Weather Shocks and Sectoral Dynamics in European Economies

Daniele Colombo[*] Laurent Ferrara[†]

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Abstract

This paper investigates the dynamic effects of weather shocks on economic activity in Europe's three largest economies: Germany, France, and Italy. We develop a novel approach to measuring country-level exposure to abnormal weather, based on grid-level data weighted by economic activity. We construct five harmonized weather indices—heat, cold, drought, precipitation, and wind—and, using a Bayesian SVAR framework, assess their impact on output and prices across major sectors: energy, construction, manufacturing, and services. The results show that weather shocks have both direct and indirect effects on economic activity, with substantial heterogeneity across shock types and production sectors.

JEL classification: C32, E23, Q54.

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[*]London Business School. Email: dcolombo@london.edu

[†]Skema Business School – University Côte d'Azur. Email: laurent.ferrara@skema.edu

1 Introduction

What are the macroeconomic impacts of weather shocks? Are these effects confined to sectors that are directly exposed to climatic conditions, or do indirect spillovers throughout the broader economy also play a significant role? Furthermore, to what extent does the type of weather shock shape the nature and magnitude of these effects? We investigate these issues by proposing a novel approach to measuring country-level exposure to abnormal weather and analyzing the macroeconomic effects of five distinct types of shocks—cold, heat, drought, precipitation, and wind—within a Bayesian Vector Auto-Regression framework.

The complex interplay between economic activity and climate is widely acknowledged in the economic literature, with substantial agreement that economic activity contributes to long-term impacts on the climate (see, e.g., Nordhaus, 1991 for a seminal theoretical contribution). In contrast, there is less consensus regarding the extent to which weather events influence economic activity and on the channels of transmission through which these effects may materialize. While much of the existing literature has focused on temperature-largely due to the accessibility of extensive temperature data-recent studies have begun to expand the focus to other weather events and to increasingly utilize composite indices to capture the broader macroeconomic implications of weather, particularly in the context of the United States (Kim et al., 2025).

In this paper, we construct novel indices of exposure to abnormal weather for the three largest European economies—Germany, France, and Italy.[1] Using high-resolution grid-cell weather data, we compute deviations from historical, calendar-specific averages and weight them by proxies of economic activity. This approach preserves spatial heterogeneity, limits the dilution of offsetting local effects, and captures regional variation in exposure based on the geographic distribution of economic activity. We then use the resulting monthly indices to analyze the effects of weather shocks on sectoral output and prices. Finally, we show that composite indices may conceal important heterogeneity in both the nature and impact of shocks, underscoring the need to examine distinct shocks separately to uncover key economic mechanisms.

Assessing these effects is important because, as weather shocks become more frequent and intense due to climate change, policymakers must develop strategies to enhance economic resilience and adaptation capacity. Accurately measuring exposure to abnormal weather conditions is a crucial step toward informing targeted responses. Moreover, understanding the differentiated impacts of distinct weather shocks—including their direct and indirect

[1] The weather shock indices are available here. The dataset includes standardized exposure measures for several European countries, including those analyzed in this paper.

effects across sectors—is essential for designing effective, context-specific policy interventions.

Preview of main results. Leveraging our novel weather shock indices, we find that abnormal weather exerts significant and heterogeneous macroeconomic effects, transmitted through both direct and indirect channels. These effects differ substantially across sectors and countries. The construction sector is the most directly exposed: cold and wind shocks reduce activity, while heat shocks generate contrasting responses—stimulating construction in colder northern economies such as Germany but dampening it in warmer southern countries like Italy, consistent with a latitude-dependent effect. The energy sector is influenced through both demand and supply mechanisms: cold shocks raise heating demand, while wind affects electricity generation costs, underscoring the sector's dual sensitivity to weather conditions. Manufacturing is less directly exposed but remains vulnerable through indirect spillovers, particularly via weather-induced energy price fluctuations. Overall, these findings highlight the importance of distinguishing weather shocks by type and sector to uncover transmission channels that composite indices may hide.

This study also presents, to the best of our knowledge, the first empirical analysis of the effects of weather shocks on services in European countries. While the overall response across the sector is limited, several sub-sectors display significant sensitivity to heat shocks. These patterns are consistent with demand complementarities with construction, as output and prices in related services often move together with construction activity.

A comprehensive series of sensitivity checks indicates that our results are robust across several dimensions and that there are no significant cross-country spillovers. We further test for potential non-linearities in the effects of weather shocks-as observed with other macroeconomic shocks (see, e.g., Caggiano et al., 2022)-focusing on differences across business cycle phases (Billio et al., 2020) and seasonal variation.

Related literature and contribution. A substantial macroeconometric literature has examined the aggregate dynamic effects of structural shocks on the economy (e.g., seminal papers include Romer and Romer, 2004 on monetary policy shocks, Bloom, 2009 on uncertainty shocks, and Ramey, 2011 on government spending and fiscal shocks). We contribute to this literature by examining the macroeconomic dynamic impact of weather-related shocks. In recent years, interest in these shocks has intensified as climate hazards have become more frequent, more severe, and increasingly persistent. Such impacts have been documented across a range of domains, including 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; Ballester et al., 2023; Kim et al., 2025; Bilal and Känzig, 2024).

A key distinction in the literature is between "climate," defined as the joint probability distribution of atmospheric states (Dell et al., 2012; Hsiang, 2016), and "weather," denoting realizations of this distribution. Seminal theoretical contributions have focused on climate, particularly through integrated assessment models (e.g., Nordhaus, 1993; Hassler and Krusell, 2018), while more recent empirical work has turned to weather fluctuations. In this paper, we analyse large deviations from seasonal averages—referred to as *abnormal* weather conditions—and their temporal variation. This focus differs from studies of *extreme* weather events typically classified as natural disasters (e.g., hurricanes or floods). For instance, Strobl (2011) and Felbermayr and Gröschl (2014) examine their effects on economic activity, while Kruttli et al. (2023) and Ferriani et al. (2024) study financial consequences. We instead consider deviations from long-run seasonal norms because, although less catastrophic, such anomalies occur more frequently and can generate persistent, widespread economic effects. By analysing these recurrent shocks, we capture a broader range of weather-related disruptions relevant for aggregate fluctuations and sectoral spillovers, offering insights often overlooked in studies limited to rare, extreme events.

Within the empirical literature, two main econometric approaches have been adopted. Panel regressions offer the advantage of high geographical resolution and large samples, and have been employed by Starr (2000), Bigano et al. (2005), Bloesch and Gourio (2015), Wilson (2019), Billio et al. (2020), and Kotz et al. (2022), among others. However, they are limited in capturing the dynamic effects of weather shocks over time, which is crucial for assessing whether such effects are persistent or transitory. Moreover, panel regressions are often ill-suited when heterogeneity across units is substantial. In contrast, Structural Vector Autoregressive models effectively trace dynamic responses through impulse response functions (see, e.g., Ciccarelli et al., 2023; Kim et al., 2025). In this study, we employ a SVAR framework with Bayesian estimation techniques, which enhance stability when working with large datasets (Bańbura et al., 2007; Giannone et al., 2015). This approach allows us to recover dynamic responses while also estimating sectoral effects.

Several papers have examined the agricultural sector, arguably the most directly exposed to weather shocks. Evidence shows that adverse conditions reduce output and raise prices (see, e.g., Ciscar et al., 2011; Gallic and Vermandel, 2020). More recently, the literature has expanded to other sectors that may be impacted, with particular emphasis on the channels through which severe weather influences the broader business cycle (Graff Zivin & Neidell, 2014; Arent et al., 2015; Bloesch & Gourio, 2015; Donadelli et al., 2017; Wilson, 2019; Roth Tran, 2022; Downey et al., 2023; Kim et al., 2025). We contribute to this growing field by analyzing sectoral output and prices in manufacturing, energy, and construction, and by providing, to our knowledge, the first empirical analysis of services in European countries.

A large literature examines whether weather shocks operate through demand or supply channels. Several studies highlight supply-side mechanisms, where adverse conditions negatively affect production factors (Burke et al., 2005; Deryugina & Hsiang, 2014; Graff Zivin & Neidell, 2014; Donadelli et al., 2017; Kalkuhl & Wenz, 2020; Baleyte et al., 2024). Wilson (2019) and Bloesch and Gourio (2015) further show that employment growth is highly sensitive to weather fluctuations. Other work emphasizes demand-side channels: Ciccarelli and Marotta (2021) demonstrate that physical risks act as negative demand shocks, Roth Tran (2022) show that weather shocks are transmitted through consumer demand, and Bigano et al. (2005) find that tourism is positively correlated with temperature. Auffhammer and Mansur (2014) provides a comprehensive review of the empirical relationship between climate conditions and energy consumption. Our results suggest that weather shocks operate through both demand and supply channels. Cold and wind shocks reduce construction output, while heat shocks stimulate it, particularly in Northern Europe. The energy sector is affected through both channels: cold weather raises heating demand, while wind influences supply by altering electricity generation costs.

Finally, our results are consistent with previous studies documenting substantial heterogeneity in the effects of weather shocks across both sectors (Parnaudeau & Bertrand, 2018; Acevedo et al., 2020) and countries (Billio et al., 2020; Olper et al., 2021). In particular, we find evidence of a latitude effect: the construction sector is highly sensitive to weather shocks, with cold temperatures and wind reducing activity, while heat shocks have positive effects in northern countries like Germany but negative effects in southern countries such as Italy.

Outline. The remainder of the paper is organised as follows. Section 2 describes the construction of the weather indices and the macroeconomic data used in the analysis. Section 3 presents the empirical strategy and econometric methodology. Section 4 reports the empirical findings. Finally, Section 5 concludes. Additional figures, robustness checks, and technical details are provided in the Supplemental Appendix.

2 Data

We construct a set of novel weather indices to capture exposure to abnormal weather, which we can interpret as macroeconomic shocks (Ramey, 2016). We then analyze their transmission to key sectors—manufacturing, energy, construction, and services—using data on sectoral output, producer prices, and consumer prices. The analysis also incorporates standard macroeconomic indicators, including unemployment and short-term interest rates. Our empirical investigation is based on a monthly panel covering January 1990 to December 2019.

2.1 Weather data

We construct indices of abnormal deviations across five weather dimensions: cold, heat, drought, precipitation, and wind. This reflects growing recognition that economic activity responds to a broader set of conditions beyond temperature, which has traditionally dominated the empirical literature (see, e.g., Burke et al., 2005; Acevedo et al., 2020; Lucidi et al., 2022; Natoli, 2022; Bilal and Känzig, 2024). Recent studies have proposed composite measures—such as the ACI[2] for North America—that integrate multiple weather variables (Kim et al., 2025). Following this approach, we develop a Composite Weather Index (CWI) by aggregating the five components into a unified measure of overall abnormal weather. While the CWI provides a convenient summary of weather variability, we show that such aggregation can mask the heterogeneous effects and transmission channels of individual shocks.

A key challenge lies in determining how to construct the weather shocks. Our approach is guided by the objective of accurately capturing a country's economic exposure to abnormal weather conditions, while ensuring comparability across countries and across different types of weather shocks. First, we leverage high-resolution gridded weather data to compute abnormal deviations at the grid-cell level, which we then aggregate to the country level—the relevant unit of analysis for our study. This approach mitigates the risk of aggregation bias that arises when offsetting weather conditions across regions within a country are averaged out. Second, in aggregating grid-level data, we weight by proxies of economic activity, following Gortan et al. (2024). This ensures that regions with greater economic relevance contribute proportionally more to the country-level index.[3] Failing to account for the geographical distribution of economic activities may lead to biased estimates of the economic effects of weather. Third, we adopt a harmonized methodology across all five weather dimensions-cold, heat, drought, precipitation, and wind-ensuring consistency in measurement and facilitating a coherent comparative analysis across types of shock.

We construct each of our weather indices in the following manner. Let $W_{c,d}$ denote the

[2] American Academy of Actuaries (2016).

[3] For example, abnormal weather in the industrialized North of Italy is likely to have a stronger impact on aggregate outcomes than in the less industrialized South. In addition, computing deviations at the grid-cell level before aggregation helps mitigate aggregation bias: if Northern Italy experiences unusually cold temperatures while Southern Italy experiences unusually hot temperatures in the same month, the economic impact is the sum of both regional effects, rather than the effect of the average temperature at the country level.

daily weather variable of interest-such as average temperature or total precipitation-at grid cell c on day d.

1. **Detrending.** Following 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.

2. **Threshold computation.** For each grid cell, we compute calendar-month-specific percentiles $W_{c,\tilde{t}}$, which serve as exceedance thresholds. We favor month-specific thresholds to account for strong seasonal patterns in weather data, while avoiding the noise associated with day-specific values. This also achieves seasonal adjustment by construction.

3. **Exceedance value.** For each calendar month, we compute the cumulative value of observations exceeding the corresponding threshold:

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

   where D_m denotes the number of days in a calendar month m, y indexes the year, and $\mathbb{1}\{.\}$ is an indicator function equal to 1 when the daily observation is above the respective month-specific threshold.

4. **Spatial aggregation.** We then aggregate grid-cell-level exceedance values to the country level using weights based on proxies for economic activity and administrative boundaries from the GADM dataset, following Gortan et al. (2024). We use nocturnal light intensity (Li et al., 2020) as the preferred proxy over alternative weights.[4] The aggregated index for country C is denoted $WM_{m,y}^C$.

5. **Standardization.** Finally, we standardize the index using month-specific standard deviations $\bar{W}_m^C$:

$$\frac{WM_{m,y}^C}{\sigma_m^C}.$$

   This step adjusts for seasonal variability in weather conditions, allowing for meaningful comparisons across time and across weather variables.

