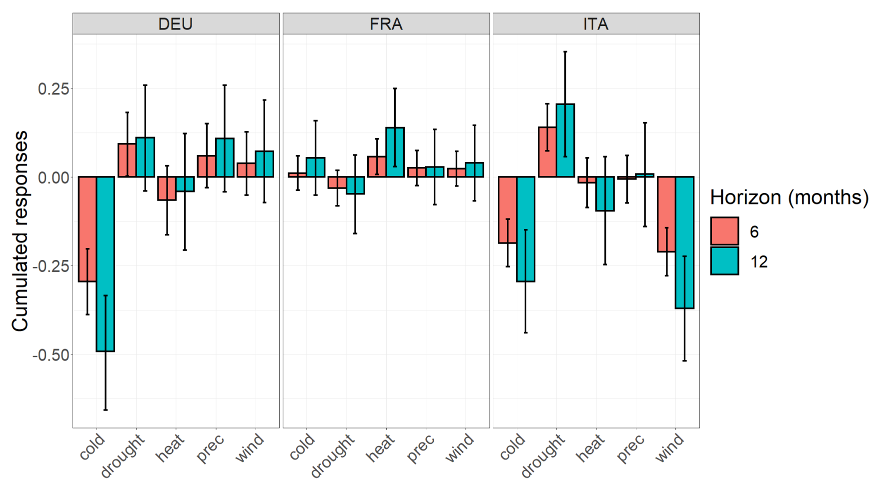


Figure 11: *Cumulated IRFs at 6 and 12 months of HICP inflation in services to the five weather shocks for all countries.*

Figure 12 illustrates the cumulative responses of various French service subsectors, ranging from G (*Wholesale and retail trade*) to N (*Administrative and support*

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

service activities), as detailed in Table 1. Compared to the production sectors analyzed in the previous sections, the response of service sector production to weather-specific shocks is relatively muted. Nonetheless, heat shocks induce the most pronounced reactions within the service sector. Notably, four sub-sectors—*Wholesale and retail trade* (G), *Transportation and storage* (H), *Accommodation and food services* (I), and *Administrative and support service activities* (N)—show significant responses. Additionally, heat shocks lead to increased construction activity (see Figure 9). Consequently, this increase in construction affects complementary services, such as retail trade and transportation (sectors G and H). Since both prices and output in these services move in the same direction, this reinforces the evidence these effects are driven by changes in demand.

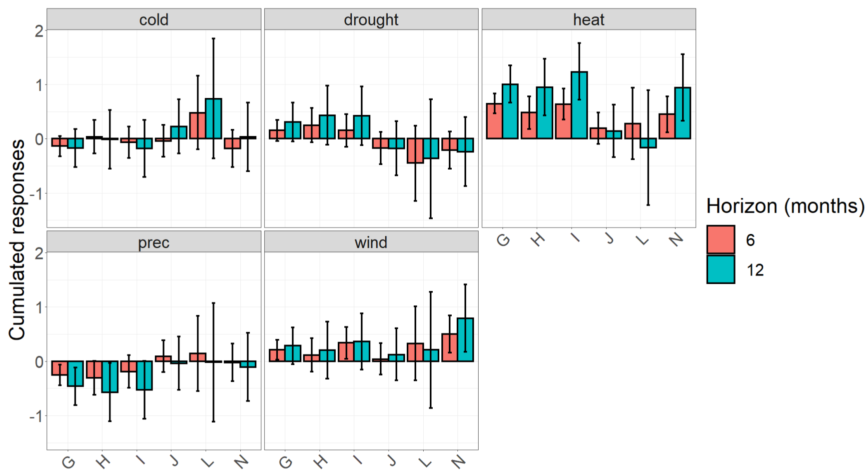


Figure 12: *Cumulated IRFs at 6 and 12 months of French production in services to the five weather shocks. G: Wholesale and retail trade, H: Transportation, I: Accommodation, J: Communication, L: Real estate, N: Administrative support.*

In this section we provided an empirical analysis of the dynamic effects of weather-specific shocks on the service sector, with a detailed focus on France due to the availability of comprehensive monthly data. Our findings indicate that, while service production generally exhibits a muted response to these shocks compared to other sectors, heat shocks notably provoke significant reactions in specific sub-sectors. The analysis also reveals that these shocks often influence complementary sectors, like construction, driving demand in associated services. Moreover, the impact on service prices varies across countries. Specific weather shocks, such as cold shocks in Germany and Italy, and drought and wind shocks in Italy, demonstrate significant effects, again suggesting the presence of demand complementarities between services and the construction sector. These results underscore the complex and heterogeneous nature of weather-related economic impacts on services across different regions.

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. Specifically, this would imply that weather shocks have a more pronounced effect on sectoral production during recessions compared to expansions. To evaluate this hypothesis, we estimate non-linear impulse response functions (IRFs) to a composite weather shock on manufacturing production across three countries. Our methodology involves estimating non-linear Local Projections as described by equation (3), where we posit two regimes of economic growth by using the European Sentiment Index (ESI) as the transition variable. The ESI, a composite index based on various surveys conducted by the European Commission, reflects business cycle conditions—showing low values during periods of economic downturns and high values during periods of economic upturns. This index is widely used in practice and tracks euro area business cycles in real-time, as demonstrated by Bańbura and Modugno (2014). Figure 14 displays the IRFs of manufacturing production in both economic growth regimes for the three countries. Blue lines represent the IRFs during high-growth periods, while black lines denote those during low-growth periods.

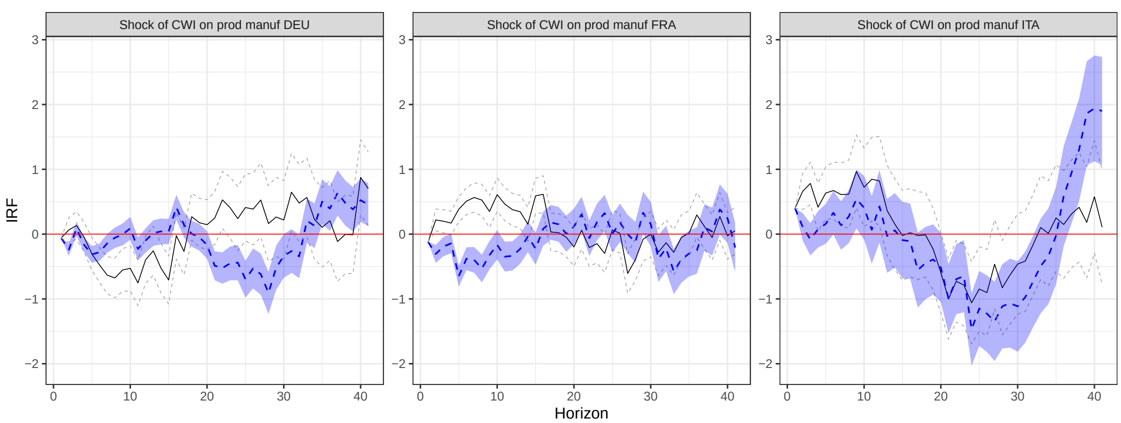


Figure 13: *Non-linear responses with respect to the business cycle of manufacturing production to the composite weather shock CWI. Blue lines correspond to the high-growth regime and black lines to the low-growth regime.*

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.

