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Heatwaves, coldwaves, floods, and droughts: the short-term impact of extreme weather events on economic activity

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Abstract

This paper examines the short-term macroeconomic and sectoral effects of extreme weather events in Germany, France, Italy, and Spain. We construct novel indicators of extreme temperature and precipitation based on percentile thresholds of long-run historical distributions and estimate their impact through country-specific structural Bayesian VAR models. The analysis documents sizable and heterogeneous effects on real GDP, HICP, and sectoral activity over a one-year horizon. Temperature extremes primarily affect industrial and energy-related sectors, with Germany exhibiting the strongest vulnerability to heatwaves. Precipitation extremes mainly impact construction and mining, with Spain featuring the largest exposure to floods and droughts. Sectoral composition plays a key role in shaping transmission, with pharmaceuticals, electricity, construction, and mining displaying distinct and recurrent patterns. Given their impact on prices, extreme weather event shocks may exert inflationary pressures without hurting activity, or induce demand-type of effects on the overall economy, with different effects across countries.

JEL Classification: E23, E32, Q54, R11

Keywords: extreme weather events, sectoral output, structural BVAR, short-term risks

Non-technical summary

Extreme weather events have become more frequent in recent decades and are increasingly relevant for short-term economic developments. Episodes such as heatwaves, coldwaves, floods, and droughts can disrupt production, affect energy demand, damage infrastructure, and constrain labour supply. Understanding how these events translate into short-run fluctuations in economic activity is therefore important for economic forecasting, risk assessment, and policy design.

This paper studies the short-term economic effects of extreme weather events in the four largest euro area economies—Germany, France, Italy, and Spain. The analysis focuses on four types of extremes: extremely high temperatures (heatwaves), extremely low temperatures (coldwaves), extremely high precipitation (causing floods), and extremely low precipitation (droughts). Extreme events are defined using long historical climate records, so that they capture genuinely rare and severe weather conditions rather than normal seasonal variation.

The study combines these climate indicators with monthly economic data and examines how output responds over the year following an extreme weather event. It looks not only at overall economic activity, measured by monthly real GDP, but also at a wide range of sectors, including mining, manufacturing and its main subsectors, energy, construction, and market services. This allows the analysis to identify which parts of the economy are most affected by different types of weather extremes.

The results show that extreme weather events have economically meaningful effects in the short run, but their impact varies widely across countries, sectors, and types of events. Germany appears particularly vulnerable to temperature extremes. Heatwaves lead to sustained declines in economic activity, especially in manufacturing, mining, and services, while coldwaves initially reduce output before giving rise to partial recoveries later on. Spain, by contrast, is most affected by precipitation extremes, with both heavy rainfall and droughts generating persistent losses in economic activity. France and Italy tend to be more resilient overall, although they are not immune to disruptions. In Italy, some extreme weather events—–particularly heavy rainfall and dry spells—–are followed by temporary increases in activity, partly reflecting reconstruction efforts and favourable conditions for construction and services. France generally experiences more moderate effects, with gains and losses across sectors often offsetting each other at the aggregate level.

At the sectoral level, several common patterns emerge across countries. Construction is overall disrupted by periods of very heavy rainfall, reflecting the exposure of building activity to adverse weather conditions. Mining and energy-related activities are sensitive to both temperature and precipitation extremes, while electricity and gas production typically increase during cold spells due to higher heating demand. The pharmaceutical sector stands out as particularly vulnerable to extreme heat, possibly reflecting its reliance on temperature-sensitive transport and water-dependent logistics.

Overall, the findings highlight that extreme weather events represent a material source of short-term economic risk. Their effects depend not only on the type of event, but also on countries' production structures and sectoral composition. The results underscore the importance of incorporating climate-related risks into short-term economic analysis, forecasting, and scenario design, as well as the need for policies that enhance resilience in the most exposed sectors.

1 Introduction

Extreme weather events have become increasingly frequent and disruptive over past decades, affecting both short-term dynamics and long-term trends in economic activity. Climate anomalies such as heatwaves, coldwaves, floods, and droughts pose risks to production, supply chains, and labour markets, impacting different sectors to a varying extent. For instance, heatwaves and coldwaves could bring construction to a halt. Floods and droughts may disrupt production in agriculture, leading to lower yields and higher food prices. At the same time extreme weather events may also spur demand for energy or reconstruction works. Not only do these events affect immediate output, but they also generate cascading effects on overall activity via supply chains. Understanding the economic consequences of these extreme weather events is therefore crucial for forecasters, policymakers and economic agents, seeking to refine projections and construct alternative scenarios, enhance economic resilience and design effective mitigation strategies.

This paper examines the near-term impact of extreme weather events on economic activity across the four largest euro area economies—Germany, France, Italy, and Spain. By leveraging high-frequency climate and economic data, this study assesses how different types of extreme weather events propagate to sectors such as mining, manufacturing, energy, construction, and (market) services. The analysis aims to identify sector-specific exposures and the channels through which weather extremes affect aggregate output across the four countries. Throughout the paper, the terms *heatwaves*, *coldwaves*, *floods*, and *droughts* correspond, respectively, to months characterised by *extremely high temperature*, *extremely low temperature*, *extremely high precipitation*, and *extremely low precipitation*.

To this end, we proceed in two steps. In a first step, we construct novel measures of extreme weather events drawing from the Weighted Climate Dataset (Gortan et al., 2024). Each measure of extreme weather event is computed as the number of consecutive days within a month in which a weather event (temperature or precipitation) is "extreme", that is either below or above a predefined threshold. To capture low and high extremes, thresholds are chosen as the respective 5th and 95th percentiles of the country-specific historical distribution (1940-2023) of the weather events.[1] Across countries, as expected, extremely high and low temperature events tend to be concentrated in the summer and the winter months, respectively; episodes with extremely high and low precipitation instead tend to occur mostly in the autumn and the spring months,

[1] Robustness exercises consider alternative percentiles of the historical distribution.

respectively. This clustering of different types of extreme weather events in different seasons allows us to have a clear interpretation of the nature of the shocks and, thus, of their economic impact. Moreover, as a validation for our narrative, we show that, over time, these extreme weather events are aligned with well-known climate episodes in our considered countries.