Analogous to the ACI for North America, the CWI is then constructed as the unweighted average of the five individual weather shock components: cold, heat, drought, precipitation,

[4]This is not a substantive choice as the other weighting schemes discussed in Gortan et al. (2024) give very similar results.

and wind. Figure 1 displays the country-specific CWIs for Germany, France, and Italy, along with their smoothed versions based on a five-year moving average. The disaggregated weather components underlying each country's CWI are shown in Supplemental Appendix A, in Figures A16, A17, and A18, respectively. The Supplemental Appendix also provides further details on the computation of the weather shocks and the underlying data sources.

Constructing weather shocks in this manner offers several advantages. First, seasonal adjustment-crucial when working with weather variables-is achieved by construction. Second, the resulting series are effectively standardized, facilitating interpretation and cross-country comparison.[5] From an economic perspective, measuring deviations from calendar-month-specific historical averages allows us to focus on the effects of abnormal weather conditions-conceptually similar to deviations from a steady state. Moreover, focusing on *large* deviations is particularly relevant, as these are less likely to be anticipated by economic agents and thus harder to incorporate into decision-making processes prior to their realization. The monthly frequency at which we construct our shocks is important in this regard, and it also supports the assumption of exogeneity of weather shocks with respect to the macroeconomic variables considered in our analysis.[6] Furthermore, our shock measures have the desirable property of capturing not only isolated extreme events but also the accumulation of multiple, economically relevant deviations occurring within the same month. While a single large weather event might be mitigated by adaptive behavior, repeated abnormal conditions over a short period are more likely to disrupt economic activity (Natoli, 2022).

How should we interpret the dynamic responses of sectoral output and prices to these shocks? We consider a scenario in which a country experiences a month of unusually intense weather-defined as one standard deviation above its typical seasonal average. Because the shocks are standardized, the resulting estimates are comparable across countries and types of weather events, while still reflecting each country's own historical climate patterns.

Supplemental Appendix B outlines the relationship between our weather indices and those previously proposed in the literature. We conduct several robustness checks to validate our findings and the construction of the weather shocks, as detailed in Supplemental Appendix D. These include alternative constructions of the shocks, different percentile thresholds, a falsification test, and comparisons with alternative country-level aggregation methods. We also show that our results are not driven by natural disasters, drawing on data from the EM-DAT International Disaster Database. Across all exercises, the main results remain robust, reinforcing the validity of our identification strategy and interpretation of the shocks.

[5]Month-specific standardization yields a series with unit standard deviation, analogous to conventional standardization procedures.

[6]Forecast accuracy for temperature and other weather variables tends to deteriorate rapidly with forecast horizon, even when using state-of-the-art models. See, e.g., Lopez-Gomez et al. (2023).

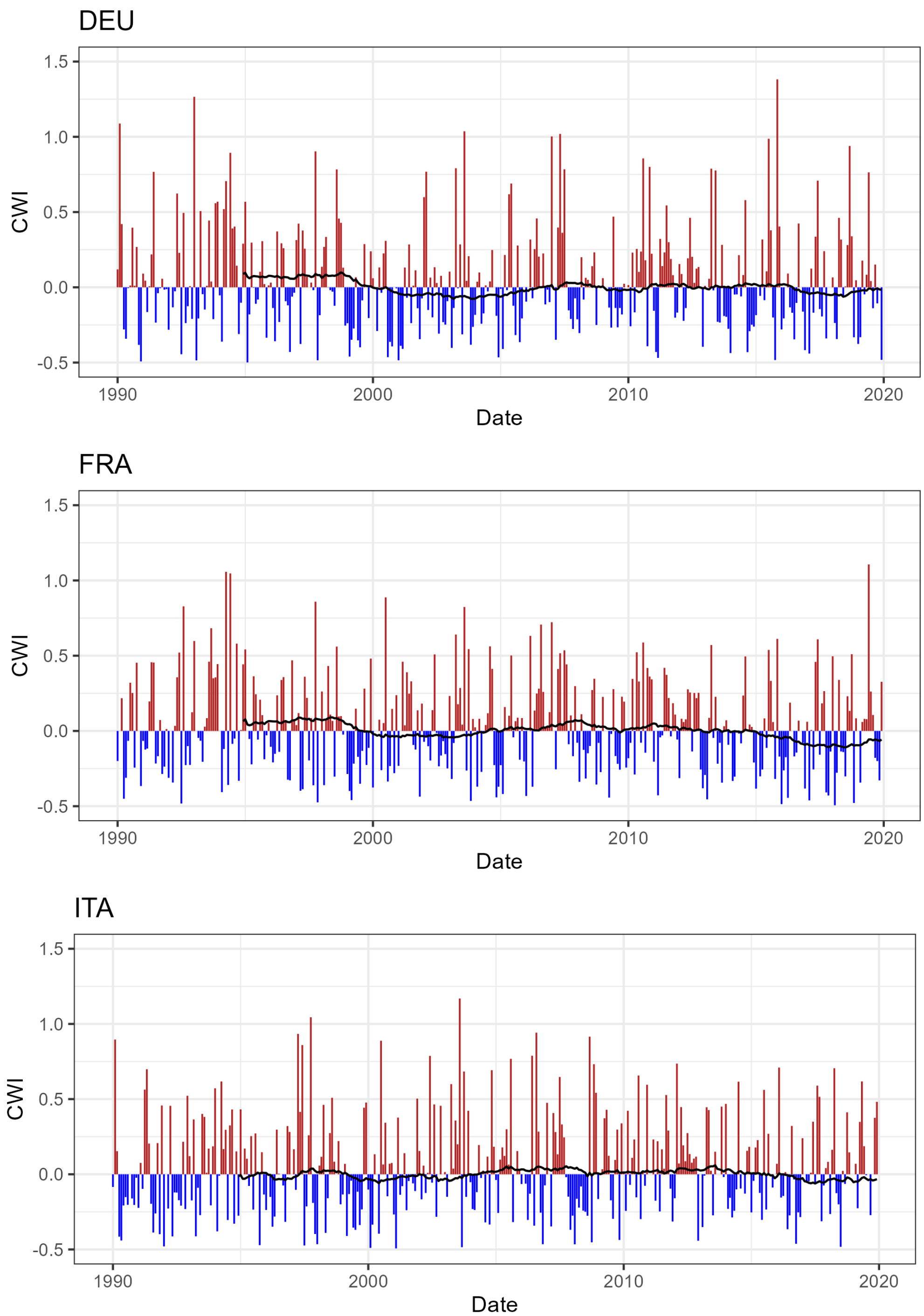


Figure 1: *Composite Weather Indices for Germany, France and Italy. Positive values in red and negative values in blue. The solid black line is a 5-year moving average.*

2.2 Aggregate and sectoral economic data

The aggregate macroeconomic variables used in the empirical analysis include the unemployment rate and the ECB's main refinancing rate, proxied by the three-month Euribor. We also incorporate a broad set of sectoral production indices from Eurostat, classified according to NACE Rev.2. Specifically, we cover sectors from Section B to Section N, excluding Section K (financial and insurance activities). As listed in Table 1, these include Manufacturing (C); Electricity, gas, steam and air conditioning supply (D); Construction (F); Wholesale and retail trade (G); Transportation and storage (H); Accommodation and food services (I); Information and communication (J); Real estate activities (L); and Administrative and support services (N). Due to data limitations, monthly indicators for service sectors (G to N) are only available for France. We exclude Section A (agriculture), which-despite its relevance in the literature on weather shocks-lacks consistent monthly coverage. From Eurostat, we also

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*

collect producer price indices for sectors C (Manufacturing) and D (Electricity, gas, steam and air conditioning supply),[7] along with consumer price indices for energy and services.[8]

3 Econometric approach

Our econometric analysis aims to estimate impulse response functions (IRFs) for each weather shock. For baseline estimation, we employ Structural Vector Autoregressions (SVARs) and use Local Projections (LPs) (Jordà, 2005) to assess potential nonlinearities in shock transmission.

[7]For sector F (Construction), the producer price index is available only at annual frequency.

[8]SERV: Services (overall index excluding goods); NRG: Energy, from the Eurostat *prc_hicp_midx* dataset.

3.1 SVAR modelling

Consider the following structural VAR(p) model:

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{w}_t, \tag{1}$$

where $\mathbf{y}_t$ is a vector containing the endogenous variables in the following order: weather index, sectoral production indicators, producer and consumer prices, unemployment rate, and short-term interest rates. The vector $\mathbf{w}_t$ is a vector of structural shocks. The model is "structural" because the elements of $\mathbf{w}_t$ are mutually uncorrelated, i.e. $\mathbb{E}(\mathbf{w}_t\mathbf{w}_t') = \mathbf{\Sigma}_w$ is diagonal. Since the matrices $\mathbf{B}_0$ and $\mathbf{w}_t$ are generally unobserved, we rely on the reduced-form representation to estimate the model:

$$\begin{aligned}\mathbf{y}_t &= \mathbf{B}_0^{-1}\mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_0^{-1}\mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{B}_0^{-1}\mathbf{w}_t \\ &= \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t,\end{aligned}$$

where we estimate the reduced-form parameters $\mathbf{A}_1, \ldots, \mathbf{A}_p, \mathbf{\Sigma}_u$, and the reduced-form residuals $\mathbf{u}_t$ using Bayesian methods. Following Giannone et al. (2015), we implement standard Minnesota, sum-of-coefficients, and dummy-initial-observations priors. Technical details are provided in Supplemental Appendix C. The key equation linking the reduced-form innovations to the structural shocks is:

$$\mathbf{u}_t = \mathbf{B}_0^{-1}\mathbf{w}_t. \tag{2}$$

Our objective is to identify the effects of a weather shock on the system, which corresponds to recovering the relevant column of the impact matrix $\mathbf{B}_0^{-1}$. This is achieved via a Cholesky decomposition of $\mathbf{\Sigma}_u$, using the predefined ordering of variables. This identification strategy implies that economic variables do not contemporaneously affect severe weather outcomes *within the same month*. However, the longer-term dynamics of the system may allow for feedback from economic conditions to weather-related variables over time.

3.2 Non-linear Local Projections

As an alternative to Vector Autoregressive (VAR) models, Jordà (2005) proposed the Local Projection (LP) approach for estimating impulse response functions. This method offers a flexible estimation framework, particularly well-suited for incorporating non-linearities. LPs directly estimate the IRFs for a variable of interest x_t using a sequence of horizon-specific regressions of the form:

$$x_{t+h} = c^h + \beta_h \nu_t + \mathbf{\Gamma}_h(B)\mathbf{y}_{t-1} + u^h_{t+h} \qquad \text{for} \quad h = 0, 1, \cdots, H, \tag{3}$$

where ν_t denotes a weather shock of interest, and $\mathbf{y}_t$ is a vector of control variables similar to those included in the SVAR specification in equation (1). This specification allows us to estimate the dynamic response of x_{t+h} to a weather shock ν_t, conditional on past information in $\mathbf{y}_{t-1}$. β_h represents the response of x_{t+h} to a shock occurring at time t, and the IRF is given by the sequence of estimated coefficients $\beta_h{}_{h=0}^{H}$.

The local projection equation (3) can be extended to a non-linear framework by allowing for the existence of two distinct regimes, each associated with different parameter values. To estimate these regime-specific parameters, we interact the regressors on the right-hand side of equation (3) with regime-switching probabilities. Specifically, we multiply the regressors once by $(1 - F(s))$, interpreted as the probability of the economy being in the first regime, and once by $F(s)$, the probability of being in the second. This regime-dependent structure yields the following non-linear, horizon-specific specification:

$$x_{t+h} = (1-F(s_{t-1}))[c^h_1+\beta_{1,h}\nu_t+\mathbf{\Gamma}_{1,h}(B)\mathbf{y}_{t-1}]+F(s_{t-1})[c^h_2+\beta_{2,h}\nu_t+\mathbf{\Gamma}_{2,h}(B)\mathbf{y}_{t-1}]+u^h_{t+h}. \tag{4}$$

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

$$F(s_t) = \frac{e^{-\gamma \hat{s}_t}}{1 + e^{-\gamma \hat{s}_t}}, \;\; \hat{s}_t = \frac{s_t - \mu}{\sigma} \tag{5}$$

where s_t denotes the transition variable used to differentiate between regimes in which potential non-linear effects are estimated, while μ and σ represent its mean and standard deviation, respectively. For instance, when s_t is specified as a business cycle indicator, the transition function $F(s_t)$ approaches zero during downturns (regime 1) and one during expansions (regime 2). The resulting estimates yield impulse response functions to the weather shocks conditional on each regime.

4 Results

This section presents the results of our empirical analysis based on the data and models described above. We begin by examining the impact of individual weather shocks—heat, cold, drought, precipitation, and wind—on sectoral production and prices, and then compare these with the dynamic effects of the Composite Weather Index. We then present additional results on the services sector, explore potential non-linearities, and assess the presence of cross-country spillovers. The analysis focuses on the three largest economies in Europe: Germany, France, and Italy. Since the response variables are expressed as year-on-year growth rates, the estimated IRFs indicate whether a variable grows at a faster or slower rate relative to its counterfactual path in the absence of the shock, over a 12-month horizon.

4.1 Weather-specific shocks

To enable cross-country and cross-sector comparisons, and to assess the time required for variables to return to baseline levels, we report both impact and cumulative IRFs at selected horizons. Where relevant for illustrating key features of the transmission of the shocks, we also present selected IRFs in extended form. The analysis focuses on the responses of three sectoral outputs, along with sectoral prices—specifically, manufacturing and energy producer prices, as well as the energy component of consumer prices.

4.1.1 Cold shock

Figure 2 presents the impact responses and the cumulative effects at the 3- and 6-month horizons following a cold shock across all countries. A number of regularities emerge. The construction sector exhibits an immediate decline in output, which persists in the short term but starts recovering after a few months. This transitory contraction is likely driven by the direct effects of adverse weather conditions that impede construction activity.