5.3 Non-linearity to the season

We also examine potential non-linearities related to seasonal variations. To achieve this, we apply the same non-linear Local Projections method, but use a sine function as the transition variable. This function is designed to be 0 in January and reach 1 in July, thereby capturing seasonal effects throughout the year. Our analysis focuses on the impact of the CWI index on production sectors. Our findings reveal no significant evidence of non-linearities in the effects when considering the seasonal component. One reason for this may be the way we compute weather shocks—by taking deviations from month-specific percentiles—which mitigates the issue of seasonal non-linearities. This approach helps control for seasonal patterns and reduces their potential impact on our results. However, it is worth noting that while we do not observe pronounced seasonal non-linearities when using the composite index, there could be nuanced non-linear effects associated with specific weather-related shocks. This potential complexity warrants further investigation in future research.

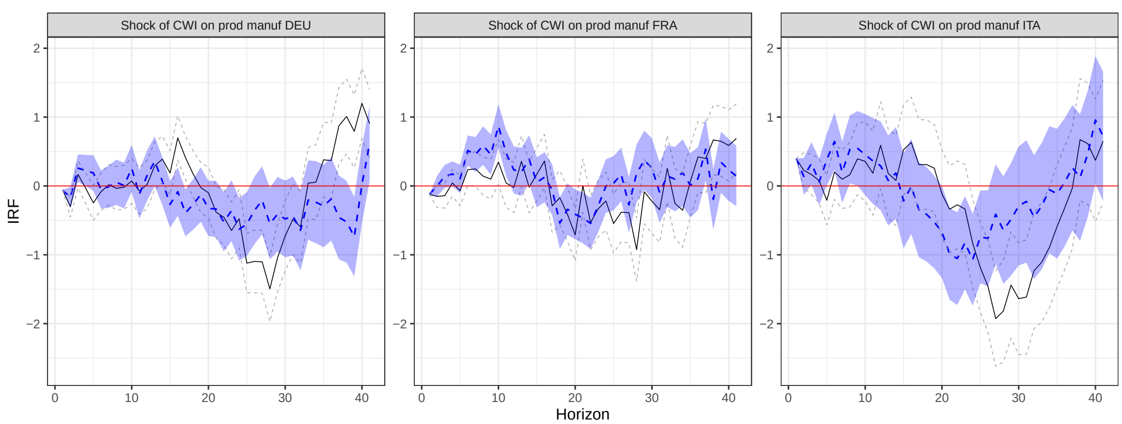
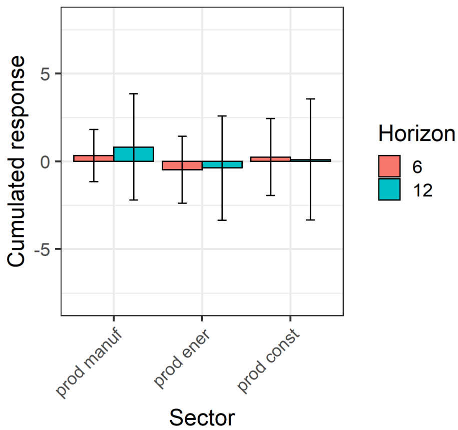


Figure 14: *Non-linear responses with respect to the season of manufacturing production to the composite weather shock CWI. Blue lines correspond to Summer and black lines to Winter.*

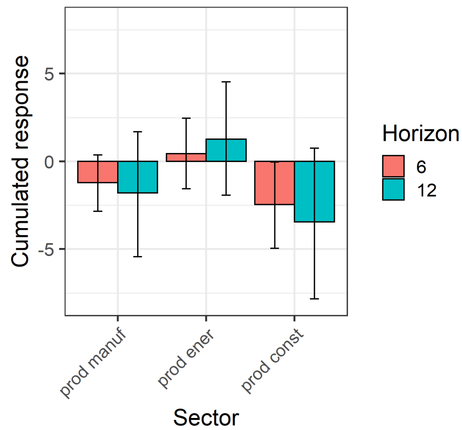
5.4 Cross-country spillovers

A potential concern when estimating separate SVAR models for each country is the presence of cross-country spillovers, particularly when shocks are correlated across countries. Indeed, the contemporaneous correlation between CWI indices is 0.71 for Germany and France, 0.33 for Germany and Italy, and 0.48 for France and Italy.

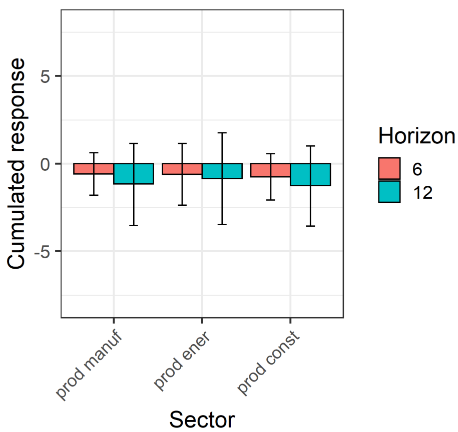
To investigate the presence of potential spillovers, we replicate the analysis from the previous section, substituting the domestic CWI shock with the residual part of the foreign CWI shock that is not explained by the domestic shock. This involves first estimating a regression of the foreign CWI on the domestic CWI, then using the residuals from this regression in our benchmark SVAR model to compute IRFs. The results, presented in Figure 15, show that cumulated impulse responses are non-significant at both 6- and 12-month horizons. This suggests that cross-country spillovers are not a concern in our application.



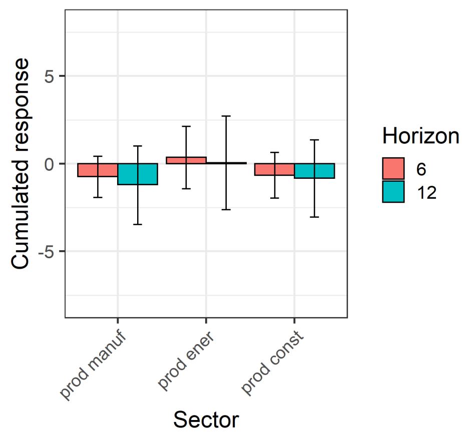
French CWI on German sectors



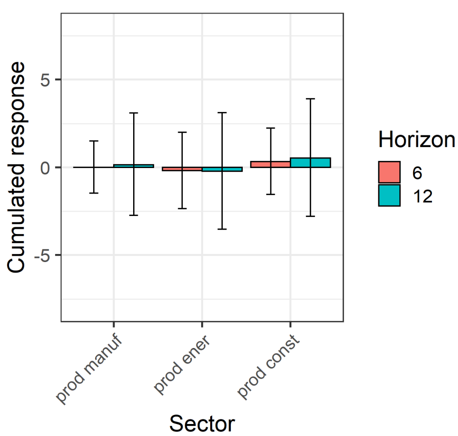
Italian CWI on German sectors



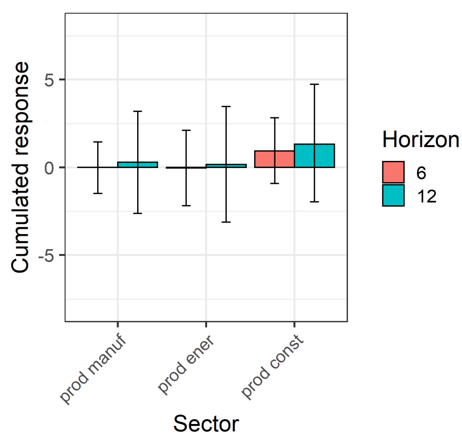
German CWI on French sectors



Italian CWI on French sectors



German CWI on Italian sectors



French CWI on Italian sectors

Figure 15: *Cumulated responses to a shock in the residual foreign CWI on domestic sectors. The whiskers represent 90% confidence intervals.*