In a second step, we estimate a set of structural Bayesian vector autoregression (SBVAR) models to gauge the short-term economic impact of these extreme weather events. Specifically, we assess the effects of extreme weather events on real GDP and production in the main macroeconomic sectors—as well as the largest manufacturing subsectors—over a 12-month horizon. Our sample spans the period between January 1999 to December 2023 in Germany, France, Italy and Spain. Following Ciccarelli et al. (2024) and Colombo and Ferrara (2024), to ensure a parsimonious specification, we estimate a separate model for each combination of country, type of weather event and, in its augmented version, sector. Following the naming convention by Plagborg-Møller and Wolf (2022), we include our measure of extreme weather event as an "internal instrument" in the model, thus placing it as the most exogenous variable and identifying extreme weather event shocks through a recursive scheme.[2]

The main findings for each type of extreme weather event can be summarised as follows. First, extremely *high temperature* shocks have especially adverse effects in Germany, with a particularly negative impact on mining, manufacturing and services. By contrast, these shocks support overall activity over the entire horizon in France, with output gains in manufacturing, construction and services. Moreover, extreme heatwaves adversely affect activity in the pharmaceutical sector in most countries throughout the horizon (potentially due to its reliance on river transport and associated water levels, especially in Germany). Considering the effects on prices, extremely high temperature shocks tend to have a demand-side nature, with prices and activity moving in the same direction, although significant effects can be identified only in Germany.

Second, extremely *low temperature* shocks cause immediate GDP declines in Germany and Italy, followed by delayed positive effects. These varying effects over the horizon are driven by negative effects in mining, construction, and some manufacturing subsectors (electrics and machinery) that prevail in the near term, and by positive effects on electricity and gas and other manufacturing subsectors (motor vehicles) that become more pronounced later in the horizon.

[2]This identification strategy assumes only a weak exogeneity of the instrument, as it accounts for possible effects of economic variables on the climate variables beyond the contemporaneous impact. Results are broadly robust to alternative specification with fully exogenous extreme weather events, and are available from the authors upon request.

These shocks have positive effects on Spain's industrial sectors, but no significant effects on GDP. Moreover, extremely low temperature shocks support production in the electricity and gas sector in all countries throughout the horizon, likely due to increased demand for heating. Looking at the reaction of prices, the demand-supply nature of these shocks is ambiguous, as cold extremes may raise either activity or prices, but not both.

Third, extremely *high precipitation* shocks thwart GDP on impact in Germany, France and Spain, mainly due to downturns in construction in all three countries as well as mining (France and Spain), manufacturing (Spain) and services (France). These shocks further adversely affect Spain's output in a more protracted fashion across many sectors. By contrast, they induce positive delayed effects on GDP in Italy, associated with construction, market services, and pharmaceuticals. Looking at the implications for prices, extreme rainfalls exhibit a demand-side nature, when significant, but with cross-country heterogeneity.

Finally, extremely *low precipitation* shocks impair overall economic activity only in Spain, where mining and manufacturing particularly suffer over the entire horizon. By contrast, these shocks tend to have positive effects on GDP in the near term in Italy, with a broad-based favourable impact across many sectors. As expected, the weather-dependent construction sector is generally negatively impacted by extremely high precipitation in the short run and benefits from periods of extremely low precipitation across countries. By contrast, motor vehicle production appears largely unaffected by extreme precipitation. Considering the impact on the nominal side, extremely low precipitation shocks also tend to have a demand-side nature, when significant.

Related literature. The empirical literature on the economic impact of climate events has expanded markedly in recent years, reflecting both the rising incidence of extreme weather events and the increasing availability of high-frequency meteorological and economic data. Within this body of work, studies differ systematically along several dimensions. These design choices shape both identification and interpretation, and delimit which channels can be assessed.

A first dimension concerns the geographic scope. Some studies adopt a single-country perspective, often motivated by the availability of granular exposure data and the desire for tight identification (Kruttli et al., 2025). Other studies focus on cross-country or within-country panels to estimate average effects and explore heterogeneity across income groups, regions or institutional environments (Faccia et al., 2021, Berg et al., 2023, Ciccarelli and Marotta, 2024, Bodenstein and Scaramucci, 2024, Ehlers et al., 2025, Usman et al., 2025). Finally, similarly to our paper, some studies sit between these approaches and analyse some large advanced economies with harmonised data (Cevik and Gwon, 2024, Colombo and Ferrara, 2024, Ciccarelli et al., 2024).

A second dimension is the time span used to estimate economic responses. A few papers exploit long historical panels to disentangle adaptation, nonlinearities, and slow-moving impacts (Berg et al., 2023, Bodenstein and Scaramucci, 2024). However, especially in cross-country analyses, most papers—including ours—focus on more recent samples, in which both meteorological reanalyses and macro-financial series are more reliable and more consistently measured across countries (Ehlers et al., 2025, Cevik and Gwon, 2024, Colombo and Ferrara, 2024, Ciccarelli et al., 2024, Ciccarelli and Marotta, 2024).

Third, depending on the design of the research question, studies vary in terms of the frequency of the data and the horizon of the impact. At one end of the spectrum, several cross-country studies use annual data to assess medium-run output losses or persistent level effects (Berg et al., 2023, Ciccarelli and Marotta, 2024, Usman et al., 2025). At the other end, event-based analyses around specific episodes use daily or even intra-daily information to capture immediate financial or behavioural responses (Kruttli et al., 2025). As in the case of our paper, a growing middle ground uses monthly or quarterly frequency to link weather events to macroeconomic outcomes (Cevik and Gwon, 2024, Ciccarelli et al., 2024, Colombo and Ferrara, 2024, Natoli, 2023). Some contributions explicitly contrast short-run and medium-run responses within a unified framework (Bodenstein and Scaramucci, 2024, Ehlers et al., 2025).

Fourth, the literature is focussing on different types of climate events. A large part of the recent literature emphasises temperature-related events, including heat anomalies and heatwaves (Faccia et al., 2021, Ciccarelli et al., 2024, Berg et al., 2023, Cevik and Gwon, 2024, Natoli, 2023). A complementary strand extends the analysis to include hydrological extremes, such as droughts and floods (Usman et al., 2025, Colombo and Ferrara, 2024), including the present study. Finally, disasters (such as hurricanes, earthquakes, and landslides) feature prominently in event-study work (Kruttli et al., 2025), as well as studies of long-run macroeconomic effects (Bodenstein and Scaramucci, 2024, Ciccarelli and Marotta, 2024, Ehlers et al., 2025).

Fifth—and crucial for identification—the literature varies in how climate events are defined, i.e., what constitutes an "unexpected" or "extreme" weather event. One approach defines climate events as deviations from a long-run mean (Cevik and Gwon, 2024, Ciccarelli et al., 2024). A related approach uses threshold dummies—e.g., "extreme" quarters or seasons—based on deviations from a long-run mean by at least a given number of degrees, which simplifies non-linearities but abstracts from variation in intensity beyond the threshold (Faccia et al., 2021). Another branch, including the present study, defines shocks via percentile-based extremes, focusing explicitly on tail realisations and thereby aligning more closely with the concept of "rare events" (Natoli, 2023, Usman et al., 2025, Colombo and Ferrara, 2024). Finally, some work uses damage-based measures, which can be attractive for capturing economically relevant severity but raises concerns about endogeneity and often motivates IV strategies or careful controls (Bodenstein and Scaramucci, 2024, Ciccarelli and Marotta, 2024, Ehlers et al., 2025).