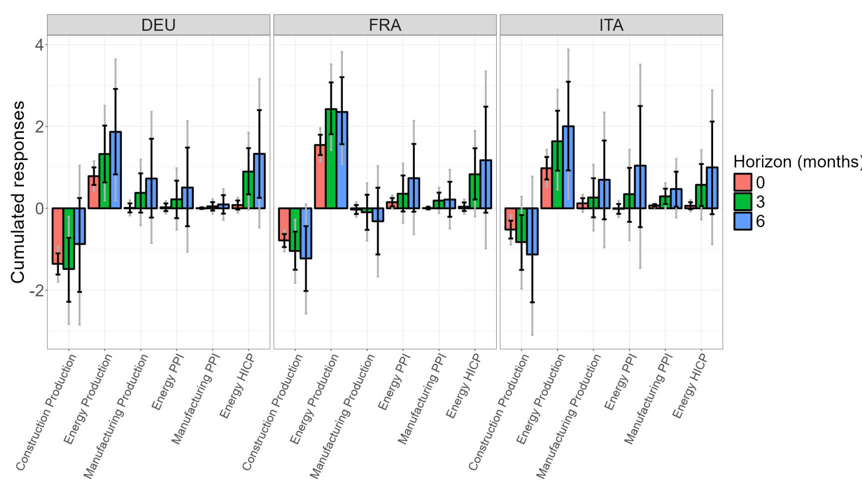


Figure 2: *Impact (red) and cumulative responses at 3 months (green) and 6 months (blue) to a cold shock, with 68% and 90% confidence intervals shown as black and gray whiskers, respectively.*

The energy sector is substantially affected by a cold shock, with production increasing persistently across countries. While producer price indices exhibit only mild and statistically insignificant increases, consumer prices respond significantly, albeit with a lag. To examine the transmission mechanism in greater detail, we present selected extended impulse responses, which shed light on how the shock propagates through the economy via the energy sector (see Figure 3). Following a one standard deviation cold shock, energy production in France registers the largest impact response, increasing by more than 1.5%. Italy and Germany also experience positive responses, with increases of approximately 1% and 0.8%, respectively. The dynamics are broadly similar across the three countries, with the IRFs reverting to the baseline level within five months. Consumer prices respond significantly, peaking within four months of the shock. In contrast, producer prices adjust more slowly.

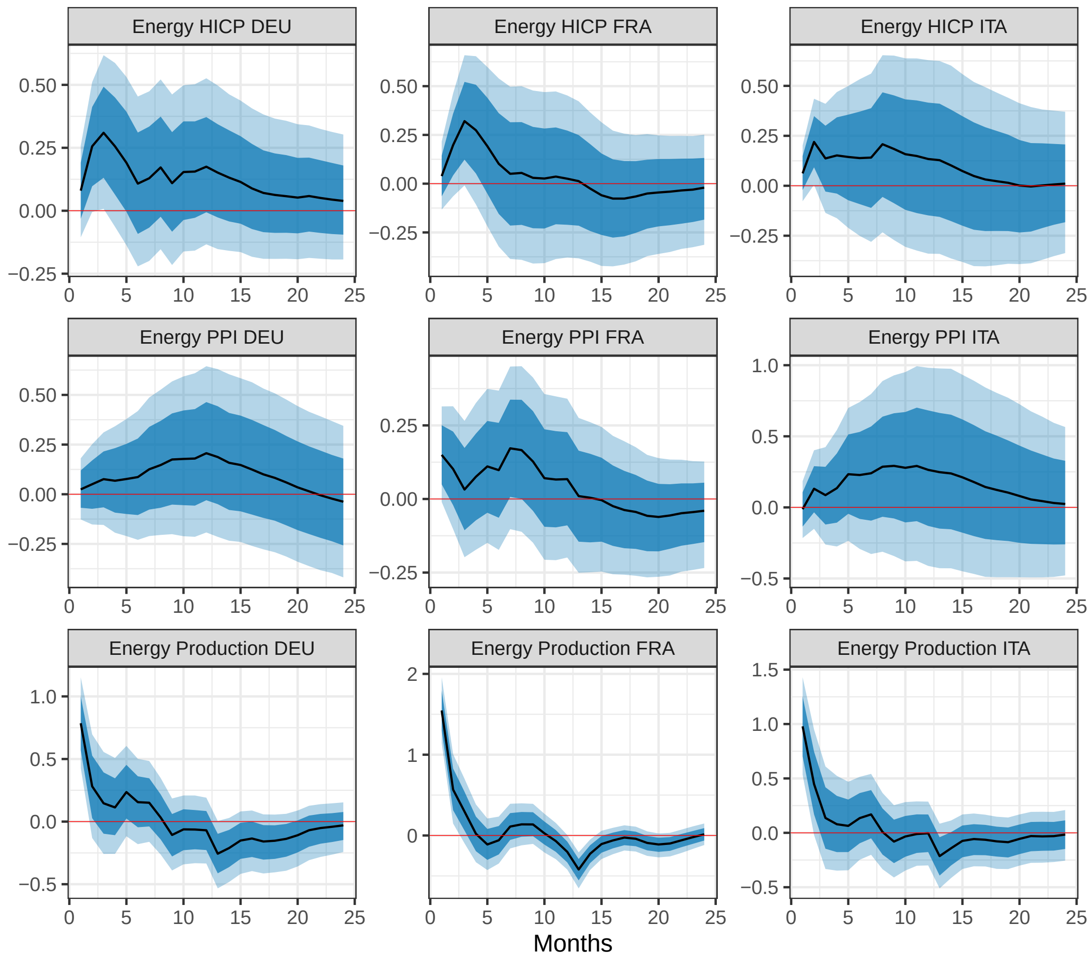


Figure 3: *Impulse responses of output and prices of the energy sector to a cold shock, with 68% and 90% confidence intervals in shades of blue. The responses are presented for Germany (left column), France (middle column), and Italy (right column).*

Although increases are observed in all countries, the response is statistically significant only in France on impact.

These findings point to a demand for heating channel. A cold temperature shock raises the demand for heating, which in turn drives up energy production and leads to higher energy prices. This interpretation is consistent with the results of Lucidi et al. (2022) regarding price dynamics, as well as with Colombo and Toni (2024), who examine the transmission of gas price shocks within the European economy. The mild reaction in producer prices that we observe likely 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 contractual agreements that typically lock in rates, thus insulating companies from market volatility (see, e.g., McKinsey, 2021). The simultaneous upward movement of both output and prices suggests that the primary transmission channel is indeed a demand shock.

Finally, output in the manufacturing sector does not exhibit a statistically significant response (see again Figure 2). In contrast, producer prices show a mild but statistically insignificant increase, possibly reflecting higher energy costs—a key input in the manufacturing process.

4.1.2 Heat shock

The impact and cumulated responses to a heat shock are presented in Figure 4. The overall dynamics broadly evolve in the opposite direction to those observed following a cold shock, though with some key differences. A heat shock leads to a substantial increase in construction output in Germany, a milder rise in France, and no significant effect in Italy. These findings underscore the sensitivity of the construction sector to weather conditions, given its reliance on outdoor activity. A heat shock tends to support production in Northern European countries such as Germany, while it has more adverse effects in Southern European countries. This geographic contrast is well documented in the empirical literature. The impact of temperature shocks varies systematically with latitude, resulting in heterogeneous effects across regions. Kalkuhl and Wenz (2020) provide evidence that changes in annual mean temperatures affect regional economic output in a non-linear fashion, with temperature increases generally boosting gross regional product in colder regions and reducing it in warmer ones (see also Billio et al., 2020). Further studies highlight that temperature shocks primarily influence the labor supply of workers in weather-exposed sectors. For instance, Graff Zivin and Neidell (2014), using U.S. data, show that high daily temperatures lead to reductions in labor supply among outdoor workers.

Energy production is again impacted via the heating demand channel, with both output and prices responding in the same direction. However, the responses are generally less significant than those observed following a cold shock. In particular, the effects are not statistically significant in Germany and Italy. Although a heat shock might be expected to

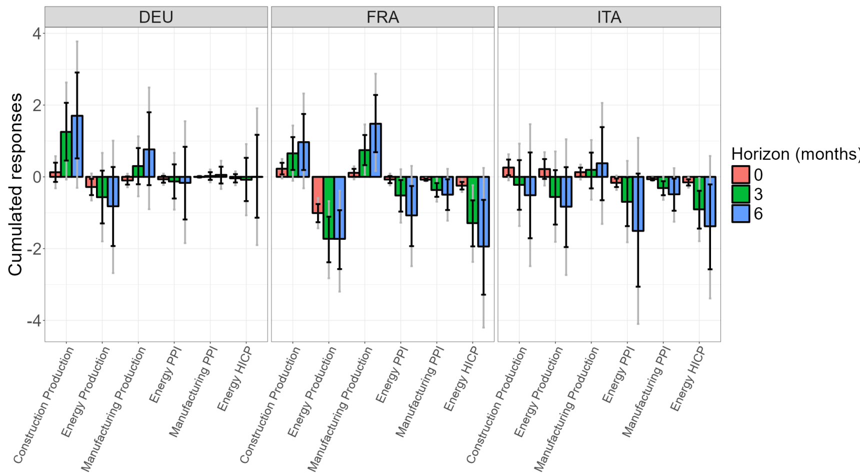


Figure 4: *Impact (red) and cumulative responses at 3 months (green) and 6 months (blue) to a heat shock, with 68% and 90% confidence intervals shown as black and gray whiskers, respectively.*

raise energy demand through increased use of air conditioning, its overall impact on energy consumption in Europe remains limited. This is primarily because air conditioning is less prevalent and less intensively used than heating across most European countries.[9]

Finally, we find that manufacturing output increases with a lag across all countries, although the effect is only marginally significant in the case of France. To investigate the potential indirect effects of weather shocks on the manufacturing sector—operating through changes in prices in the energy sector—we present the full dynamics of selected impulse response functions in Figure 5. This figure shows the effects of a heat shock, which leads to a significant and immediate decline in energy demand, displayed by a reduction in both production and producer prices across all countries. The reduction is primarily driven by lower household heating demand, particularly via natural gas (Colombo & Toni, 2024). Consequently, energy prices for producers 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 exhibiting significant persistence. The peak of the IRFs for manufacturing output occurs between 9 and 15 months after the initial shock. This increase in overall activity is also reflected in

[9]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 many more than the cooling degree days in Europe (Eurostat, 2023).

the responses of the unemployment rate.

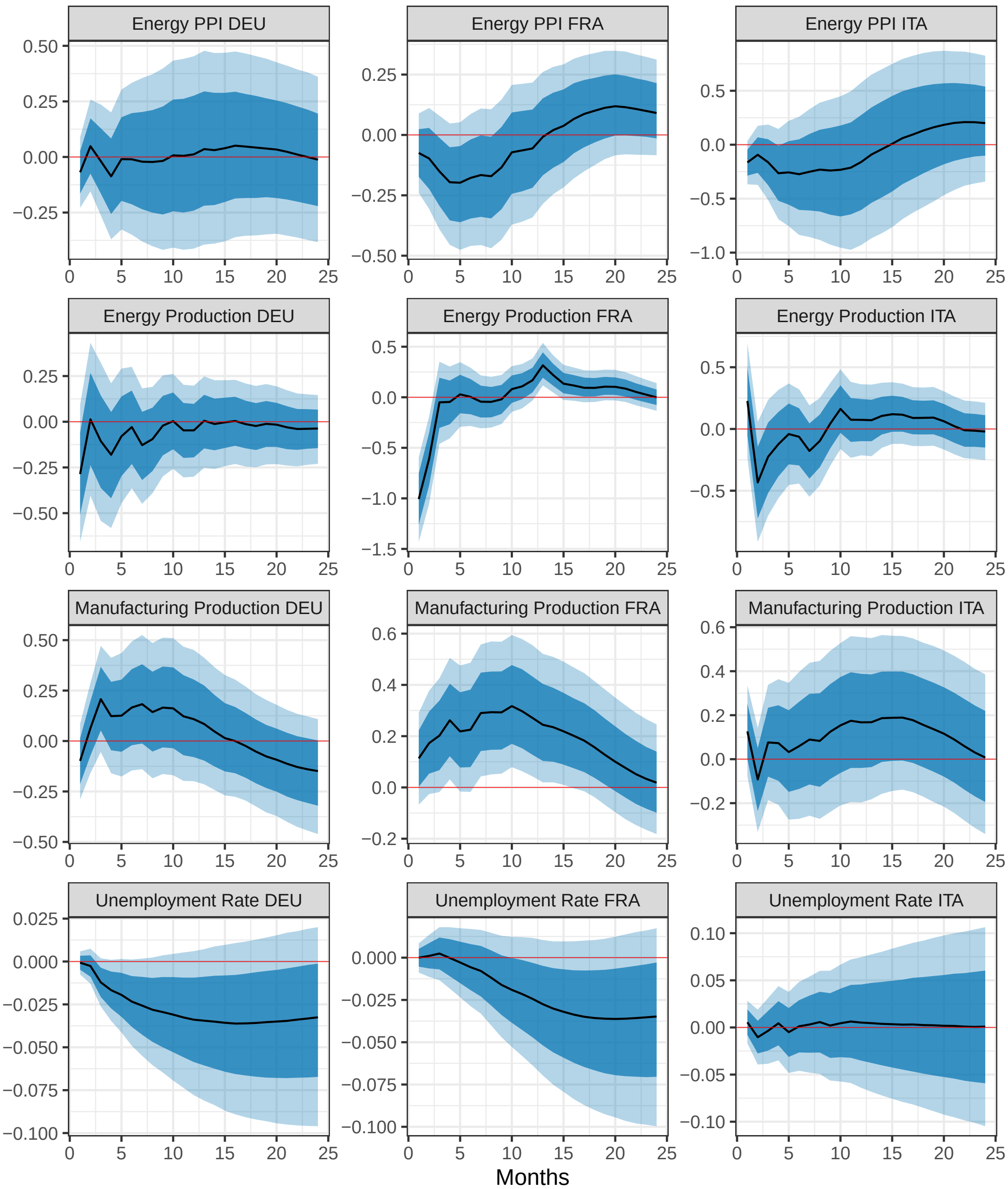


Figure 5: *Impulse responses of output and prices of the energy sector to a heat shock, with 68% and 90% confidence intervals in shades of blue. The responses are presented for Germany (left column), France (middle column), and Italy (right column).*

4.1.3 Precipitation and drought shocks

Figure 6 and Figure 7 present the impact and cumulative responses to precipitation and drought shocks, respectively. The effects on energy production differ markedly across countries. In Italy, precipitation shocks reduce energy output, while drought shocks have a mild positive effect. In contrast, France exhibits a negative response to drought shocks, and Germany shows no significant response to either shock. These heterogeneous patterns likely reflect structural differences in the energy mix and sensitivity to climatic conditions. In Italy, where hydropower represents a larger share of electricity generation, energy production is more directly exposed to precipitation-related variability. Conversely, in France, the negative impact of drought shocks may stem from the reliance on nuclear power, which depends on river water for cooling. During droughts, lower water levels and thermal discharge constraints can limit nuclear output. Germany, with a more diversified and less climate-sensitive energy portfolio—including a reduced role for both hydropower and nuclear—exhibits greater resilience to such weather shocks. Consistently, when significant, energy producer prices tend to move in the opposite direction to energy production in response to weather shocks.