6 Conclusions

This paper investigates the short- to medium-term dynamic impacts of weather shocks on sectoral production and prices in Germany, France, and Italy, the three largest European economies. We introduce an innovative monthly composite weather index (CWI), constructed from daily weather data. This index captures deviations from seasonal weather trends—such as cold and heat conditions, drought, precipitation, and wind—aggregated at the country level and weighted by proxies of economic activity. This novel approach provides a refined measure of weather's economic impact. Our analysis extends the existing literature by examining a broader range of sectors and weather shocks beyond the traditional focus on temperature. We utilize Structural Vector Autoregression (SVAR) models to estimate impulse response functions for both composite and weather-specific shocks.

Our findings reveal several key insights. The construction sector is directly affected by weather conditions; cold shocks cause significant declines in output, while wind shocks also have a negative impact, though less pronounced. Notably, heat shocks benefit construction in northern Europe (e.g., Germany, a colder country) but are detrimental in southern Europe (e.g., Italy, a warmer country), highlighting a significant latitude effect. Second, the energy sector is influenced through both demand and supply channels. Temperature fluctuations increase the demand for heating during cold spells, while wind affects the supply side by altering the cost of electricity production. This dual impact demonstrates that weather conditions can alter the sector's dynamics from multiple angles. Third, the manufacturing sector is less directly affected by weather shocks. Instead, it experiences indirect impacts primarily through changes in energy input costs: weather-related disruptions in the energy market influence manufacturing output via fluctuations in energy prices. Moreover, there is substantial heterogeneity in sectoral responses across countries. France shows considerable resilience to weather shocks, with manufacturing largely unaffected except by heat through energy costs. In contrast, Italy exhibits heightened vulnerability, particularly in the construction sector, which suffers significant and persistent declines due to adverse weather conditions. This finding aligns with previous research by Billio et al. (2020) and Olper et al. (2021).

The present study is, to the best of our knowledge, the first to explicitly explore the effects of weather shocks on the services sector. We find that services exhibit demand complementarities with construction, as output and prices tend to move together. However, our analysis is limited to France due to data constraints. Finally, our results do not reveal significant non-linearities related to the business cycle or seasonal variations in response to weather shocks. Furthermore, cross-country spillovers from weather shocks do not appear to be a significant issue.

In light of these findings, we recommend the implementation of a coordinated European energy policy to mitigate the economic fluctuations caused by weather-related disruptions. This policy should address the observed sectoral and geographical differences to better manage the impact of weather shocks on economic activity.

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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, daily temperature corresponds to the *2m temperature* (daily mean) variable; daily total precipitation corresponds to *total precipitation*; and maximum daily wind 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.[17] To measure drought we instead use the SPEIbase dataset v.2.9 (Beguería et al., 2023).[18] Finally, to proxy for economic activity at the grid level we use night-time light intensity[19] from Li et al. (2020). These are used to weight weather observations at the grid-cell level when aggregating to a lower spatial resolution, as in Gortan et al. (2024).

The computation of the heat, precipitation and wind shocks is exactly as presented in section 3.1.1. The computation of the cold shock is naturally adapted to account for daily temperature observations that are below the 5$^{\text{th}}$ percentile instead of above the 95$^{\text{th}}$. For the drought shock we consider the monthly Standard Precipitation Index with a 3 months accumulation period $SPEI3_{j,k}$. Since the SPEI is available at the cell level and it is already standardised and thresholded at the source, we limit ourselves to perform the aggregation procedure and standardisation of the aggregated country level variable as follows. 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.

Figures 16, 17, and 18 illustrate the individual weather components of the Composite Weather Indices (CWIs) for Germany, France, and Italy, respectively. Importantly, due to the methodology employed in computing the weather shocks—where positive values indicate a shock and zero represents no shock—different weather shocks that are negatively correlated do not offset each other. For instance, heat and cold shocks, as well as drought and precipitation shocks, do not neutralize one another.

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

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

[19] Measured in 2015.