Finally, the literature features substantial variation in the considered economic outcomes. The macro-oriented literature often focuses on aggregate activity measures (Berg et al., 2023, Bodenstein and Scaramucci, 2024, Ehlers et al., 2025). These measures are supplemented by inflation and interest rates when the objective is to assess monetary policy trade-offs (Faccia et al., 2021, Ciccarelli and Marotta, 2024), although some studies emphasise the role of supply constraints (Cevik and Gwon, 2024), while others explore sectoral transmission mechanisms (Ciccarelli et al., 2024). European applications that exploit harmonised monthly indicators often incorporate industrial/sectoral production, labour-market variables, and price indices in a joint framework to describe propagation across sectors and macro aggregates (Colombo and Ferrara, 2024). At the micro and finance end, the focus shifts to asset prices, volatility, and risk premia (Kruttli et al., 2025) or balance sheets and lending conditions (Ehlers et al., 2025).

Overall, among the contributions discussed above, the paper most closely aligned with our objective and empirical setup is Colombo and Ferrara (2024), given its emphasis on weather shocks in monthly frequency and their propagation to production/activity indicators in European economies. Our paper, however, improves upon this benchmark in two main respects. First, we provide a clearer and more transparent definition of extremes by constructing shocks relative to the entire (country-specific) historical distribution, rather than relying on month-specific distributions. This approach yields comparable, and well-identified events, as each type of shock is clustered in specific months (e.g., extremely cold weather in winter months). Hence, our approach allows for a clearer economic interpretation of the economic impact of extreme weather events and their transmission channels across countries and sectors, thus enhancing the usefulness of the results for short-term macroeconomic analysis and forecasting. Second, our paper broadens the scope of economic outcomes by including (i) a measure of overall economic activity (real GDP) and (ii) a richer set of sectors, especially within manufacturing, as well as the geographic scope of the analysis by including Spain.

The remainder of the paper is structured as follows. Section 2 describes the climate and economic data. Section 3 lays out the baseline empirical methodology. Section 4 discusses the baseline results across the different types of events, countries, and sectors. Section 5 presents results from robustness checks. Section 6 concludes.

2 Data

This section describes the sources and the computations of the climate and economic indicators used in the empirical analysis. Unless otherwise stated, the reported statistics and results refer to our benchmark sample, which comprises the largest four euro area countries, namely Germany, France, Italy, and Spain, between January 1999 and December 2023.

As regards our climate indicators, we use data from the Weighted Climate Dataset (Gortan et al., 2024). This dataset builds on raw gridded climate data from four sources, including the fifth generation ECMWF atmospheric reanalysis (ERA5) of the global climate covering the period from January 1940 to December 2023. Reanalysis datasets are widely used in climate monitoring applications, including by the World Meteorological Organization (WMO) and the IPCC (Hersbach et al., 2020). In particular, ERA5 integrates climate models with historical observations to ensure consistency over time and improve accuracy, particularly in grid areas not covered by direct measurement stations, with a fine grid resolution of $0.25° \times 0.25°$. This dataset offers monthly records for two main weather events, namely average temperature (measured in Celsius degrees, C) and total precipitation (in millimeters, mm), as well as other derived variables. Specifically, from this dataset we select weighted means for each of the four countries considered, using as weights the population in each grid cell, based on 2015 data (which broadly corresponds to the middle of our sample).[3]

In our analysis, each measure of extreme weather event is computed as the number of consecutive days within a month in which a weather event – temperature or precipitation – is "extreme" – either above or below a pre-defined threshold. As observed by Stephenson (2009), a threshold-based approach typically implies that "extremeness" is defined as a rarity. Given the arbitrary nature of the selection of a threshold, we select a baseline and conduct robustness checks using alternative definitions. Specifically, we select the 5th and the 95th percentiles from our

[3] We use population-weighted temperature and precipitation to measure climate exposure because GDP responds to conditions experienced by firms and production rather than land area.

reference distribution to identify extremely low and high temperature/precipitation, respectively, as our baseline thresholds (Climate.gov, 2020), while we consider other thresholds (i.e., 10th and 90th as well as 1st and 99th) in robustness checks (Natoli, 2023).

Formally, extreme weather events are identified using a threshold-based approach applied to daily temperature and precipitation data. Let c index countries, d days, and t months. For each country c, we consider daily observations of a generic weather variable $X_{c,d}$, where X denotes either average surface temperature or total precipitation. To define extremeness, we construct the empirical distribution $\mathcal{F}_c(X)$ using the entire historical sample of daily observations for country c, spanning the period from January 1940 to December 2023. Let $q_c^\alpha(X)$ denote the α-quantile of this country-specific historical distribution. Extreme weather events are then measured at the monthly frequency as the number of days within a month for which the daily realisation of the weather variable exceeds (or falls below) a fixed percentile threshold of the historical distribution. Specifically, extreme weather events in the upper distribution are defined as

$$E_{c,t}^{\text{high}}(X) = \sum_{d \in t} \mathbf{1}\left\{X_{c,d} > q_c^{0.95}(X)\right\}, \tag{1}$$

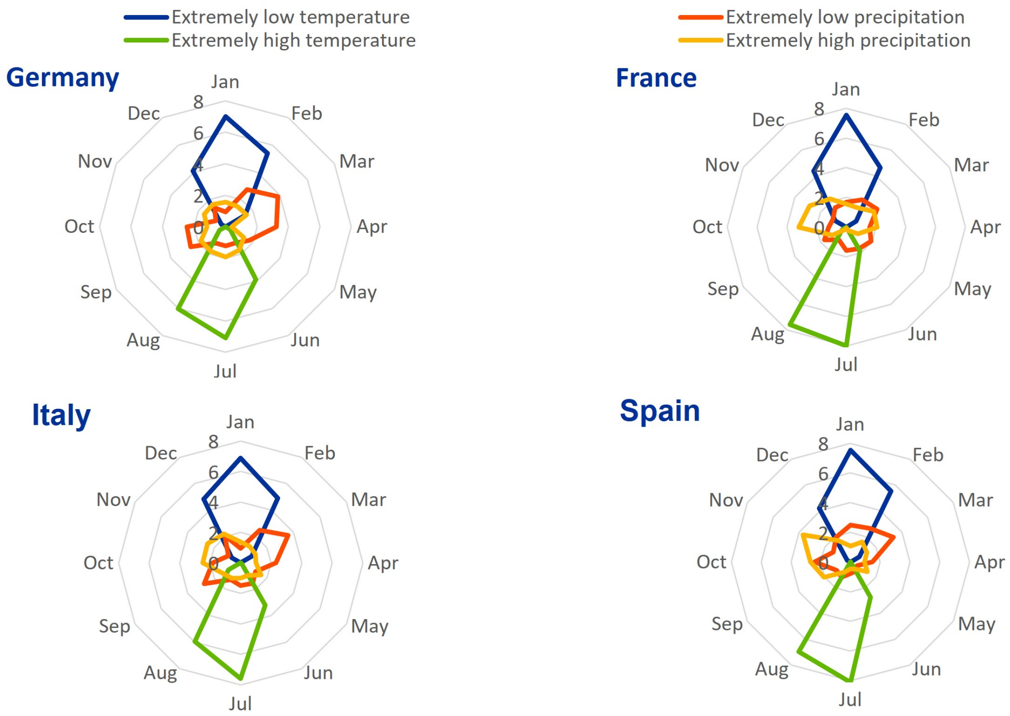
while extreme weather events in the lower distribution are defined as

$$E_{c,t}^{\text{low}}(X) = \sum_{d \in t} \mathbf{1}\left\{X_{c,d} < q_c^{0.05}(X)\right\}. \tag{2}$$