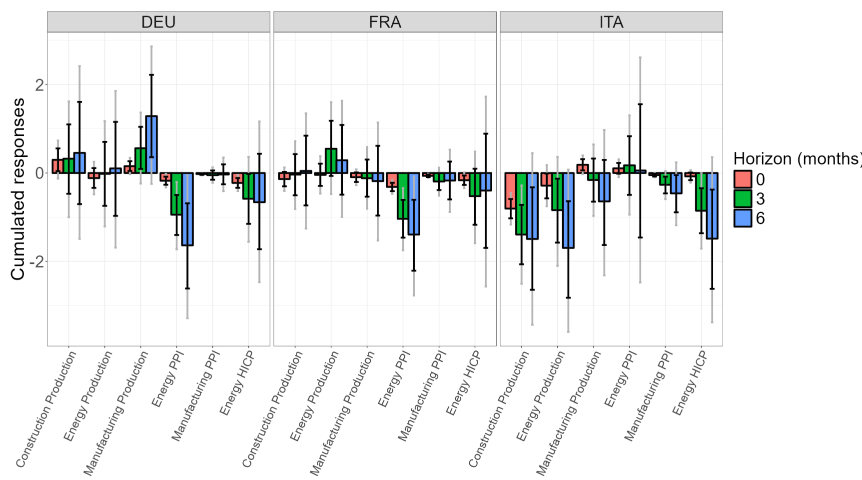


Figure 6: *Impact (red) and cumulative responses at 3 months (green) and 6 months (blue) to a precipitation shock, with 68% and 90% confidence intervals shown as black and gray whiskers, respectively.*

Conversely, manufacturing production in Germany appears highly sensitive to these shocks, expanding in response to precipitation shocks and contracting following drought shocks. Italy exhibits the opposite pattern, albeit with less pronounced effects: precipitation shocks are associated with a decline in output, while drought shocks lead to a positive response. In France, the manufacturing sector shows limited sensitivity to either type of shock. These cross-country differences—where France emerges as the most resilient and Italy as the

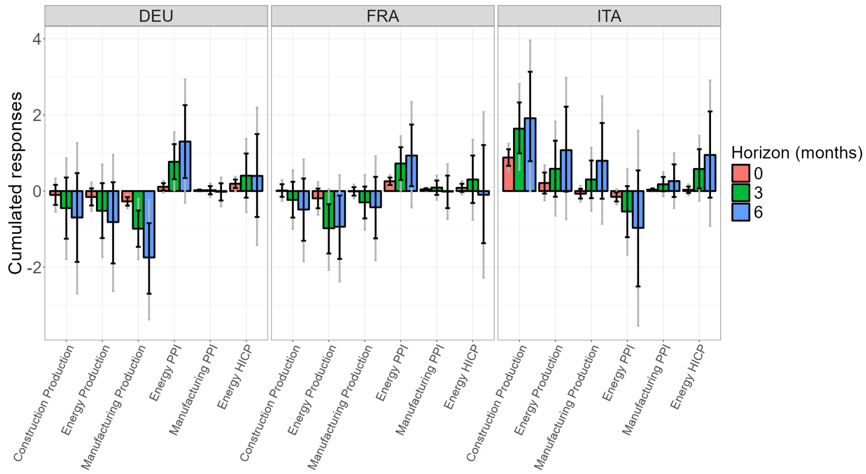


Figure 7: *Impact (red) and cumulative responses at 3 months (green) and 6 months (blue) to a drought shock, with 68% and 90% confidence intervals shown as black and gray whiskers, respectively.*

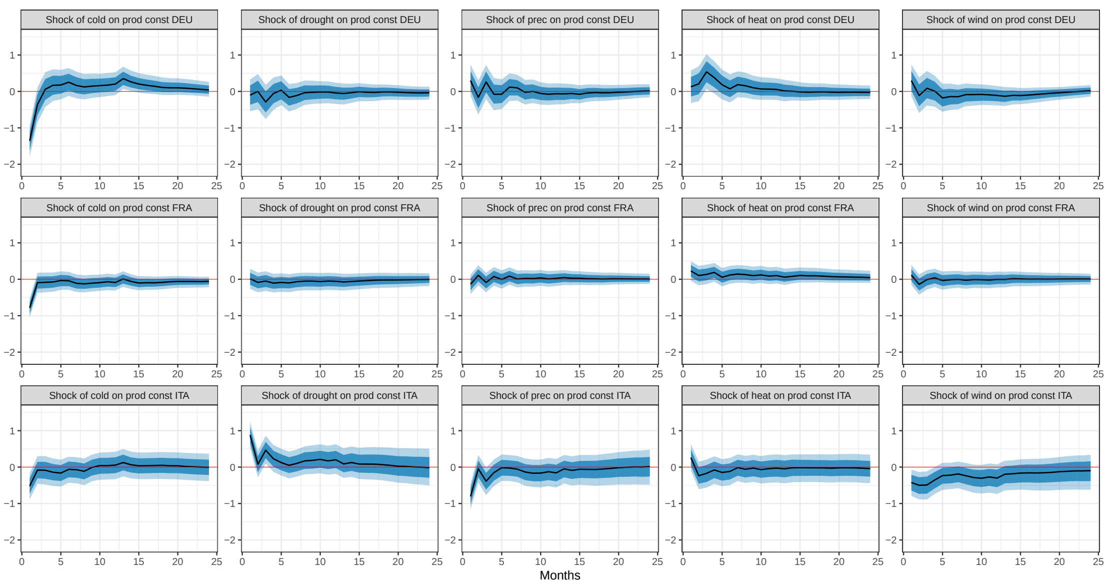


Figure 8: *Impulse responses of construction production to each type of weather shock (columns), with 68% and 90% confidence intervals in shades of blue. Responses are shown for Germany (top row), France (middle row), and Italy (bottom row).*

most affected—are consistent with the findings of Billio et al. (2020) and Olper et al. (2021).

The construction sector, despite being directly exposed to weather conditions, does not exhibit significant responses to either shock in France or Germany. In contrast, in Italy, precipitation shocks have a persistent negative effect, while drought shocks have a persistent positive effect. Figure 8 provides a more detailed view of the construction sector's response to each weather shock through extended impulse responses. Cold shocks consistently reduce construction output on impact across all countries, with the largest effect observed in Germany, followed by France, and the smallest in Italy—reflecting differences in average temperature levels across countries. Among the three countries, Italy stands out as the only case where the construction sector responds significantly to all five weather shocks. Cold, precipitation, and wind shocks are associated with negative effects, while drought and heat shocks lead to positive responses, with impacts reaching up to 1% on impact—patterns that align with intuitive priors. Drought and wind shocks exhibit the most persistent effects.

4.1.4 Wind shock

Impact and cumulative responses to a wind shock are depicted in Figure 9. Our findings reveal a significant decline in construction activity in Italy, with output falling by around 2% within six months of the shock. In contrast, Germany and France do not exhibit significant responses. The persistence of the effect in Italy is further illustrated in the bottom-right panel of Figure 8, which shows an initial decline in construction output growth of approximately 0.5%, followed by a gradual return to the steady state over the course of a year. This pronounced impact can largely be attributed to the sector's exposure to wind conditions, which can disrupt construction activity by necessitating the suspension of crane operations and delaying ongoing projects. Such adverse effects appear less severe in Germany and France.

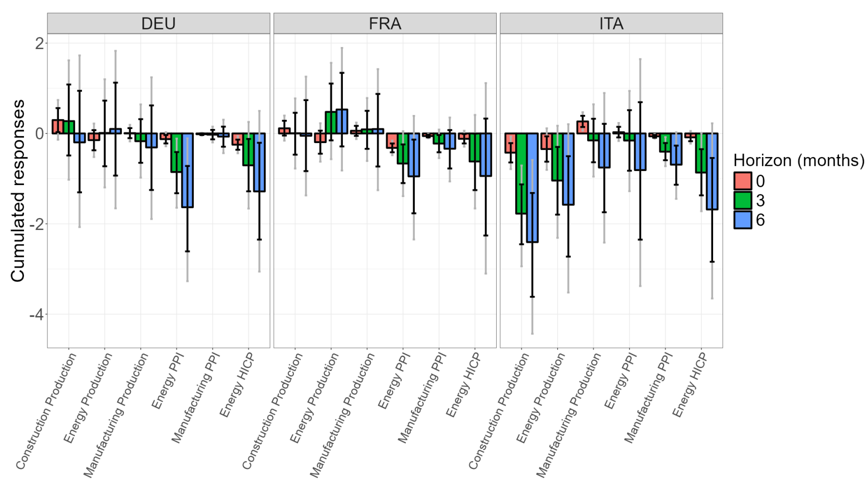


Figure 9: *Impact (red) and cumulative responses at 3 months (green) and 6 months (blue) to a wind shock, with 68% and 90% confidence intervals shown as black and gray whiskers, respectively.*

A second notable finding concerns the dynamic response of the energy sector to a wind shock. Energy prices in all three countries tend to decrease for both producers and consumers. This widespread impact on energy prices can be attributable to the increase in wind energy production.[10] Despite comparable shares of renewable energy production across Germany, France, and Italy,[11] 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). Consistently, we find a stronger negative effect on energy PPI in Germany, followed by France, with a negative but statistically insignificant effect in Italy. Germany benefits from a more diversified and technologically advanced energy mix, contributing to lower electricity generation costs relative to Italy. In contrast, Italy faces higher costs due to its greater reliance on natural gas and less favorable conditions for renewable energy deployment. France, by comparison, maintains relatively low generation costs, primarily as a result of its substantial dependence on nuclear power, which provides a stable and cost-effective energy source. Consumer energy prices decline by a similar magnitude across all three countries, with the effect materializing with a lag.

Finally, the manufacturing sector does not appear to be significantly impacted by wind shocks.

4.2 Dynamic effects of weather shocks on services

We now investigate the dynamic effects of weather-specific shocks on the service sector, with a focus on France, where detailed monthly data on services output are available. While monthly data on services prices are available for all three countries, output data are only accessible for France.[12] Impulse responses to the weather shocks are estimated by incorporating services prices and output into the baseline specification, applying the same methodology used for other sectors in the previous section. While service production generally responds less strongly to weather shocks than other sectors, temperature shocks elicit significant reactions in several sub-sectors. The findings also highlight spillovers from complementary sectors, such as construction, suggesting demand-driven effects. Overall, the results point to the heterogeneous and region-specific nature of weather-related impacts on the service

[10] 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 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. A key mechanism through which wind power influences electricity prices is marginal pricing, whereby the price at any location and time is determined by the cost of the most expensive generator required to meet demand. Since wind power is often among the lowest-cost sources available, its presence tends to 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).

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

[12] Detailed data on services sector production are available for Germany only from 2016 onwards and are not available for Italy at the time of writing (see Eurostat).

economy.

Figure 10 presents the impact and cumulative impulse responses of services inflation to the different weather-specific shocks across countries. The responses display considerable cross-country heterogeneity, with service prices generally showing mild reactions to weather shocks. However, when statistically significant, these responses tend to align with the direction of the response observed in construction output, suggesting the presence of demand complementarities—that is, increased (or decreased) activity in construction may influence the demand for certain service categories, thereby affecting their prices. This pattern is evident in the case of cold shocks, which lead to a significant decline in services inflation in Germany, and in the price response to heat shocks in France (see Figures 2 and 4 for comparison).