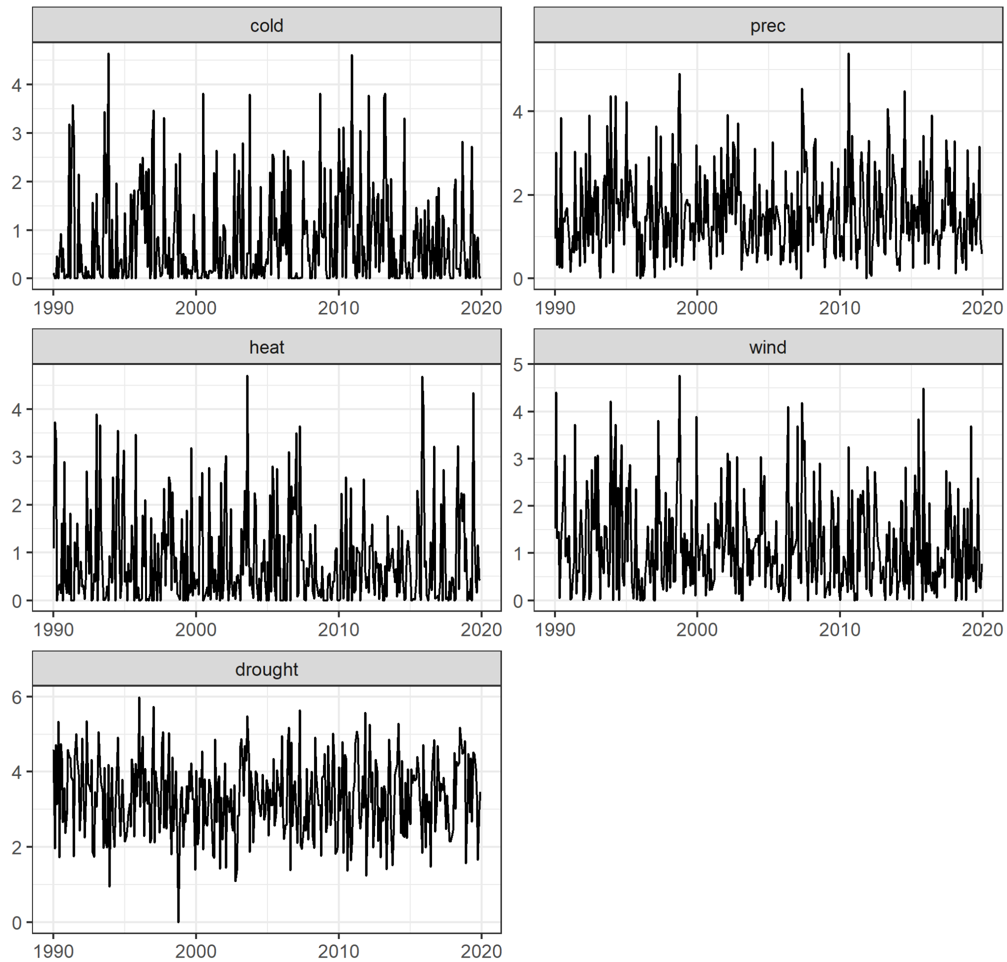

Figure 16: *The 5 components of the CWI for Germany.*

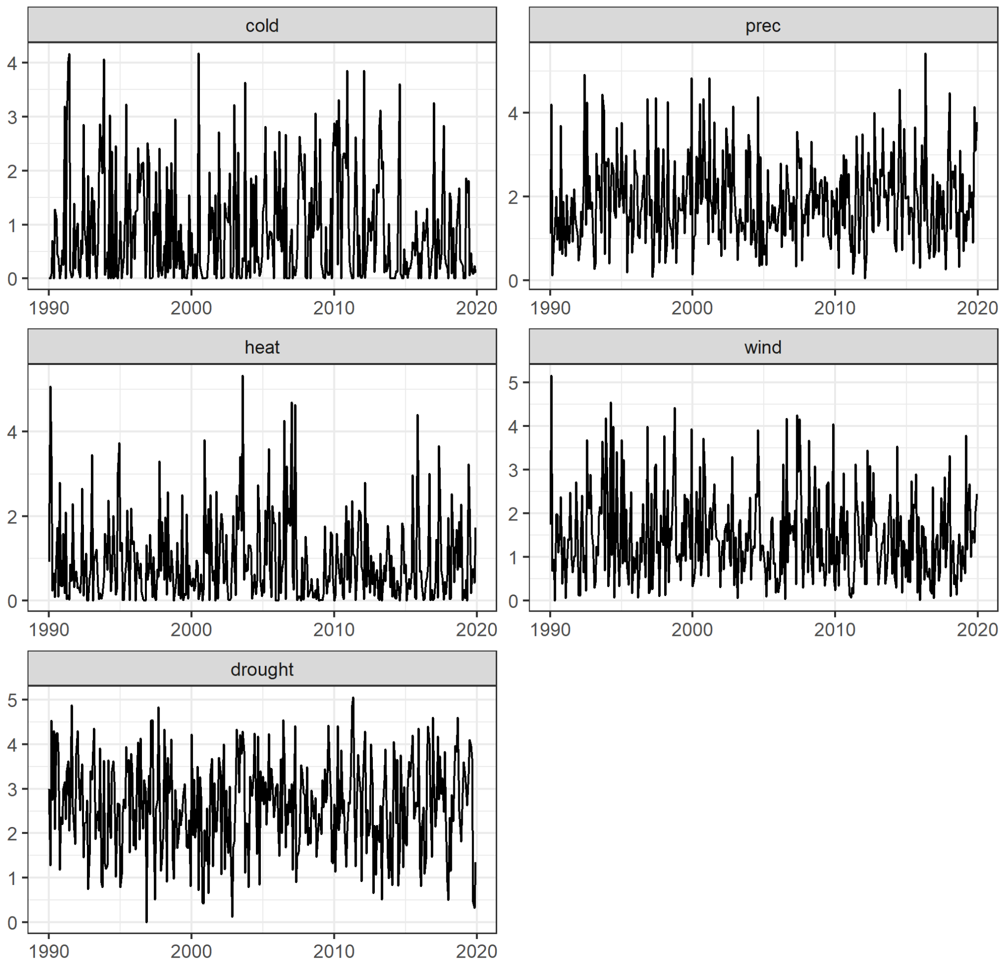

Figure 17: *The 5 components of the CWI for France.*

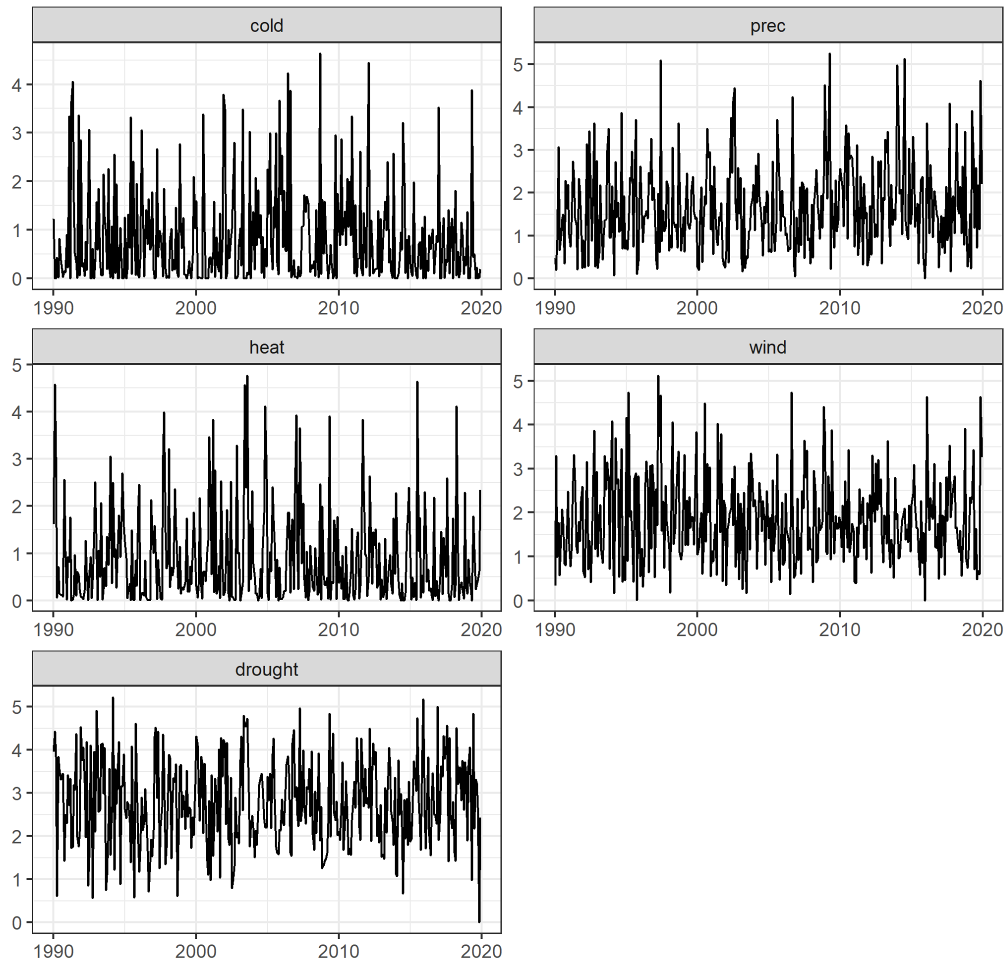

Figure 18: *The 5 components of the CWI for Italy.*

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: Robustness checks[20]

3.1 Falsification test by randomising the dates of the weather shocks

The initial robustness exercise we propose is a falsification test. In this test, we randomly shuffle the observations of the weather indices, reassigning them to different months rather than their actual month of observation. The remainder of the analysis is then conducted following the standard procedure. Figure 19 (equivalent of Figure 2) shows the result of this excercise. The IRFs are non-significant, suggesting that our weather shocks do not exhibit spurious effects and reinforcing the validity of our original findings.