Applying this definition to temperature and precipitation yields four distinct indicators: extremely high temperature, extremely low temperature, extremely high precipitation, and extremely low precipitation. Each indicator captures both the occurrence and the duration of extreme weather conditions within a given month.

As our reference distribution, we use the entire historical distribution of weather events between January 1940 and December 2023 separately for each specific country. Considering the entire historical distribution, rather than a season-specific distribution, to identify extreme weather events has several advantages. First, it implies that extreme occurrences for each type of weather event tend to be clustered in a specific season. As shown in Figure 1, across all the countries in our sample, extremely low temperature is nearly always recorded between December and February and its frequency peaks in January, while extremely high temperature is generally limited to July, August and, to a lesser extent, June. Further, although with a lower degree of

Figure 1: Distribution of extreme weather events across months (number of days)

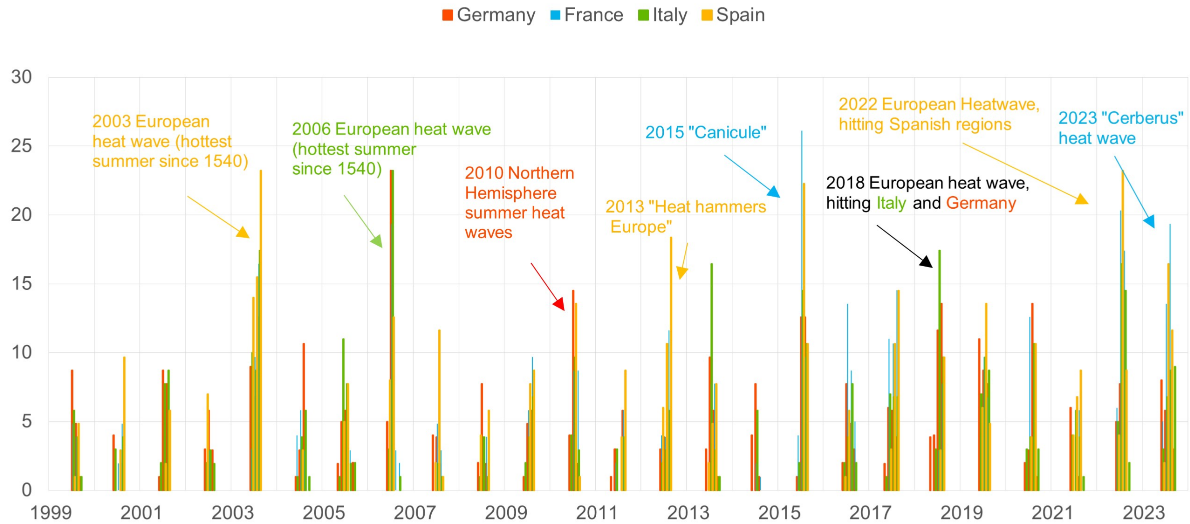


Sources: Weighted Climate Dataset and ECB staff calculations.
Notes: The figure shows the number of days within a month with extremely low temperature (temperature below the 5th percentile) and extremely high temperature (above the 95th percentile), as well as extremely low precipitation (precipitation below the 5th percentile) and extremely high precipitation (above the 95th percentile), relative to the historical distribution between January 1940 and December 2023.

seasonal concentration compared with extreme temperature, extremely low precipitation typically occurs between February and April, while extremely high precipitation tends to be observed more frequently in October and November, with some cross-country heterogeneity. As such, each type of weather event has a distinct nature and, thus, a clear economic interpretation. Second, this approach ensures that, even when there are events from different seasons, their magnitudes are anyway comparable as they are assessed against the same threshold. Finally, the large longitudinal dimension of our reference distribution, which covers the universe of weather events over the entire sample period from 1940 to 2023, ensures comprehensive historical coverage.

Conversely, other studies identify weather events based on month-specific reference distributions (Ciccarelli et al., 2024, Natoli, 2023, Usman et al., 2025). This approach implies that different types of weather events may occur in the same season. For instance, a particularly high temperature in January may have opposite effects on sectoral activity (e.g. higher construction output due to favourable outdoor conditions, lower energy production due to lower heating

Figure 2: Extremely high temperature (number of days)

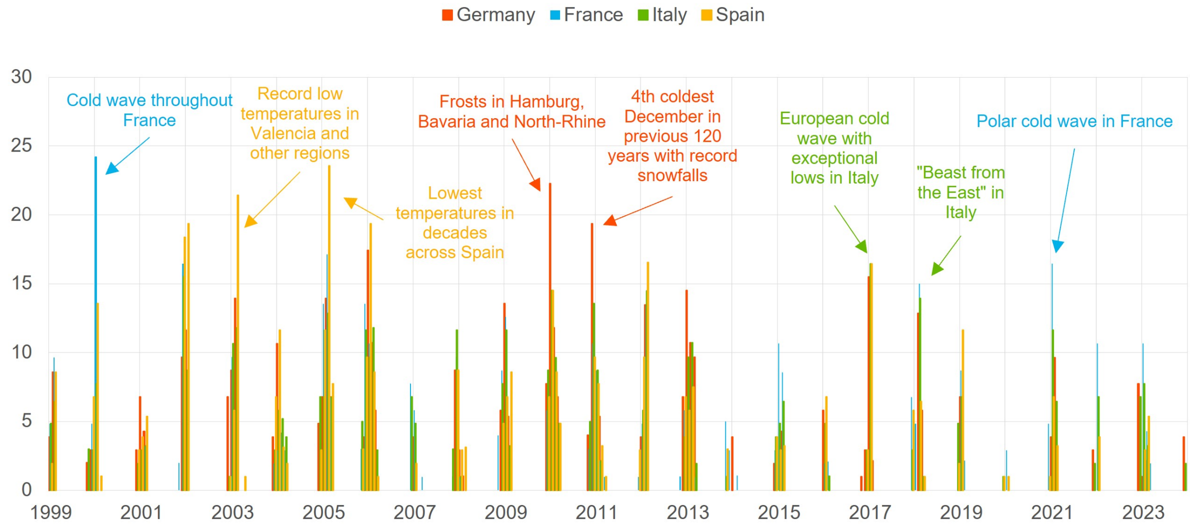


Notes: The figure shows the number of days with a temperature above the 95th percentile of the distribution in the period 1940-2023.

needs, etc.) compared with the same type of event in July (e.g. lower construction output due to mandatory constraints during the hottest hours, higher energy production due to higher cooling needs, etc.). As such, the identified weather events have a mixed nature, which blurs their economic interpretation. To address this issue, these studies typically split the events by season, then expanding (but also complicating) the analysis of their economic impact to a wide range of different weather events. Compared with these studies, our analysis focuses on fewer and more distinct types of weather events.