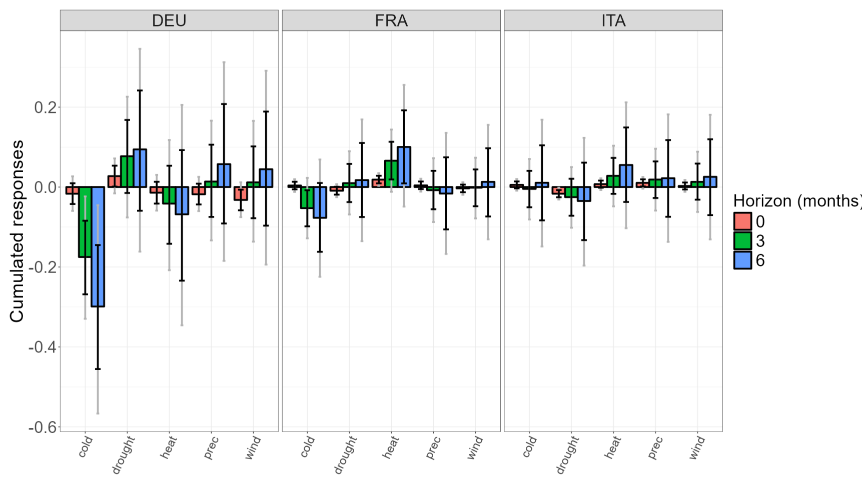


Figure 10: *Impact (red) and cumulative responses at 3 months (green) and 6 months (blue) of services inflation (HICP) to the five weather shocks, with 68% and 90% confidence intervals shown as black and gray whiskers, respectively.*

Figure 11 reports the responses of production in various French service sub-sectors, ranging from G (*Wholesale and retail trade*) to N (*Administrative and support service activities*), as defined in Table 1. Compared to the production sectors analyzed previously, the response of service sector output to weather shocks is relatively limited. Nonetheless, heat shocks generate the most pronounced reactions, with four sub-sectors showing statistically significant responses.

These findings, together with the observed increase in construction activity following heat shocks, suggest that construction activity may stimulate demand in complementary service sectors such as retail and transportation. The fact that both prices and output in these sectors move in the same direction further supports the interpretation that these effects are demand-driven.

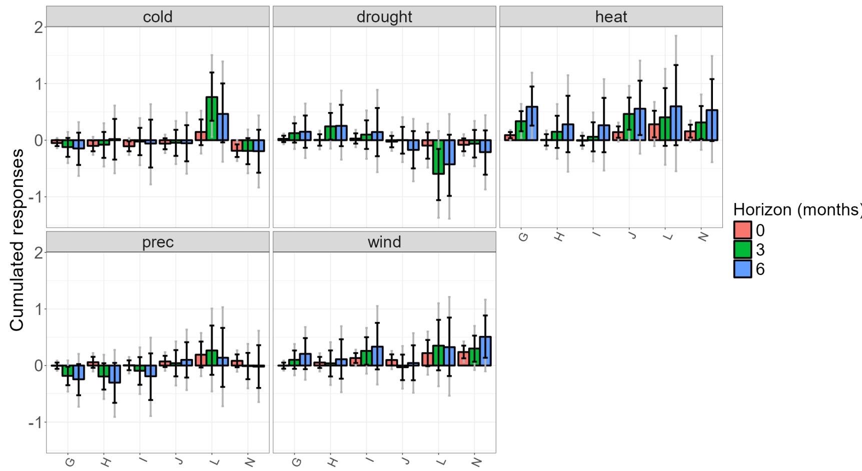


Figure 11: *Impact (red) and cumulative responses at 3 months (green) and 6 months (blue) of French services production to the five weather shocks, with 68% and 90% confidence intervals shown as black and gray whiskers, respectively. G: Wholesale and retail trade, H: Transportation, I: Accommodation, J: Communication, L: Real estate, N: Administrative support.*

4.3 On the use of composite weather indices: CWI shock

Throughout Section 4.1, we examined the economic effects of various individual types of weather shocks, emphasizing their distinct transmission channels. In recent years, however, the use of composite weather indices has gained prominence in the literature (see, e.g., Kim et al., 2025). This raises the question of whether such indices can provide additional insights beyond those offered by individual weather shocks.

Figure 12 presents the impulse responses of sectoral production to a composite weather shock in each country. The index is constructed as the average of the five individual components, following the approach of the ACI[13] for North America. As expected, construction activity declines across all countries, reflecting the sector's direct sensitivity to adverse weather conditions. What underlies this result? A comparison with the responses in Figure 8 suggests that, for Italy, the pattern closely mirrors that of a wind shock. For France and Germany, the interpretation is less straightforward. In France, the negative response may be primarily driven by cold shocks—consistent with cold being the only individual shock with a statistically significant effect—though this appears partially obscured in the composite

[13] American Academy of Actuaries (2016).

response. In Germany, the outcome likely reflects a combination of cold and heat shocks, resulting in a less clear-cut overall effect.

For the energy sector, which we found to be strongly affected by individual shocks-particularly cold-there is limited evidence of a significant response to the composite index. Only Italy displays a statistically significant effect, and the positive sign of this response is not straightforward to interpret. A similar pattern is observed for manufacturing, where Italy is again the only country exhibiting a significant response to the composite shock. In this case, the effect is significant only on impact, and the underlying drivers remain unclear.

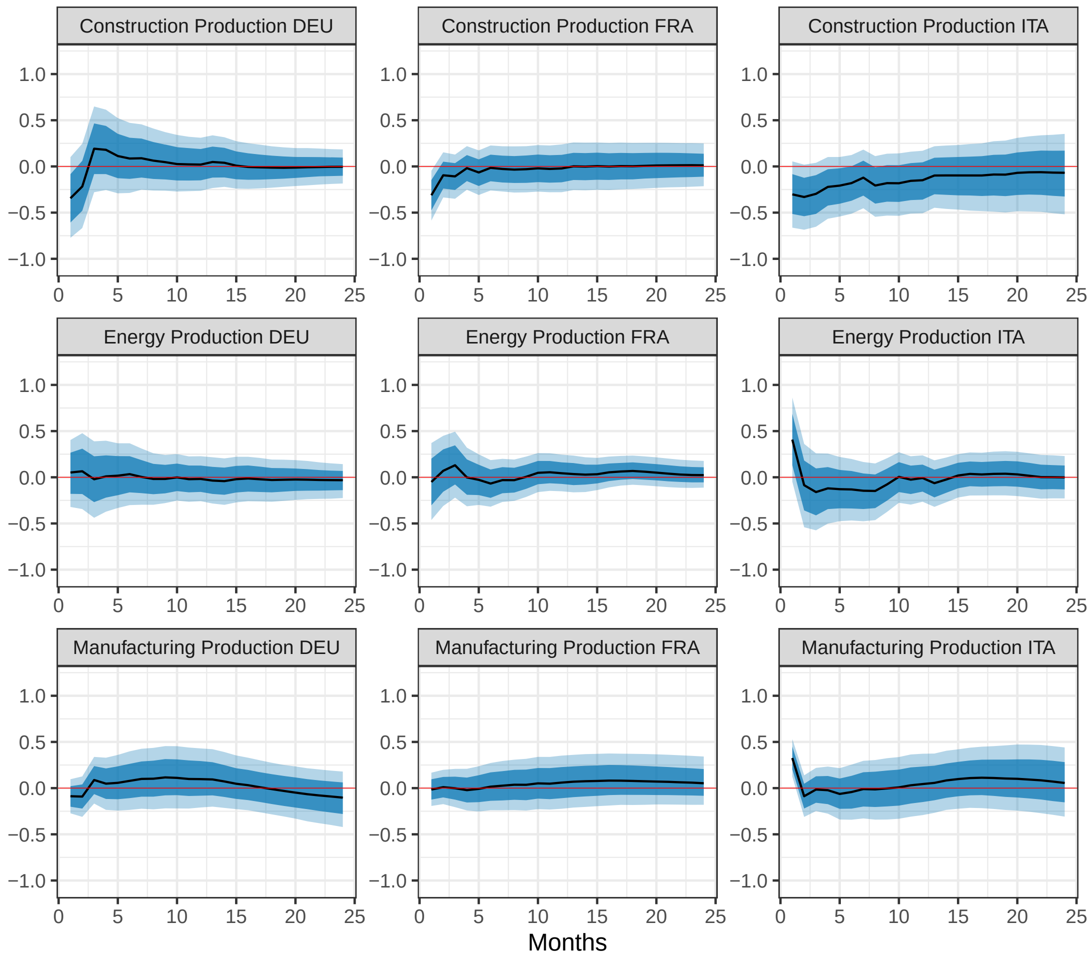


Figure 12: *Impulse responses of sectoral production to a CWI shock, with 68% and 90% confidence intervals in shades of blue. The horizontal axis denotes the horizon in months. Results are shown for Germany (left column), France (middle column), and Italy (right column).*

Overall, the responses indicate that the effects of individual weather shocks tend to be offset or obscured in the composite index. Nonetheless, while less suited to identifying specific transmission channels, composite weather indices remain informative in certain contexts. First, they provide a parsimonious summary of overall weather variability, which is particularly useful for assessing the consistency of results across sectors and countries. Second, in real-world decision-making—particularly in policy and business contexts—weather conditions are often experienced as a bundle of simultaneous anomalies rather than isolated shocks. A composite measure therefore captures the joint influence of multiple weather dimensions, providing a useful benchmark for assessing the aggregate sensitivity of economic outcomes to overall weather variability. Accordingly, while composite shocks are less informative for identifying specific mechanisms, they remain valuable for assessing the robustness and generalizability of the main findings.

4.4 Non-linearities

We now investigate the presence of non-linearities using Local Projections, as outlined in Section 3. We first assess whether the effects of weather shocks differ by season, and then test the hypothesis of Billio et al. (2020) that the impact varies across phases of the business cycle. We focus on manufacturing production, which is the largest tradable sector, less directly exposed to weather, and thus well suited to capturing indirect and cyclical effects. This choice also facilitates comparability with Billio et al. (2020). We use the composite index for this analysis, as it provides a parsimonious summary of overall weather variability while allowing us to capture broader patterns of interaction with seasonal and cyclical conditions.

Figure 13 presents the non-linear responses by season, estimated using a sine function as the transition variable. This function is constructed to take a value of 0 in January and reach 1 in July, thereby capturing gradual seasonal variation throughout the year. The results do not indicate significant non-linear effects associated with seasonality, as evidenced by the similarity with the linear responses shown in the bottom row of Figure 12. This finding supports our approach to constructing weather shocks by computing deviations from month-specific percentiles, which effectively mitigates the influence of seasonal patterns. By accounting for seasonality in the definition of weather shocks, this method helps ensure that estimated effects are not confounded by recurring seasonal dynamics.

Billio et al. (2020) suggest that weather shocks exert a stronger impact on sectoral production during recessions than in periods of expansion. To assess this hypothesis, we define two distinct regimes of economic activity using the European Sentiment Index (ESI) as the transition variable. The ESI is a composite indicator derived from a range of surveys conducted by the European Commission and serves as a proxy for business cycle conditions—taking low values during downturns and higher values during periods of expansion. It is widely used in applied research and has been shown to effectively track euro area business cycle fluctuations

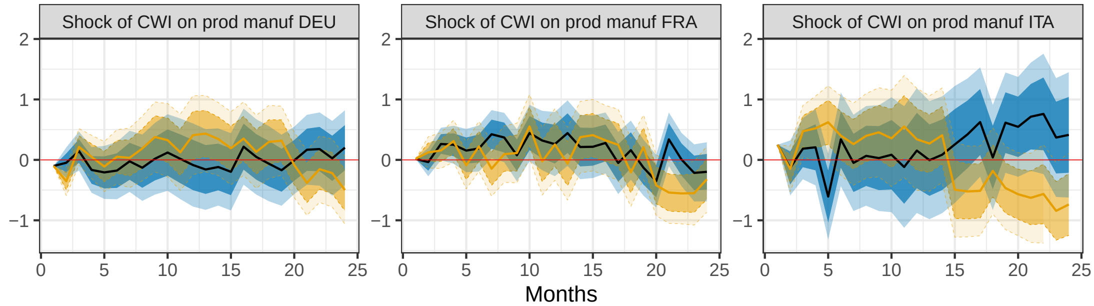


Figure 13: *Non-linear responses of manufacturing production to a CWI shock, with 68% and 90% confidence intervals, differentiated by season. The black solid lines with blue shaded confidence bands represent responses in winter, while the orange solid lines with dashed and shaded orange confidence bands represent responses in summer.*

in real time (Bańbura & Modugno, 2014). Figure 14 presents the impulse response functions of manufacturing production across the two economic regimes for the three countries in our sample.

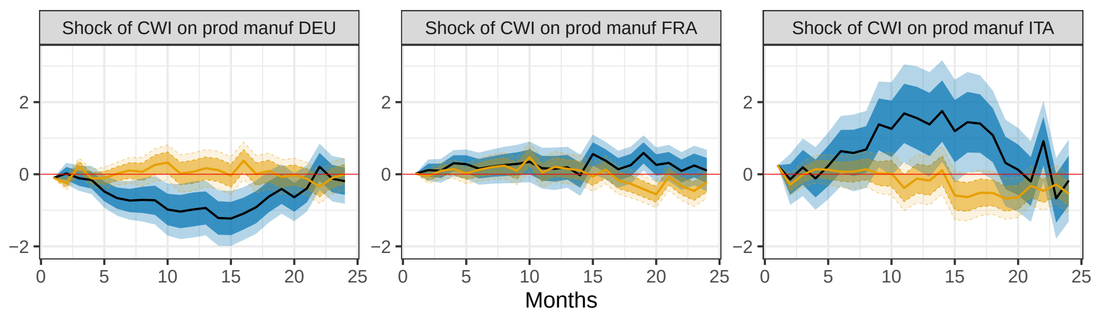


Figure 14: *Non-linear responses of manufacturing production to a CWI shock, with 68% and 90% confidence intervals, differentiated by business cycle regime. The black solid lines with blue shaded confidence bands represent responses in the low-growth regime, while the orange solid lines with dashed and shaded orange confidence bands represent responses in the high-growth regime.*

Figure 14 presents non-linear impulse responses of manufacturing production to a CWI shock across business cycle regimes. In Germany, the response is more pronounced in the low-growth regime, showing a significant and persistent contraction, while France exhibits a more muted and statistically insignificant response across regimes. In contrast, Italy displays stronger and more persistent effects in the high-growth regime, suggesting that weather shocks interact differently with cyclical dynamics across countries. These findings provide partial support for the hypothesis in Billio et al. (2020) that weather shocks have a greater impact during downturns, though Italy's response suggests that sectoral or structural factors may modulate this relationship. A more systematic investigation of the role of country-specific characteristics in shaping these non-linear effects is left for future research.