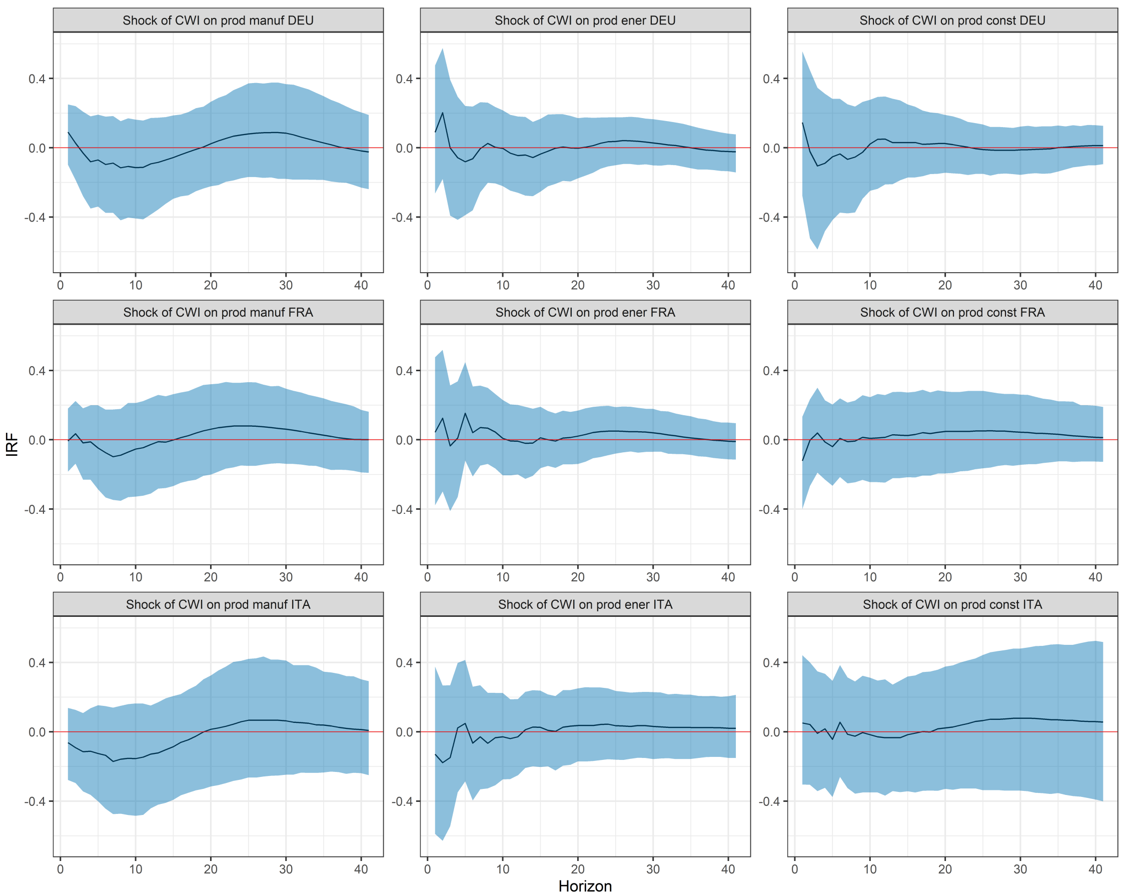

Figure 19: *IRFs of production by sectors to the randomised CWI shock, as well as 68% confidence bands.*

3.2 Number of days in which the threshold is exceeded

Instead of calculating weather shocks based on values exceeding the month-specific 95th percentile, an alternative approach is to compute them as the number

[20]For the sake of brevity, this section presents only one figure per robustness check. The full set of robustness checks for additional figures is available upon request.

of days in each month that surpass this threshold:

$$\tilde{WM}_{c,m,y} = \sum_{d=1}^{D_m} \mathbb{1}\{W_{c,d} \geq W_{\tilde{t}}\}$$

This method accounts for accumulation effects, reflecting situations where economic activity is postponed due to adverse weather events (Natoli, 2022). Due to the standardization process and the similarity in daily exceeding values, the resulting weather shocks are highly comparable. Figure 20 illustrates the alternative computation of the shock for Germany, showing results that are nearly identical to those obtained using the baseline computation, thereby yielding virtually equivalent outcomes in the empirical analysis.