Turning to the dynamics of our climate indicators, we can validate our extreme weather events by connecting them with well-known climate episodes in the four countries over time. Figure 2 to Figure 5 show the time series of the identified extreme weather events. As shown in Figure 2, extremely high temperature takes place in the summer across the four countries and tracks well-known episodes of heatwaves in Europe over the last quarter of a century. As to specific episodes there is, for instance, the European heatwave in 2018 affecting Italy and Germany, a heatwave in 2022 noticeable in Spain and yet another in 2023 registered in France. Looking through the volatility, the number of days with extremely high temperature seems to have trended upwards, with more frequent events in recent years. Hence, as also shown in Figure B.1 in the Appendix B, the distribution of high temperature events has shifted towards the right in all countries, implying that the frequency of extremely hot days has increased over time.

Figure 3: Extremely low temperature (number of days)



Notes: The figure shows the number of days with a temperature below the 5th percentile of the distribution in the period 1940-2023. Latest observation: December 2023.

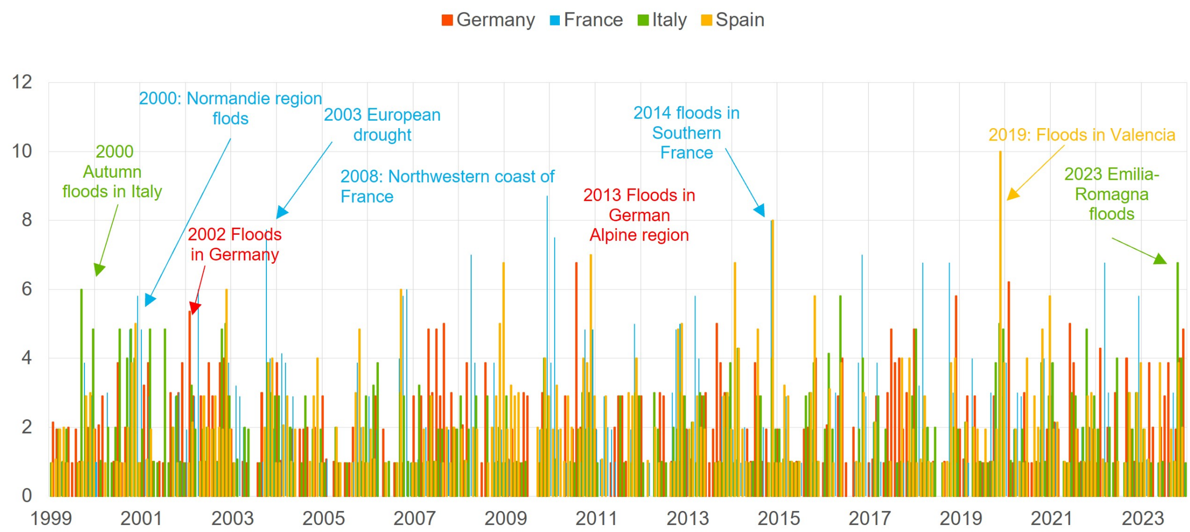
Figure 3 shows the time series of events with extremely low temperature. In contrast to high temperature, low temperature occurs during the winter and has overall followed a downward trend in the last 25 years. Moreover, the identified events also track well-known episodes of cold waves across Europe. In terms of distribution, shown in Figure B.2, extremely low temperature has become overall less frequent and its average duration in a month also decreased in all countries. These trends broadly confirm the phenomenon of global warming observed over the last quarter of a century.

Turning to extremely high precipitation, Figure 4 shows that peaks have increased over time, with floods in Valencia in 2019 and in Emilia Romagna in 2023 being the most relevant recent episodes. Also for precipitation, the events can be associated with well-known episodes of floods and rainfalls.

Finally, as shown in Figure 5, an increasing frequency in episodes of extremely low precipitation can be observed over time, as they track well episodes of droughts. For instance, the identified events highlight the Spanish drought in 2012, the drying of the Po Valley in 2014, and, more recently, the driest April since the 1880s in Germany in 2020.[4]

[4]It is possible for both extremely high and extremely low precipitation events to occur within the same month. This can arise when a month contains days with precipitation above the 95th percentile of the historical distribution as well as days below the 5th percentile, provided that the sum of the days of such extreme days does not exceed the total number of days in the month. This feature reflects the intra-month variability of precipitation and is naturally captured by our event definition based on daily thresholds.

Figure 4: Extremely high precipitation (number of days)



Notes: The figure shows the number of days with precipitation above the 95th percentile of the distribution in the period 1940-2023. Latest observation: December 2023.

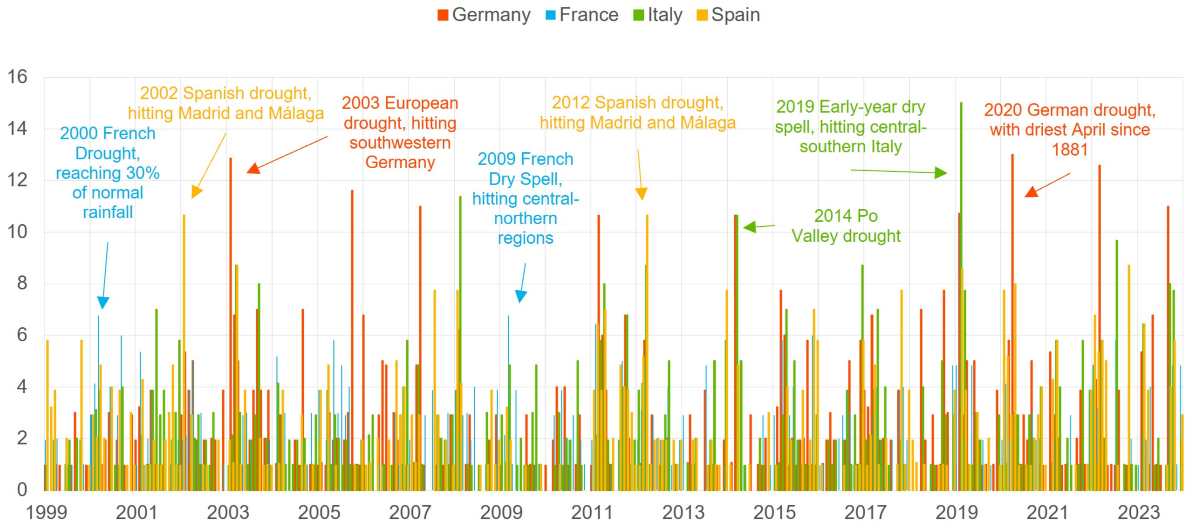
For the data on precipitation there is a slight prominence of both high and low precipitation in Spring and Autumn, though the seasonal pattern is much less pronounced than for temperatures. Hence, as also shown in Figures B.3 and B.4, the number of days with extremely high and low precipitation has increased across countries over time, signaling a higher frequency of extreme weather events. However, the average duration of high precipitation in a given month has remained broadly unchanged, indicating a similar intensity over time, whereas low precipitation has increased its average duration in a given month, indicating more intense droughts.