4.5 Cross-country spillovers

A potential concern when estimating separate VAR models for each country is that they do not account for cross-country spillovers, which could be relevant when the shocks are correlated across countries. In our setting, the contemporaneous covariance between CWI indices is relatively low: 0.09 for Germany and France, 0.04 for Germany and Italy, and 0.06 for France and Italy.

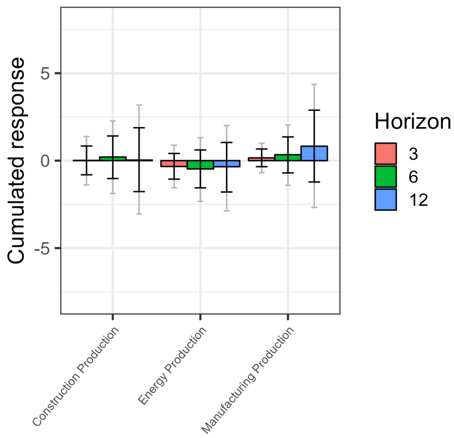
Nonetheless, to assess the relevance of such spillovers, we replicate the analysis of sectoral production by replacing the domestic CWI shock with the residual component of the foreign CWI shock that is orthogonal to the domestic one. Specifically, we first regress the foreign CWI on the domestic CWI and then use the resulting residuals as the shock variable in the SVAR model to compute the impulse responses. To ensure the absence of delayed effects, we extend the analysis to include responses up to 12 months after the shock.

The results, shown in Figure 15, indicate that cumulative responses at the 3-, 6-, and 12-month horizons are statistically insignificant, with the sole exception of a mildly significant effect on German construction production following a CWI shock in Italy. Overall, these findings suggest that cross-country spillovers are not a major concern in our empirical setting.

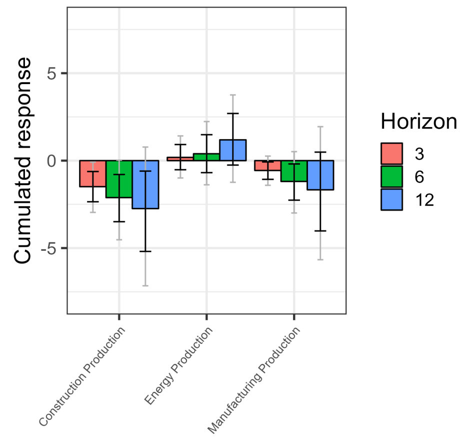
5 Conclusions

This paper introduced a novel measure of abnormal weather conditions, constructed from high-frequency, grid-level data aggregated at the country level and weighted by proxies of economic activity. By incorporating both the spatial distribution of weather and its economic relevance, the indicators provide an accurate representation of country-level exposure to different types of weather realizations. In a first application, we showed how these indices—interpretable as macroeconomic shocks—could be used to analyze the dynamic effects of weather on sectoral production and prices, offering insights into the key transmission channels through which weather influences the economy.

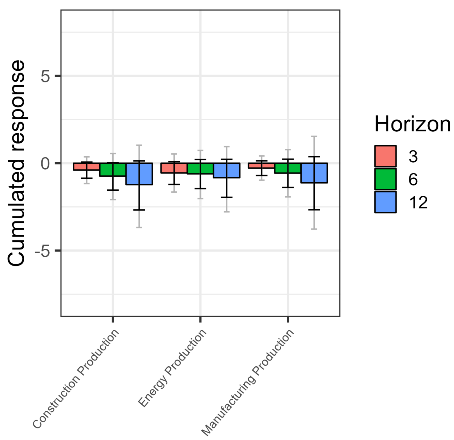
We examined the short- to medium-term dynamic effects of weather shocks on sectoral production and prices in Germany, France, and Italy—the three largest European economies. The analysis extends the existing literature by considering a wider set of sectors and weather



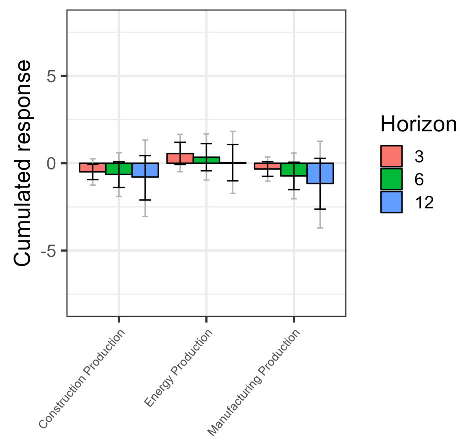
French CWI on German sectors



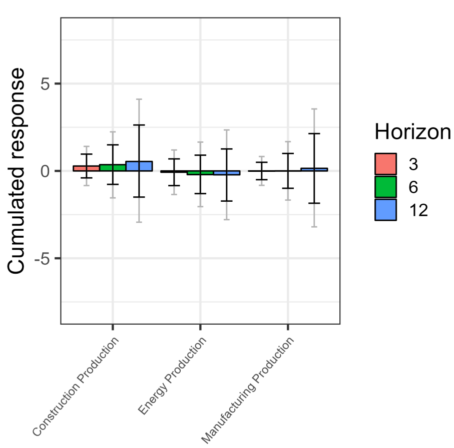
Italian CWI on German sectors



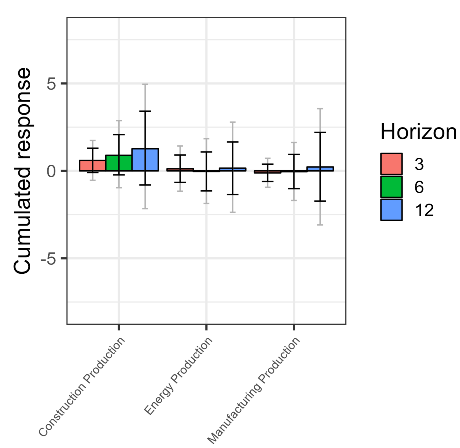
German CWI on French sectors



Italian CWI on French sectors



German CWI on Italian sectors



French CWI on Italian sectors

Figure 15: *Cumulative responses at 3 months (red), 6 months (green), and 12 months (blue) to a shock in the residual foreign CWI on domestic sectors, with 68% and 90% confidence intervals shown as black and gray whiskers, respectively.*

shocks beyond the conventional focus on temperature. Our analysis highlights several key mechanisms. 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 not 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. 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. Notably, we show that composite indices—such as the ACI (Kim et al., 2025)—are not well suited to identifying these mechanisms, as they may conflate the distinct effects of individual underlying weather shocks.

What are the policy implications of our findings? As weather shocks become more frequent and intense due to climate change, policymakers must develop strategies that enhance economic resilience and adaptation capacity. A crucial step in this direction is accurately measuring exposure to abnormal weather conditions, which is essential for informing targeted and effective policy responses. Sector-specific strategies should reflect geographic and structural differences, particularly in highly exposed sectors such as construction and energy. In parallel, coordinated efforts at the European level are needed to stabilize energy markets and support the transition toward cleaner energy sources. This is especially relevant given the indirect impact of weather shocks on manufacturing through energy price volatility.

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Supplemental Appendix

Weather Shocks and Sectoral Dynamics in European Economies

Daniele Colombo[†] Laurent Ferrara[‡]

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Contents

[†]London Business School. Email: dcolombo@london.edu
[‡]Skema Business School - Université Côte d'Azur. Email: laurent.ferrara@skema.edu

A 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.[1] To measure drought we instead use the SPEIbase dataset v.2.9 (Beguería et al., 2023).[2] Finally, to proxy for economic activity at the grid level we use night-time light intensity[3] 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 2.1. 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 use the Standardized Precipitation-Evapotranspiration Index with a 3-month accumulation window, denoted as $SPEI3_{j,k}$. Since the SPEI is already provided at the grid-cell level and comes pre-standardized and thresholded, we only apply our aggregation and country-level standardization procedure. Specifically, for each month j, we compute the mean μ_j^{SPEI3} and standard deviation σ_j^{SPEI3} of the aggregated national SPEI3 series. The final drought shock index is then obtained by standardizing the SPEI3 for each month j and year k using these month-specific parameters:

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

In the canonical interpretation of the SPEI, positive values indicate above-average precipitation, while negative values reflect below-average precipitation. To ensure consistency with the other weather components-where higher values denote more severe weather shocks-we take the negative of the standardized $SPEI3j,k$. This transformation ensures that large positive values of $SPEI3^{std}j,k$ correspond to months characterised by drought conditions.

Figures A16 to A18 display the five weather components for each country. By construction, the indices are defined such that a positive value indicates the presence of a weather shock, while a value of zero indicates its absence. As a result, negatively correlated components—such as heat and cold, or drought and precipitation—do not offset one another when

[1] https://gadm.org/.

[2] http://hdl.handle.net/10261/332007.

[3] Measured in 2015.

aggregated into the CWI. This design ensures that the distinct contribution of each shock type is preserved in the composite measure.

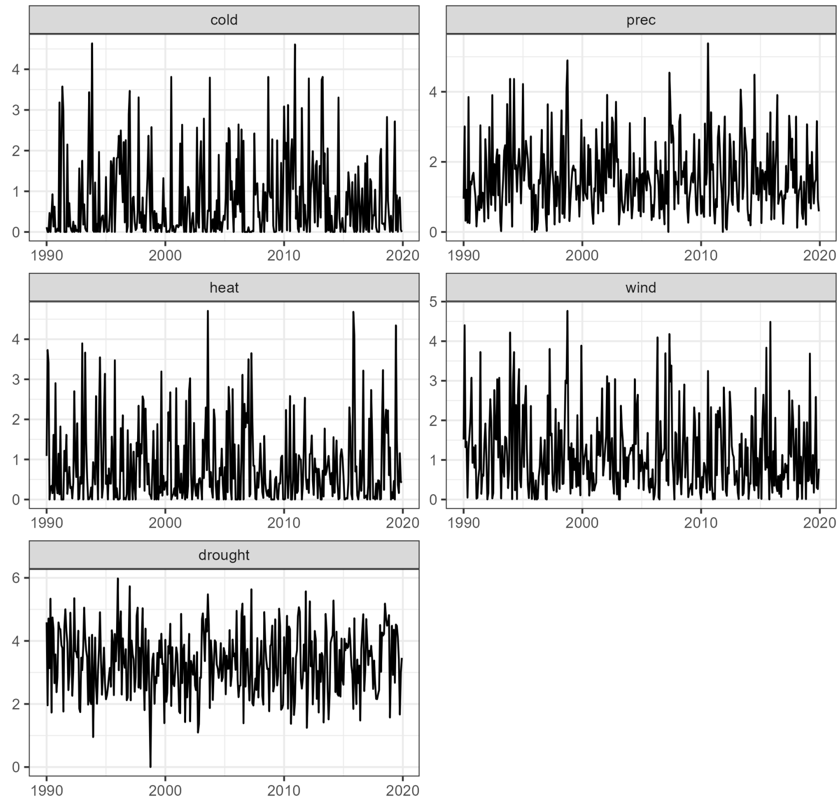

Figure A16: *The five weather components for Germany.*

B Comparison to existing weather indices

While our weather indices build on previous contributions, they also incorporate important methodological innovations. This Appendix outlines the main similarities and differences compared to the most closely related studies.

Several studies rely on deviations of weather variables from historical averages. For example, Ciccarelli et al. (2023) examine changes in mean temperature and its variability relative to long-term means, while Parnaudeau and Bertrand (2018) use monthly deviations from 30-year historical averages for temperature, precipitation, humidity, and wind speed. However, only a few contributions explicitly account for deviations from seasonal norms, as in our approach. Starr (2000) employ Heating and Cooling Degree Days (HDD and CDD), constructed relative to seasonal averages, and Bloesch and Gourio (2015) use anomalies

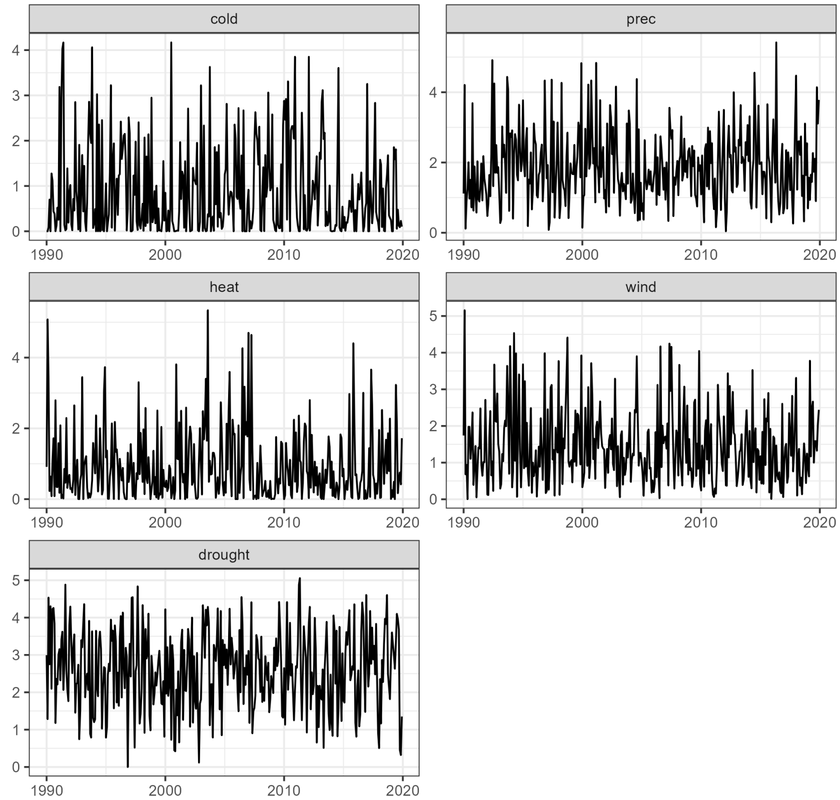

Figure A17: *The five weather components for France.*

based on calendar-month averages for temperature and snowfall. Adjusting for seasonal norms is essential to identifying genuinely abnormal weather events. This approach also provides seasonal adjustment by construction, facilitating a more accurate estimation of the economic effects of unusual weather, distinct from regular seasonal fluctuations.