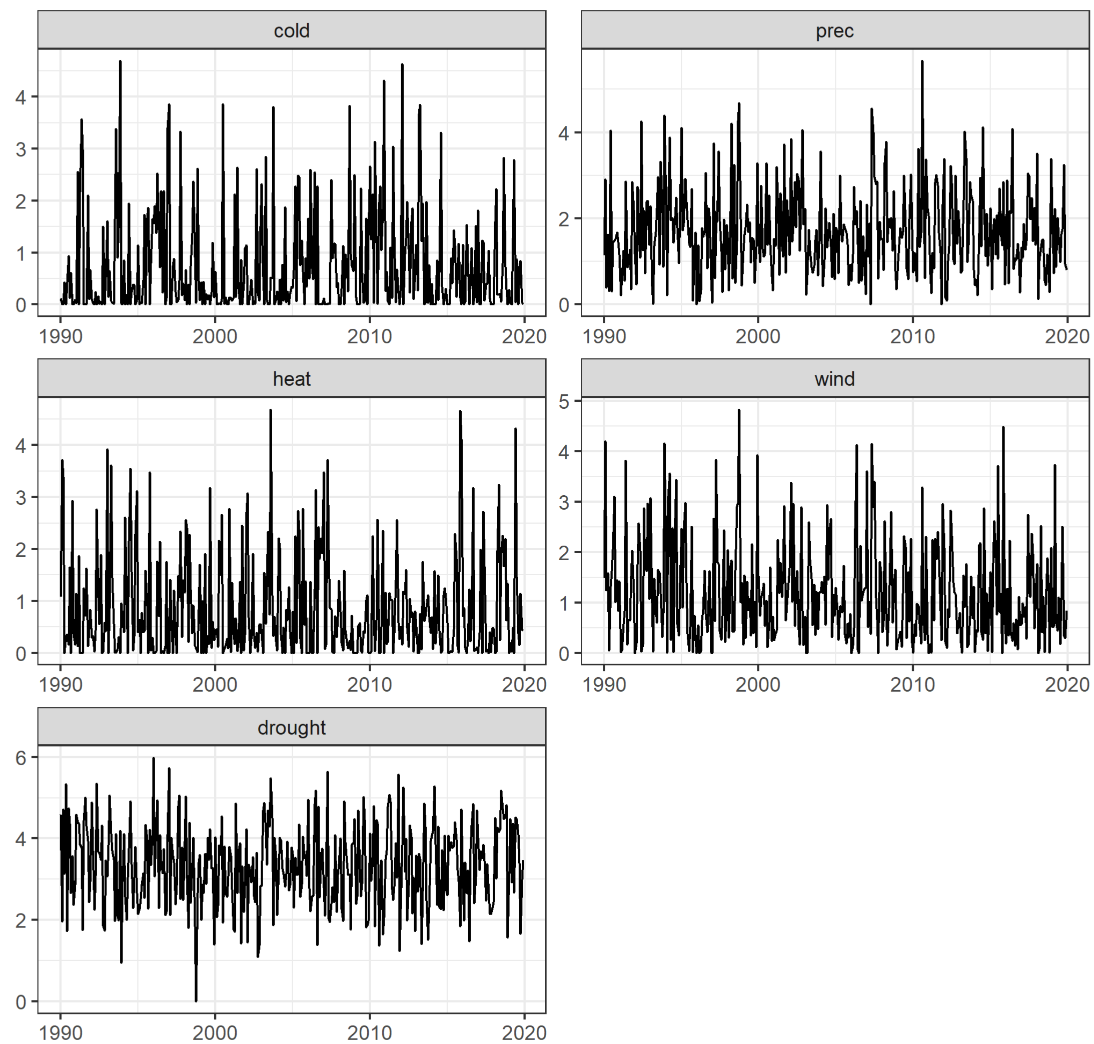

Figure 20: *Alternative computation of the weather components for Germany.*

3.3 Country level shocks instead of grid-cell level shocks

Figure 21 presents the equivalent of Figure 4, with weather shocks computed by first aggregating the weather observations at the country level and then constructing the shock by computing the exceedance values and standardizing. This approach yields less precise estimates of the effects, resulting in some responses being more confounded. For example, the energy producer price index (PPI) and energy harmonized index of consumer prices (HICP) in Germany show more variability and less clear responses.

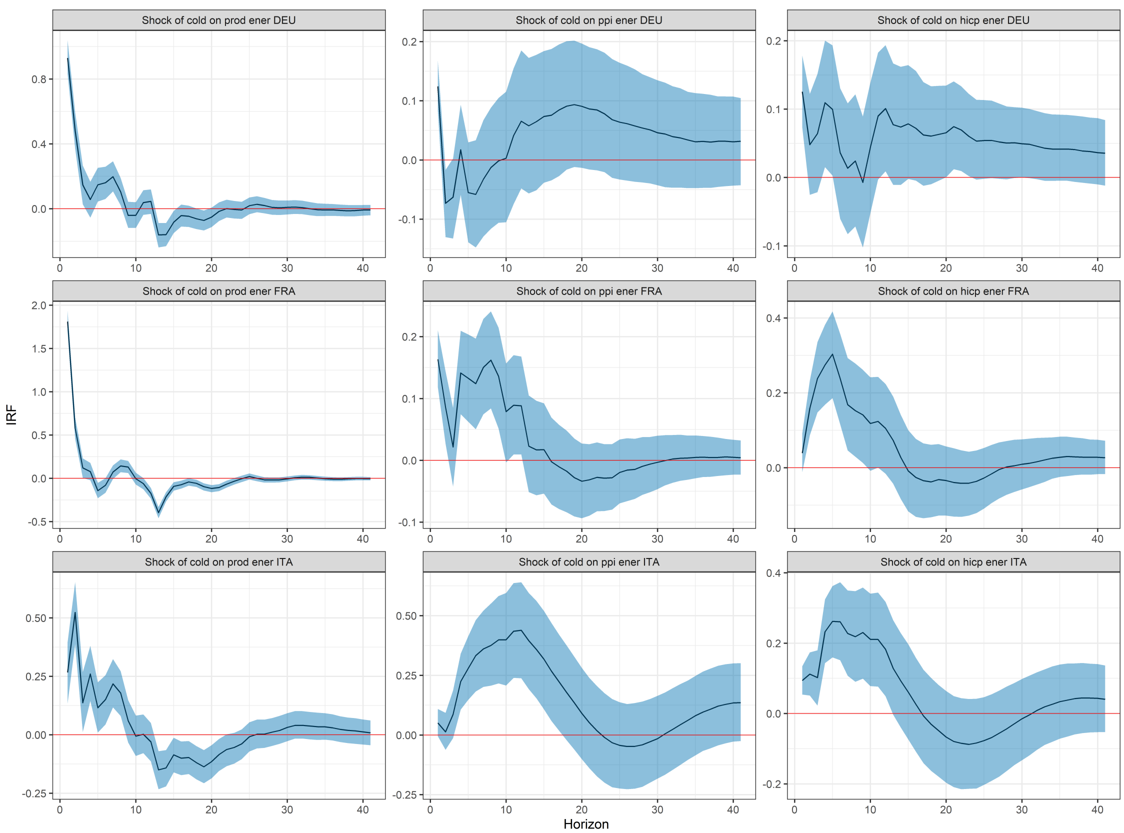

Figure 21: *IRFs of output and prices of the energy sector to a cold shock (country-level computation), as well as 68% confidence bands.*

3.4 Using different percentiles

Figures 22 and 23 demonstrate that the computation of the CWI is robust to using different percentiles as thresholds, specifically the 98^{th} and 99.9^{th} percentiles, instead of the 95^{th} used in the main body of the paper.

3.5 Excluding natural disasters

Figure 24 demonstrates that our results remain robust even when excluding months from the weather-specific indices during which natural disasters, as clas-