As regards economic indicators, we use data from Eurostat, covering key macroeconomic and sectoral activity measures. Specifically, our dataset includes sectoral output, proxied by monthly production data, in mining, manufacturing (including sub-sectors available for the NACE Rev.2 level 2 classification), energy (including electricity and gas), construction, and (market) services.[5] To estimate monthly real GDP, we proceed in two steps. In a first step, we apply the method by Chow and Lin (1971) to obtain a proxy for monthly services output, by interpolating quarterly real gross value added for market services using monthly retail sales volumes.[6] In a second step, we use again the Chow-Lin method to interpolate quarterly real GDP into monthly real GDP series using monthly industrial production (excluding construction), con-

[5] Production data from the public sector is not available.

[6] We could not use services production due to the short sample of the time series, which starts only in 2015.

Figure 5: Extremely low precipitation (number of days)



Notes: The figure shows the number of days with precipitation below the 5th percentile of the distribution in the period 1940-2023. Latest observation: December 2023.

struction production and the derived monthly services real gross value added. The rationale for this approach in estimating monthly real GDP is twofold. First, this approach ensures that real GDP reflects a broad measure of economic activity, covering all the main sectors of production. Second, it avoids contaminating the measure of real GDP with time series that could induce some spurious dynamics, such as extreme weather events.[7] To conclude, our list of economic variables also includes headline HICP.

3 Methodology

Following the approach of Colombo and Ferrara (2024), we employ a structural Bayesian vector autoregression (SBVAR) model to analyse the economic effects of extreme weather events at the country level. The model is specified as:

$$Y_t = C + \sum_{p=1}^{P} A_p Y_{t-p} + \varepsilon_t \tag{3}$$

where Y_t is a vector of endogenous variables in month t, which includes a country-specific extreme weather event indicator (number of days above/below the specified threshold for temper-

[7] By contrast, a single-step real GDP estimate, for instance in a mixed-frequency VAR model, would be affected by all the variables in the model, including the very instruments for shocks whose impact we aim to estimate.

ature and precipitation), euro area real GDP level and HICP level, country-specific real GDP level and HICP level, and, in the extended version of the model, a sectoral activity index. Moreover, A_p is a matrix of slope coefficients and C a vector of intercepts. The error term $\varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon)$ denotes a vector of reduced-form residuals in month t. As standard in the literature, we posit a relationship $\varepsilon_t = \Gamma \nu_t$, where $\nu_t \sim \mathcal{N}(0, \Sigma_\nu)$ are structural innovations and Γ is an orthogonal matrix of identifying restrictions on their contemporaneous impact on the endogenous variables.

Following the naming convention by Plagborg-Møller and Wolf (2022), we identify ν_t by including our measure of extreme weather event as an "internal instrument" in the SBVAR model. Thus, the extreme weather event shocks are identified through a recursive strategy, with the extreme weather event ordered first, as the most exogenous variable, thus assuming that extreme weather events are not affected on impact by other shocks, which is a plausible assumption, given the frequency of the data.

Our identification strategy closely follows Colombo and Ferrara (2024), who employ a recursive (Cholesky) ordering to identify weather shocks as the most exogenous variables in a monthly structural VAR framework. This approach is well suited to the analysis of extreme weather events, as meteorological conditions are plausibly unaffected by contemporaneous macroeconomic or sectoral developments at a monthly frequency. Ordering the weather indicator first therefore provides a transparent and economically grounded identification of weather shocks.

At the same time, our baseline specification allows for the possibility that weather events may exhibit some degree of endogeneity with respect to economic conditions. This endogeneity could possibly be due to the increasing predictability over time and the potential adjustment by economic agents. Moreover, it could also be due to the impact of similar events at the same time in different countries. To account for these factors, we include euro area variables in the model. Our results are robust to alternative identification assumptions. In particular, treating extreme weather events as fully exogenous yields qualitatively similar impulse responses, and the main findings are preserved under alternative threshold definitions for extreme events.

Regarding the empirical framework, the SBVAR model uses standard Minnesota priors with 6 lags.[8] We use the approach proposed by Lenza and Primiceri (2022) to address the heteroscedasticity induced by the COVID-19 pandemic. We obtain impulse response functions estimated through country-specific SBVAR models, which provide a coherent framework to di-

[8] Ramey and Zubairy (2018) find that local projections—also when combined with external instruments—deliver responses that closely match those obtained from VAR-based approaches; similar findings are also reported by Colombo and Ferrara (2024).

rectly compare the responses of different countries and sectors to the shocks.