Several studies reduce noise in weather measures by focusing on extreme deviations or applying threshold-based approaches. This methodology rests on the assumption that large shocks are less likely to be anticipated and thus are less likely to be incorporated into forward-looking behavior. For instance, Wilson (2019) count the number of days exceeding a fixed threshold to capture the persistence of extreme conditions, while Kotz et al. (2022) construct annual rainfall indices based on the number of wet days above a percentile threshold and the corresponding total precipitation. In both cases, thresholds are applied relative to unconditional distributions, rather than accounting for seasonal variation. In contrast, we adopt month-specific thresholds to better account for the pronounced seasonality in weather patterns, while also avoiding the volatility inherent in day-specific measures.

Most of the literature relies on aggregated weather data at the national or regional level

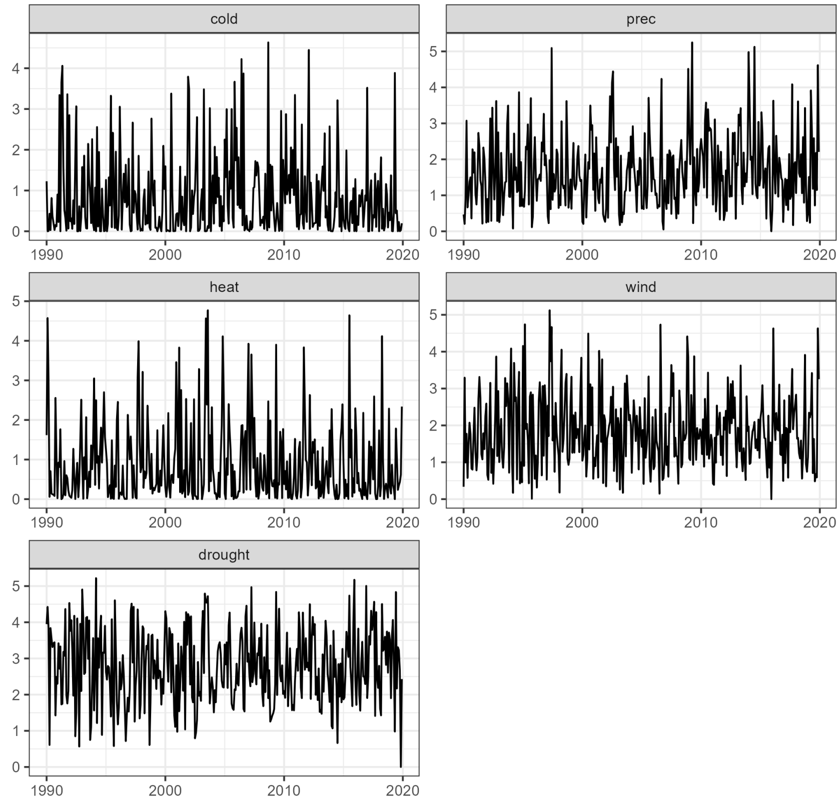

Figure A18: *The five weather components for Italy.*

(e.g., Billio et al., 2020; Ciccarelli et al., 2023; Giugliano et al., 2023), with relatively few papers using high-resolution spatial data. Bloesch and Gourio (2015) compute station-level anomalies and aggregate them by simple averaging at the state level. Kotz et al. (2022) use grid-level time series and aggregate to regions using area or population weights. Roth Tran (2020) emphasizes that the relevant economic impact depends on the abnormality of weather relative to both location and time of year, underscoring the need for spatially and temporally specific measures. Failing to account for such heterogeneity may lead to aggregation bias and attenuation of the estimated effects.

Finally, to facilitate interpretation and comparability, many studies standardize weather indices using either season-specific (Bloesch & Gourio, 2015) or month-specific (Kotz et al., 2022) means and standard deviations. We adopt the latter standardization.

We contribute to the literature by constructing measures of exposure to abnormal weather realizations across five distinct dimensions-heat, cold, drought, precipitation, and wind-defined as anomalous deviations from calendar-month-specific historical averages at the grid-cell level. These deviations are then aggregated to the country level using weights based on proxies for economic activity. To enhance interpretability and cross-country comparability, the resulting indices are standardized using month-specific means and standard deviations. This methodology provides a harmonized and granular framework, well-suited for evaluating the macroeconomic effects of abnormal weather conditions across different sectors and countries.

C Bayesian estimation

We adopt priors from the *Normal-Inverse-Wishart* family, specified as follows:

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

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

where $\mathbf{b}$, Ω, Ψ, and $\mathbf{d}$ are functions of a lower-dimensional vector of hyperparameters γ, and β denotes the vectorised coefficients of the autoregressive matrices A_j. This prior specification offers two key advantages. First, it encompasses the priors most commonly employed in the Bayesian VAR literature. Second, due to the conjugacy of the priors with the likelihood function, the marginal likelihood is available in closed form, facilitating model comparison and inference. We set the degrees of freedom for the inverse-Wishart distribution to $d = n+2$, where n denotes the number of endogenous variables in the model. This choice represents the minimum value ensuring the existence of the mean of the inverse-Wishart distribution for Σ, given by $\frac{\Phi}{d-n-1}$. The matrix Φ is diagonal, with the vector ϕ on the main diagonal.

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:

$$\underset{1\times n}{y^{++}} = \left(\frac{\bar{y}_0}{\delta}\right)' = \left[\frac{\bar{y}_1}{\delta}, \quad \cdots, \quad \frac{\bar{y}_n}{\delta}\right]$$

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

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 by Giannone et al. (2015) for additional technical details.

D Sensitivity analysis

In this Appendix, we conduct a series of robustness checks and explore alternative constructions of the weather shocks. To effectively summarize the findings, we focus on the impulse responses of sectoral production to a composite weather shock as the primary object of replication.

We begin by presenting a falsification test in which the weather indices are randomly reassigned across months, after which the full estimation procedure is repeated. The resulting impulse response functions are statistically insignificant, suggesting that our baseline estimates are not driven by spurious correlations and reinforcing the credibility of our identification strategy. Second, we consider an alternative construction of the weather indices based on the number of days in each month exceeding the defined threshold,thereby explicitly capturing accumulation effects. Next, we reverse the sequence of aggregation and thresholding by first computing monthly weather values at the country level, and then applying the thresholding and standardization procedures. This top-down approach yields attenuated and less precise responses, underscoring the advantages of our preferred granular methodology. In addition, while the baseline computation defines abnormal weather events using the 95^{th} percentile of the calendar-month-specific distribution, we show that the main results remain robust when applying more extreme thresholds, such as the 99^{th} percentile. Finally, we demonstrate that excluding months in which natural disasters have been recorded—by setting the corresponding weather shocks to zero—has virtually no impact on the estimated responses, indicating that the macroeconomic effects we identify are not driven by extreme events of this nature.

D.1 A falsification test: randomizing the dates of the shocks

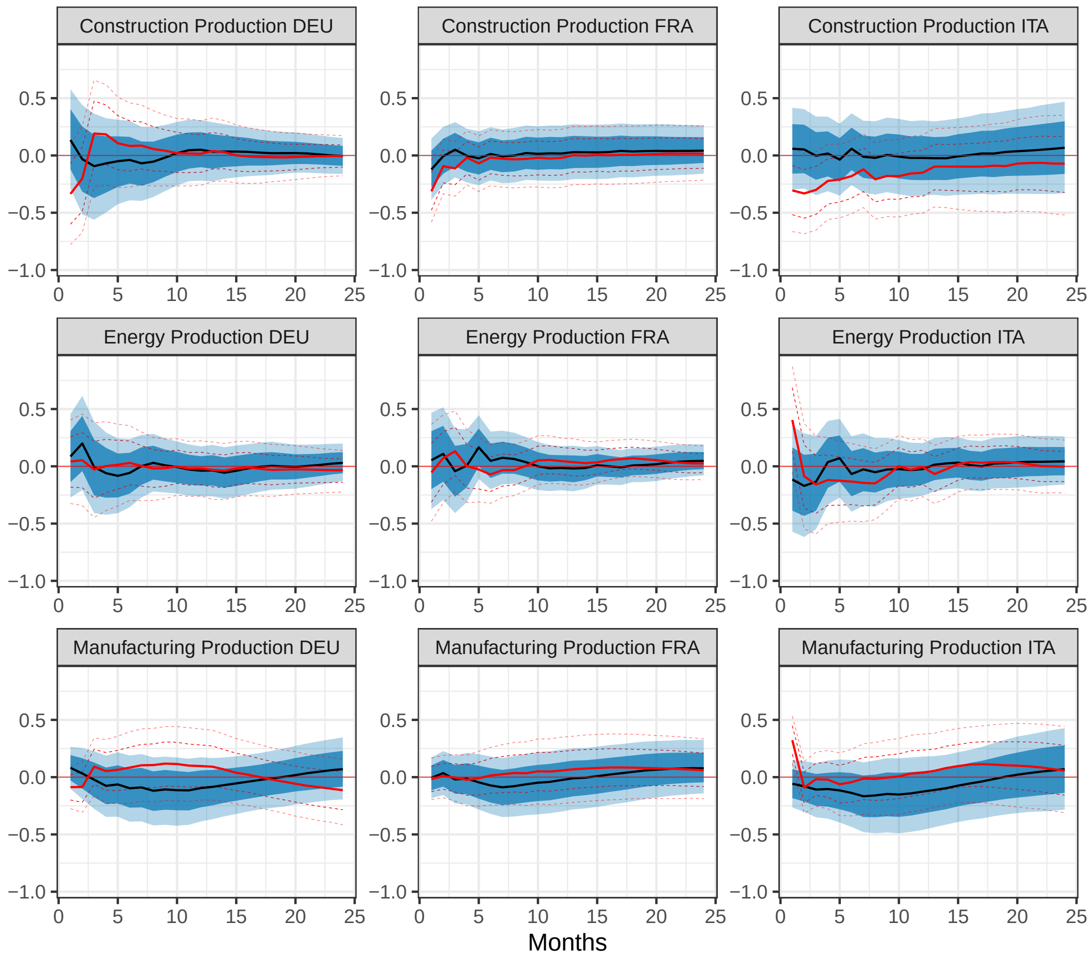

Figure D19: *Impulse responses of sectoral production to a CWI shock, with 68% and 90% confidence intervals. Randomised instrument: black solid line with blue shaded confidence bands; baseline instrument: red solid line with dotted bands The horizontal axis denotes the horizon in months. Results are shown for Germany (left column), France (middle column), and Italy (right column).*

As an initial robustness check, we conduct a falsification test in which the weather indices are randomly shuffled across months, thereby breaking any systematic temporal relationship between weather conditions and economic outcomes. The subsequent analysis follows the standard estimation procedure applied in the baseline specification. Figure D19 presents the results of this exercise. The impulse response functions are statistically insignificant, indicating that the estimated effects are not driven by spurious correlations and lending further credibility to our identification strategy.

D.2 Accumulation effects

As an alternative to defining weather shocks based on values exceeding the month-specific 95th percentile, we consider a measure constructed as the number of days in each month that surpass this threshold: $\tilde{WM}_{c,m,y} = \sum_{d=1}^{D_m} \mathbb{1}\{W_{c,d} \geq W_{c,\tilde{t}}\}$. This formulation captures

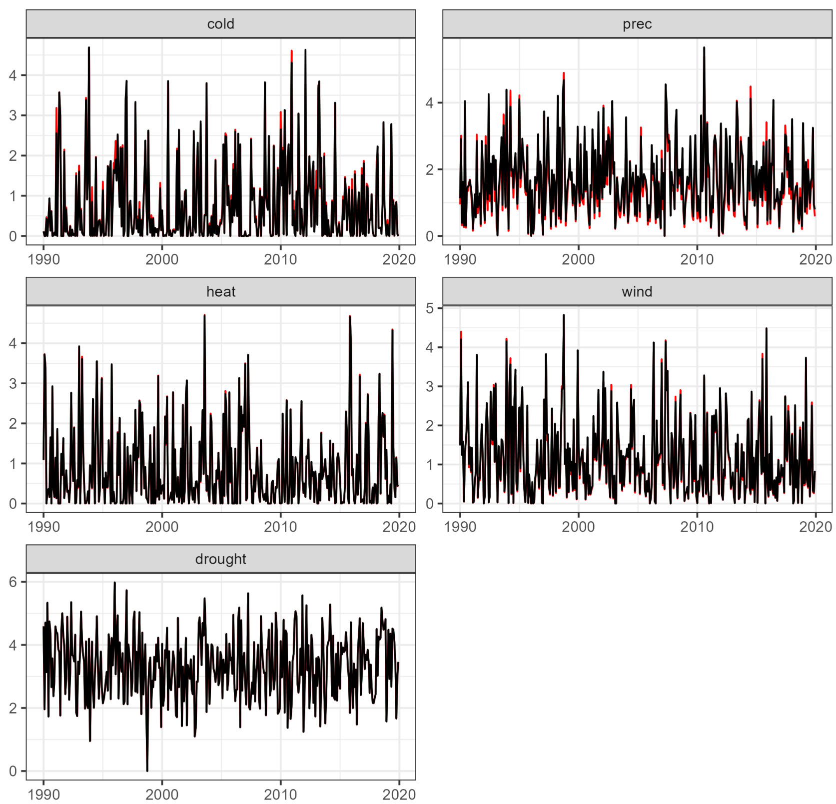

Figure D20: *The five weather components for Germany: comparison between the baseline computation (red) and an alternative measure based on the number of threshold-exceeding days.*

accumulation effects, which are particularly relevant in contexts where adverse weather leads to delays in economic activity (Natoli, 2022). Given the standardization applied and the similarity in daily exceedance patterns, the resulting weather shocks are highly comparable to those obtained using the baseline method. For instance, Figure D20 illustrates the alternative construction for Germany, which yields results closely aligned with those from the original specification. Accordingly, this alternative approach produces impulse responses that are nearly indistinguishable from those of the baseline, reinforcing the robustness of our findings.