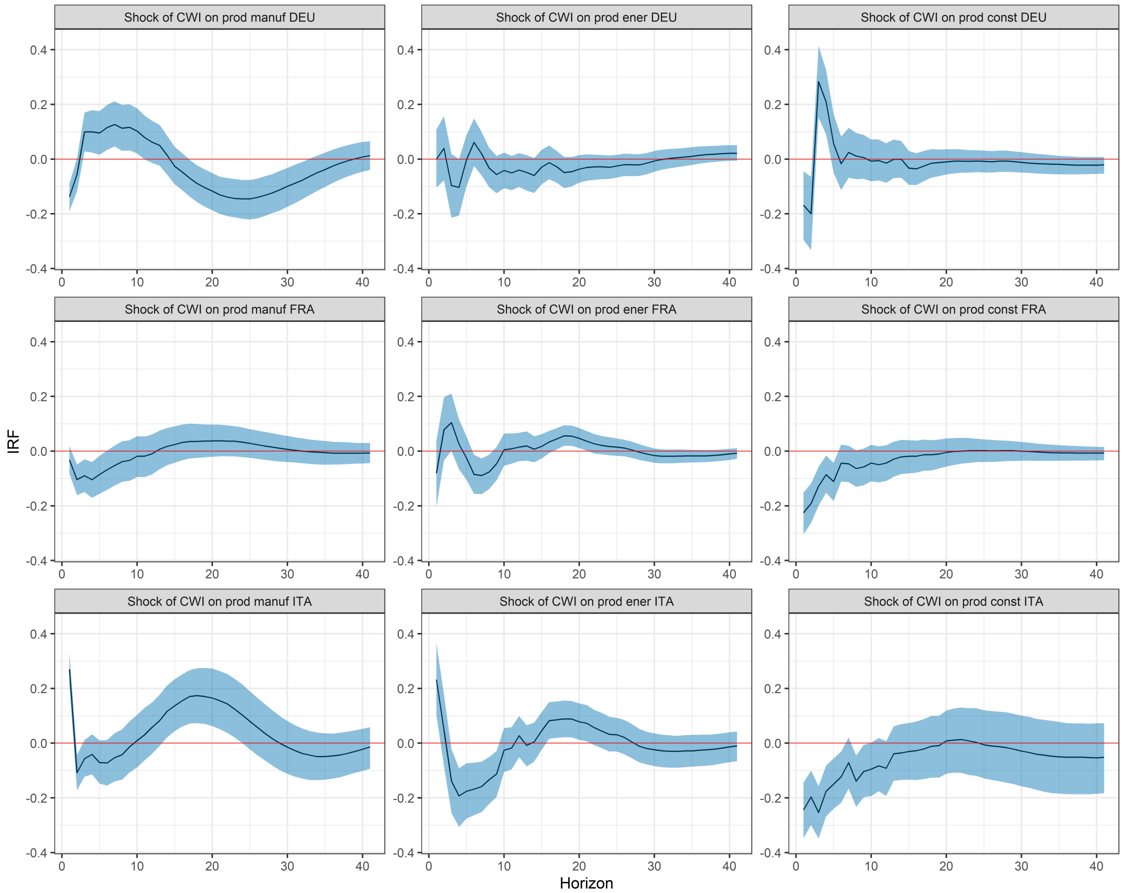

Figure 22: *IRFs of production by sectors to CWI shock computined using 98th percentiles as thresholds, as well as 68% confidence bands.*

sified in the EM-DAT dataset, occurred. The specific natural disasters excluded are detailed in Table 2.

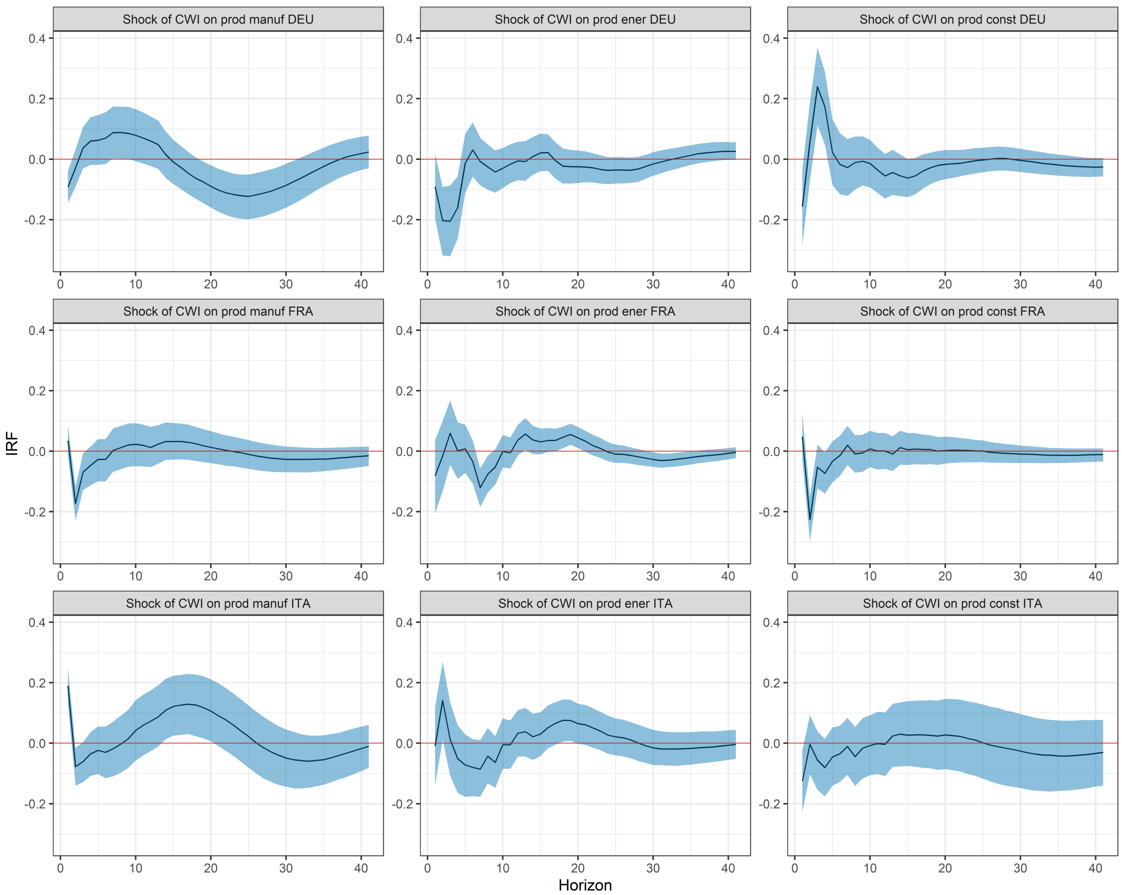

Figure 23: *IRFs of production by sectors to CWI shock computined using 99.9th percentiles as thresholds, as well as 68% confidence bands.*