4 Results

4.1 The impact of extreme weather events on overall economic activity

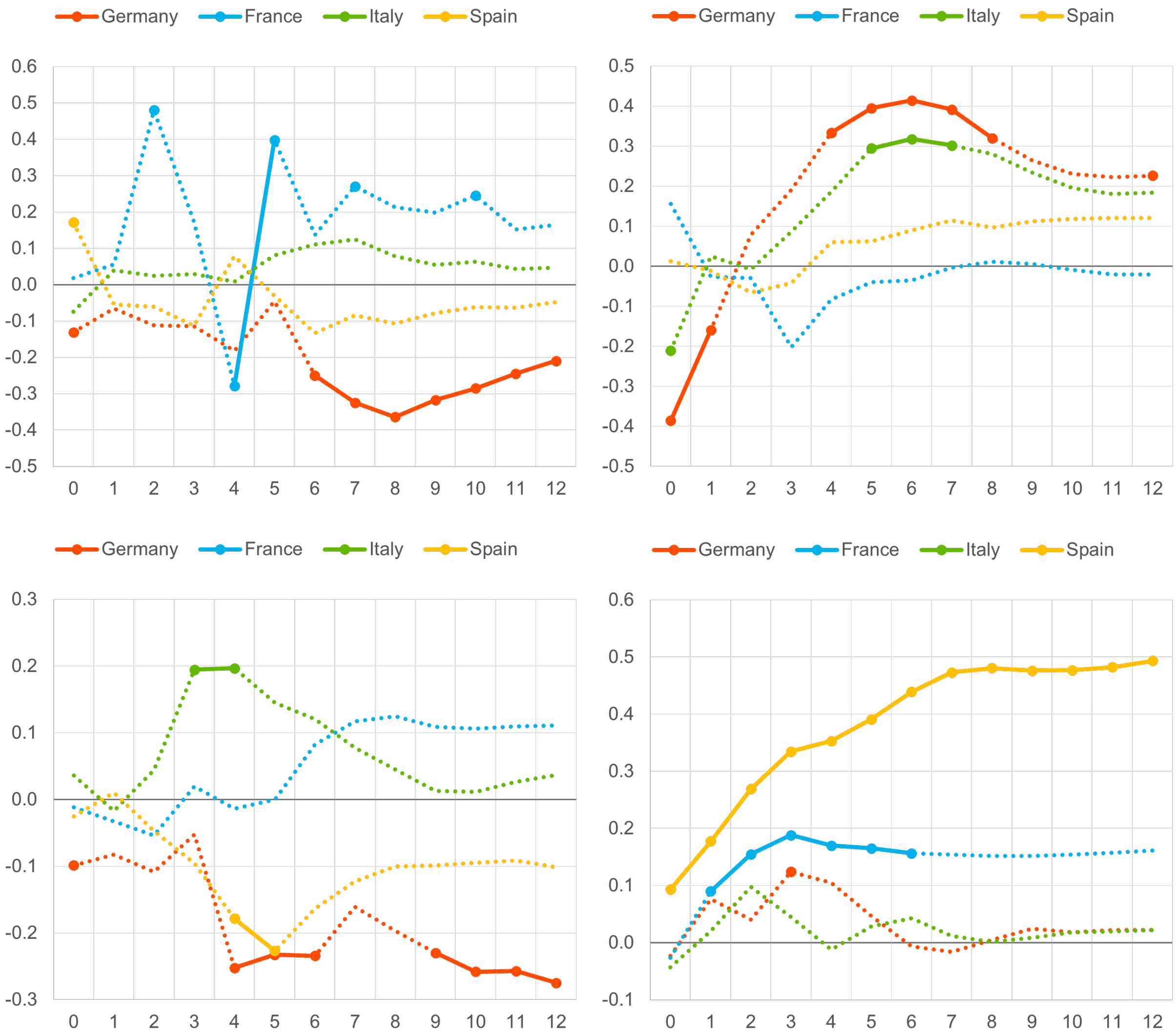
This section discusses the results of our baseline specification, focussing on the impulse response functions (IRFs) for the level of real GDP and HICP to extreme weather event shocks in Germany, France, Italy, and Spain. These results are illustrated in Figures 6 and 7. In each figure, solid lines and dots indicate statistically significant responses within the 68 percent credibility bands, while dotted lines represent non-significant responses. The figures show the IRFs over the 12 months following the shock, standardised to represent the response to one day of extreme weather.[9]

Extremely high temperature shocks. As shown in the left panels of Figure 6, one day of extreme heat induces a significant effect of -0.1 percent on the level of real GDP in Germany on impact, reaching a trough at -0.4 percent after 8 months. By contrast, extremely high temperature shocks significantly support economic activity in France over (almost) the entire horizon, with a peak effect of 0.5 percent on real GDP reached 2 months after one day of extreme heat. These shocks also significantly raise the real GDP level in Spain on impact (0.2 percent), but the effect is largely transitory. On the nominal side, prices tend to move in the same direction as quantities, as extreme heat significantly reduces HICP for Germany and Spain by 0.2-0.3 percent after 6 months, while it raises HICP for France and Italy, with the latter exhibiting a significant increase by 0.2 percent after 3 months. The positive comovement between real GDP and HICP across countries suggests that extremely high temperature tends to have a demand-side nature, although significant effects can be identified only in Germany.

Extremely low temperature shocks. As shown in the right panels of Figure 6, one day of extreme cold induces a significant contraction of real GDP in both Germany and Italy, by 0.4 and 0.2 percent, respectively. However, this impact turns positive and significant later in the horizon, peaking at 0.4 and 0.3 percent, respectively, after 6 months. Moreover, the effects of

[9] The size and occurrence of shocks are broadly comparable across countries in the way we construct the event series, as they are based on comparable quantiles of the country-specific distributions. More specifically, the average size of the extreme weather event is about 1.5 days across countries for extremely high and low temperature and extremely low precipitation, and about 1.9 days for Germany and Italy and 1.6 days for France and Spain for extremely high precipitation.