D.3 Computing the shocks at the country level

Figure D21 presents results based on an alternative construction of weather shocks, in which weather observations are first aggregated at the country level before computing exceedance values and applying standardization. This approach results in attenuated responses for some variables, most notably for energy production in Italy.

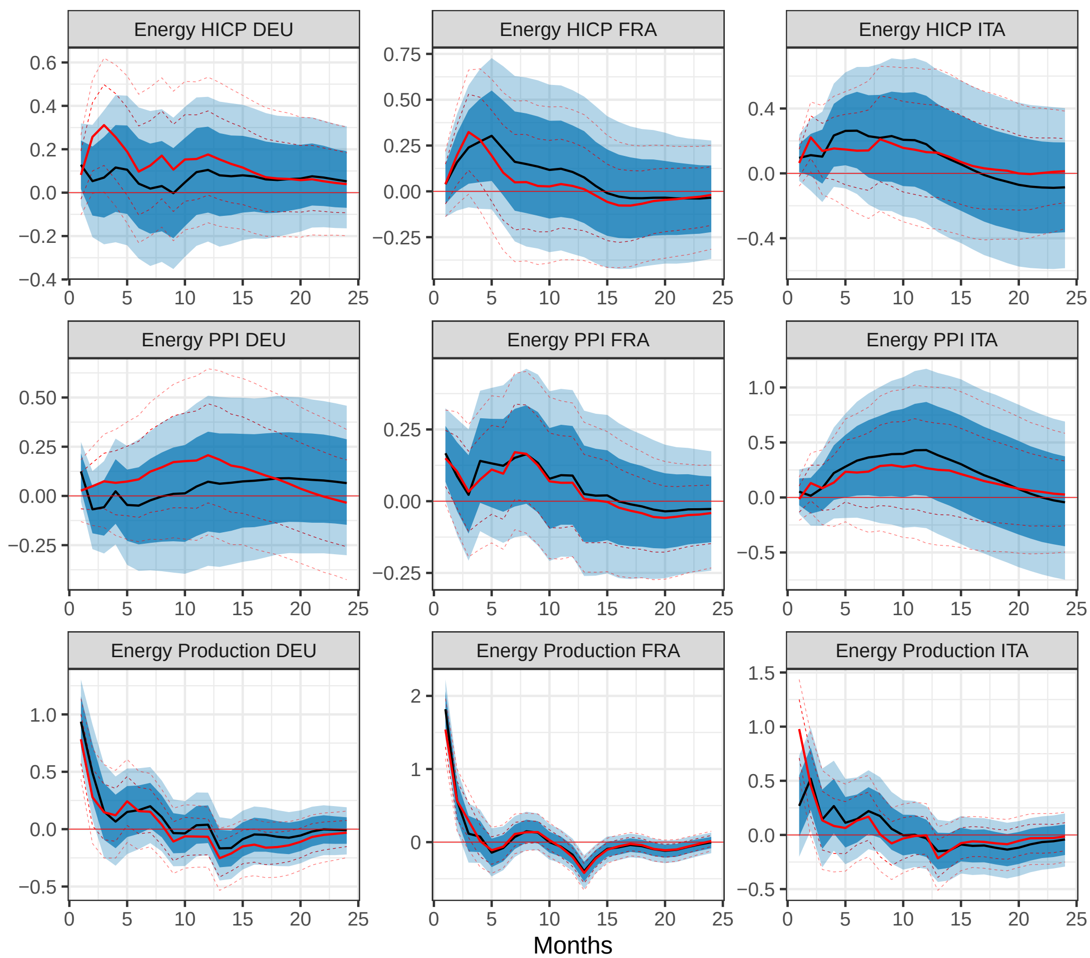

Figure D21: *Impulse responses of output and prices of the energy sector to a cold shock, with 68% and 90% confidence intervals in shades of blue. Results are shown for Germany (left column), France (middle column), and Italy (right column).*

D.4 Using different percentiles

Figure D22 shows that the CWI remains robust when computed using alternative thresholds, such as the 99th percentile, instead of the 95th used in the baseline analysis.

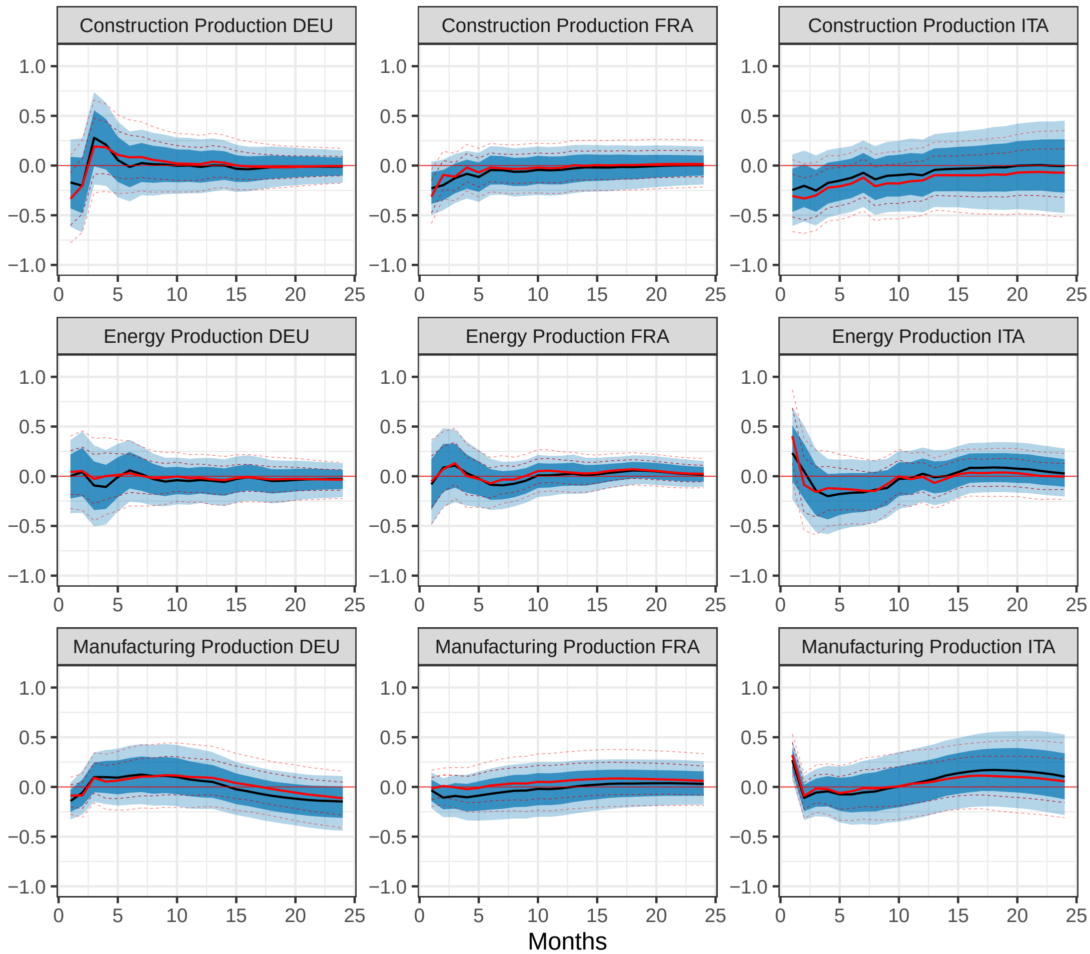

Figure D22: *Impulse responses of output and prices of the energy sector to a cold shock, with 68% and 90% confidence intervals. Shock constructed by first aggregating at the country level: black solid line with blue shaded confidence bands; baseline shock: red solid line with dotted bands. The horizontal axis denotes the horizon in months.*

D.5 Excluding natural disasters

As discussed, the weather shocks we construct capture large deviations from historical, calendar-specific averages. These shocks reflect abnormal weather conditions that disrupt the typical timing of economic activity, potentially influencing output through shifts in sectoral demand and supply. This contrasts with the weather-related events typically examined in the natural disaster literature, which emphasize the destruction of physical and human capital (see, e.g., Kruttli et al., 2023; Ferriani et al., 2024). In the European countries analyzed, such extreme events are relatively rare compared to regions like the United States, where natural disasters are larger and more frequent. To support this interpretation, we conduct

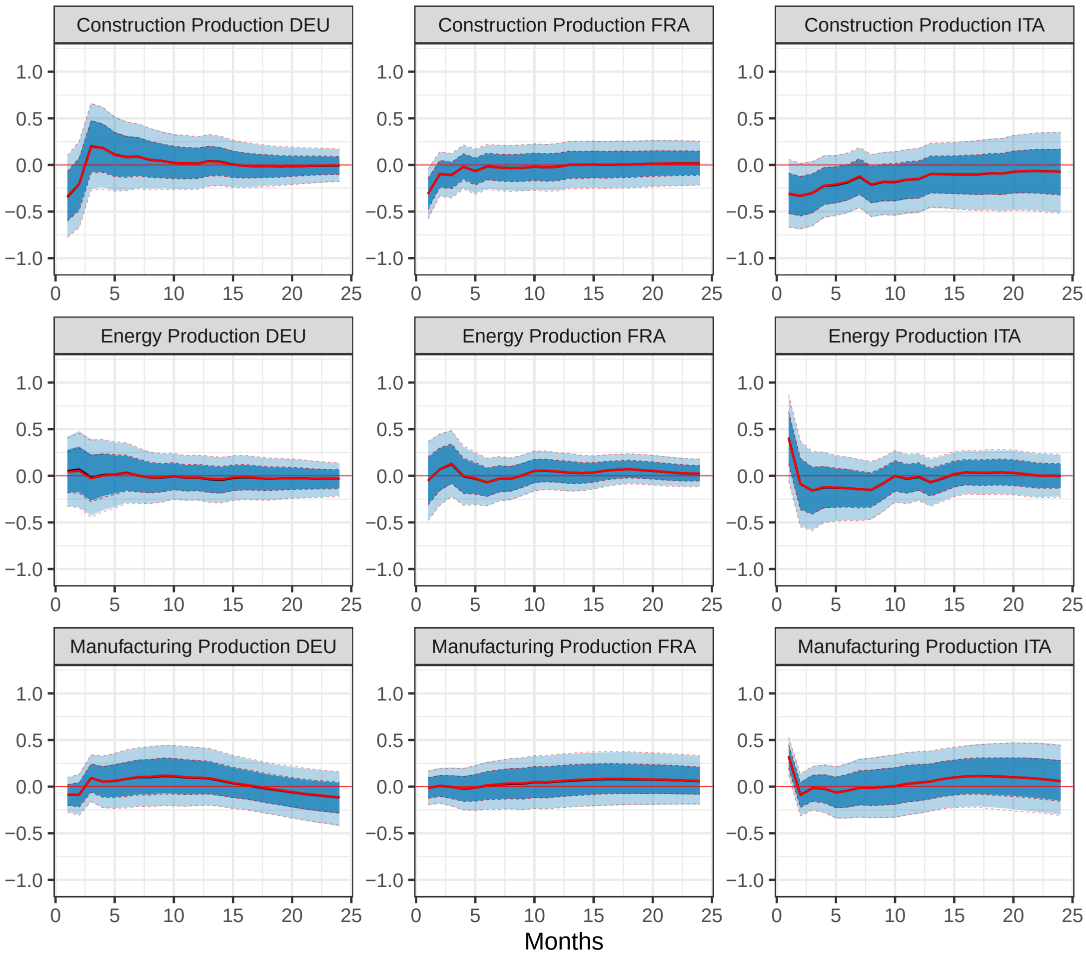

Figure D23: *Impulse responses of sectoral production to a CWI shock, with 68% and 90% confidence intervals. Shock excluding disaster months: black solid line with blue shaded confidence bands; baseline shock: red solid line with dotted bands The horizontal axis denotes the horizon in months.*

a robustness check using the EM-DAT International Disaster Database (Guha-Sapir et al., 2016). Specifically, we identify the months in which documented natural disasters occurred in Germany, France, and Italy, and set the corresponding weather shock values to zero for those months.[4] As shown in Figure D23, this adjustment has virtually no effect on our

[4] We classify a weather-related event as a natural disaster if it caused at least 100 deaths, affected 1,000 or more individuals, or resulted in estimated damages exceeding 1 million USD. Between 1990 and 2019, such events occurred in 22 months in Germany, 42 in France, and 22 in Italy.

results, indicating that the estimated impacts are not driven by natural disasters.

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*
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 D2: *Natural disasters as classified in the EM-DAT dataset.*

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