Date	Disaster Type	Total Deaths	Total Affected	Total Damage, Adjusted ('000 US$)	Country
1990-01-25	Storm (General)	8		2687818	*Germany*
1990-02-03	Storm (General)	7		1343909	*Germany*
1990-02-03	Storm (General)	23		2015864	*France*
1990-02-25	Storm (General)	15		2687818	*Germany*
1990-02-28	Storm (General)	24		2687818	*Germany*
1991-04-20	Cold wave			1658909	*France*
1992-09-22	Severe weather	47	2000	834270	*France*
1992-10-31	Riverine flood		1000	1433484	*Italy*
1993-07-05	Hail	2	1518	101294	*France*
1993-09-22	Storm (General)	10	202	1012939	*France*
1993-09-22	Storm (General)	8	1000	1266173	*Italy*
1993-12-20	Riverine flood	4		1215526	*France*
1993-12-21	Riverine flood	5	100000	1215526	*Germany*
1994-07-03	Lightning/Thunderstorms	5		1273880	*Germany*
1994-11-01	Riverine flood	68	17300	18361882	*Italy*
1995-01-21	Storm (General)	5	30000	614566	*Germany*
1995-01-21	Storm (General)	16	5000	1344362	*France*
1997-01-04	Cold wave	23	10000		*France*
1997-07-04	Riverine flood		5200	656354	*Germany*
1997-07-26	Forest fire		1259		*France*
1998-05-01	Landslide (wet)		3682	51526	*Italy*
1999-01-18	Flood (General)		1100		*France*
1999-05-11	Riverine flood	7	100000	755465	*Germany*
1999-05-30	Storm (General)	3	100020		*France*
1999-11-12	Flash flood	36	3005	878448	*France*
1999-12-24	Extra-tropical storm	15		2811033	*Germany*
1999-12-26	Extra-tropical storm	88	3400011	14055163	*France*
1999-12-27	Extra-tropical storm	8		7027581	*France*
2000-10-14	Flash flood	25	43000	13596043	*Italy*
2000-11-20	Flood (General)	5	2000	84975	*Italy*
2001-03-21	Riverine flood	3	8100	218747	*France*
2001-04-07	Riverine flood		7371		*France*
2002-08-11	Flood (General)	27	330108	18873085	*Germany*
2002-09-08	Riverine flood	23	2500	1936118	*France*
2002-10-26	Extra-tropical storm	11		2928582	*Germany*
2002-11-22	Riverine flood	2	10000	569447	*Italy*
2003-07-16	Heat wave	20089		6999853	*Italy*
2003-07-28	Forest fire	5	3004		*France*
2003-08-01	Heat wave	19490		6999853	*France*
2003-08-29	Riverine flood	2	350	1042024	*Italy*
2003-12-02	Flash flood	9	27000	2386314	*France*
2005-09-07	Flash flood	1	3000		*France*
2006-07-15	Heat wave	1388			*France*
2007-01-18	Extra-tropical storm	11	130	7763012	*Germany*
2008-02-29	Extra-tropical storm	5		1631127	*Germany*
2008-05-29	Severe weather	3		2038909	*Germany*
2008-08-03	Tornado	3	2100	108742	*France*
2009-01-23	Extra-tropical storm	11		4365193	*France*
2009-10-01	Riverine flood	35	5140	27282	*Italy*
2010-02-28	Extra-tropical storm	4		1342112	*Germany*
2010-02-28	Extra-tropical storm	53	500079	5677133	*France*
2010-06-15	Flash flood	25		2013168	*France*
2010-10-31	Storm (General)	3	5	1170321	*Italy*
2011-11-06	Riverine flood	6	2300		*France*
2012-06-01	Drought			1516849	*Italy*
2012-11-11	Riverine flood	4	1200	19120	*Italy*
2013-05-28	Riverine flood	4	6350	16205764	*Germany*
2013-06-18	Flash flood	2	2000	822851	*France*
2013-07-27	Hail			6030052	*Germany*
2013-11-18	Riverine flood	18	2700	979883	*Italy*
2014-01-18	Flash flood	2	1601	148345	*Italy*
2014-05-02	Flash flood	3	8010	148345	*Italy*
2014-11-29	Flash flood	5	3000	374571	*France*
2015-03-02	Severe weather	3		1072991	*Italy*
2015-06-29	Heat wave	3275			*France*
2015-10-03	Flash flood	20		1140902	*France*
2016-05-31	Flood (General)	7		2438717	*Germany*
2016-05-31	Flood (General)	5	24	2926461	*France*
2017-07-24	Wildfire (General)		12012		*France*
2018-01-24	Flood (General)		2750	433551	*France*
2018-10-14	Flood (General)	14	1476	396256	*France*

Date	Disaster Type	Total Deaths	Total Affected	Total Damage, Adjusted ('000 US$)	Country
2018-10-29	Extra-tropical storm	12	2200	1282006	*Italy*
2019-05-15	Flood (General)		1200		*Italy*
2019-06-24	Heat wave	567			*France*
2019-07-21	Heat wave	868			*France*
2020-07-30	Heat wave	1924			*France*
2020-10-02	Storm (General)	18	12980	1093451	*France*
2021-04-05	Cold wave			6048157	*France*
2021-07-12	Flood (General)	197	1000	43201120	*Germany*
2021-07-23	Wildfire (General)		11600	63722	*Italy*
2022-02-18	Extra-tropical storm	3		1023156	*Germany*
2022-05-30	Heat wave	8173			*Germany*
2022-05-30	Heat wave	4807			*France*
2022-05-30	Heat wave	18010			*Italy*
2022-06-04	Severe weather	1	60015		*France*
2023-05-16	Flood (General)	15	46000		*Italy*

Table 2: *Natural disasters in Germany, France and Italy as classified in the EM-DAT dataset.*

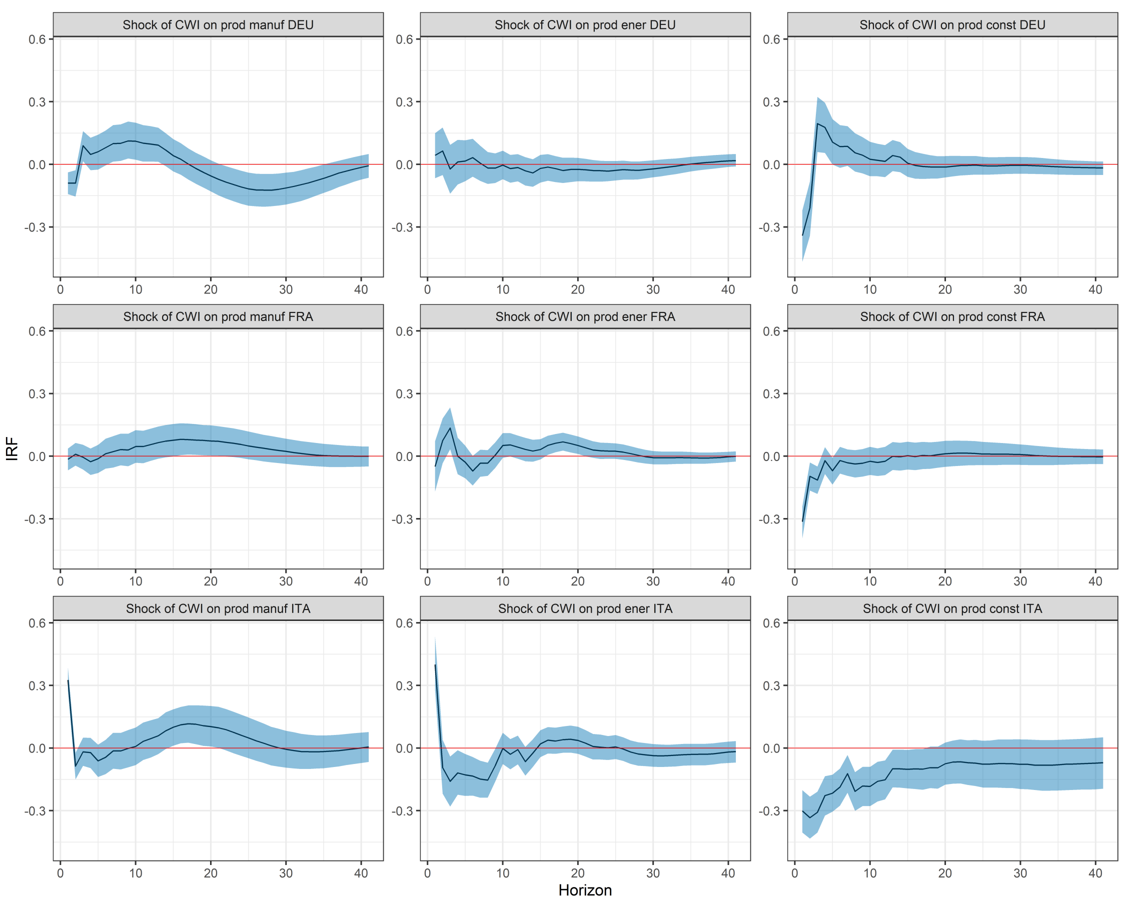

Figure 24: *IRFs of production by sectors to CWI shock excluding natural disasters months, as well as 68% confidence bands.*