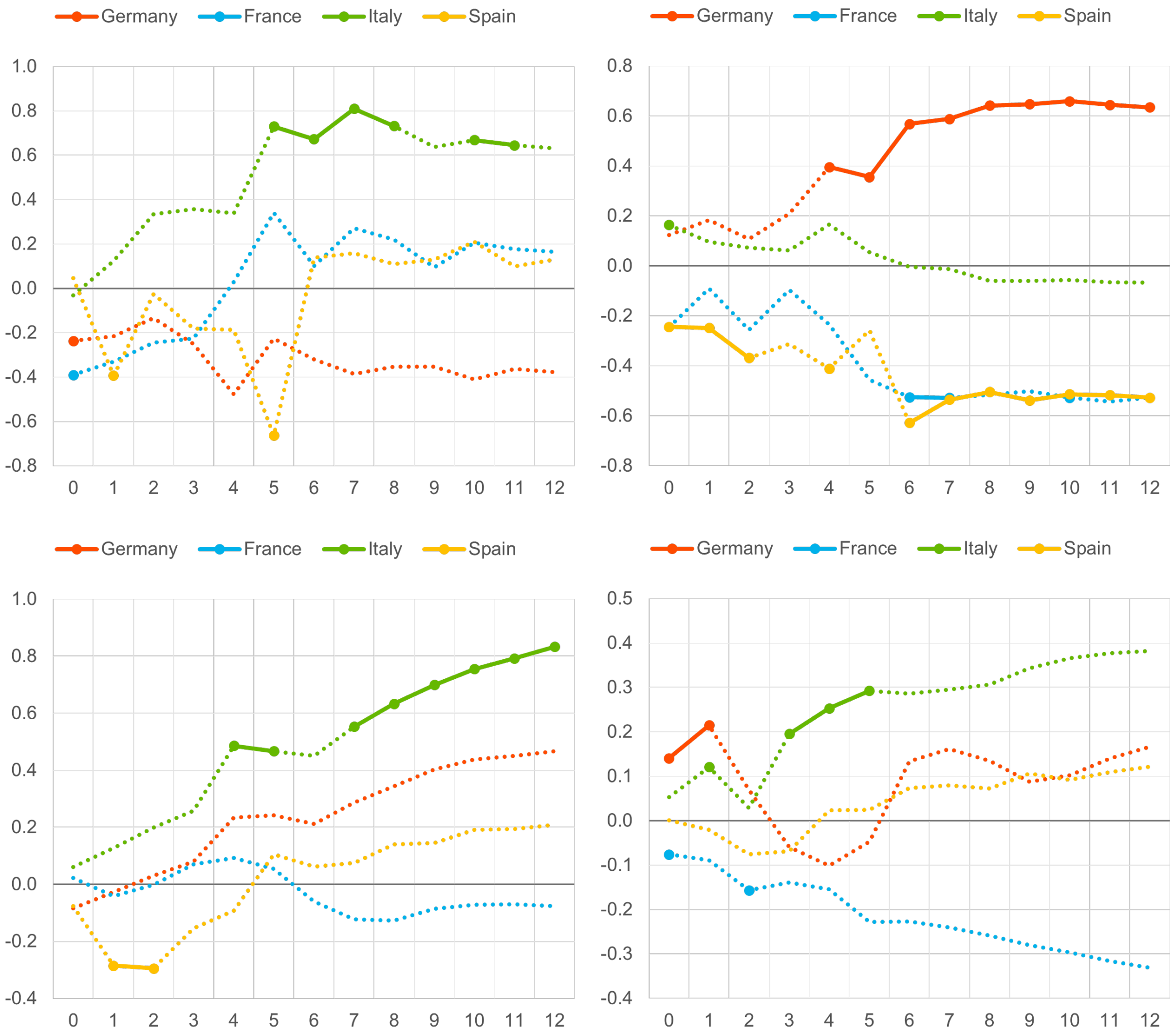
Figure 6: Impact of extremely high (left panels) and low (right panels) temperature on the level of real GDP (upper panels) and HICP (lower panels)
(x-axis: months; y-axis: percentage deviation from baseline level)



Notes: The charts show the impact of an increase by one day in the number of days in a month above the 95th (left panel) and below the 5th (right panel) percentile of the country-specific historical distribution. Dots denote responses within the 68 percent credibility bands, with solid lines connecting two consecutive significant responses and dashed lines connecting responses in other cases. The x-axis refers to the number of months over the horizon.

extremely low temperature shocks in France and Spain are not significantly different from zero. Looking at the reaction of prices, one day of extremely cold temperature induces significantly higher HICP in France (up to 0.2 percent after 3 months) and Spain (up to 0.5 percent after 8 months) in the near term and later in the horizon, but the effects are only mildly positive in Germany and negligible in Italy. Hence, while the demand-supply nature cannot be clearly pinned down, cold extremes may raise either activity (Germany and Italy), where this increase

Figure 7: Impact of extremely high (left panels) and low (right panels) precipitation on the level of real GDP (upper panels) and HICP (lower panels)
(x-axis: months; y-axis: percentage deviation from baseline level)



Notes: See notes to Figure 6.

follows an immediate contraction, or prices (France and Spain), but not both.

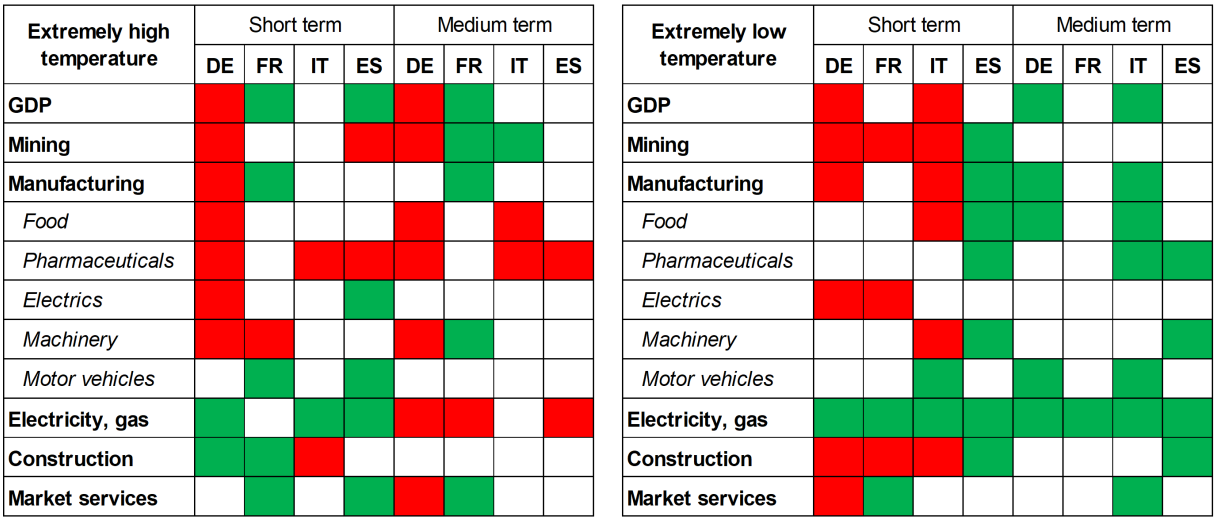
Extremely high precipitation shocks. As shown in the left panels of Figure 7, one day with extreme rainfall significantly reduces the near-term real GDP level in Germany and France (on impact) as well as Spain (after 1 month) by 0.2, 0.4 and 0.4 percent, respectively. However, this effect is temporary, except for Spain, where the impact reaches a trough of -0.7 percent after 5 months to become negligible thereafter. By contrast, extremely high precipitation shocks significantly support economic activity in Italy, with a peak effect of 0.8 percent 7 months after a day of high precipitation extreme. Looking at the implications for prices, extremely high precipitation shocks tend to have a demand-side nature, when significant, but with opposite effects depending on the country. Indeed, one day of extreme rainfall significantly raises prices in Italy up to 0.8 percent after 12 months, and it significantly reduces them in Spain by 0.3 percent after 2 months. The favourable demand effects in Italy are plausibly linked to reconstruction activity and increased demand for services following weather-related disruptions. At the same time, the adverse demand effects in Spain appear to propagate across large swaths of the economy.

Extremely low precipitation shocks. As shown in the right panels of Figure 7, one day of extremely low precipitation induces a significant increase of real GDP in both Germany (up to 0.6 percent after 10 months) and Italy (0.2 only on impact). Conversely, this type of shocks thwarts activity in France and Spain, where one more day of extreme drought reduces real GDP by 0.2 percent on impact—albeit significantly in Spain only—and about 0.5-0.6 percent between 6 and 12 months after the shock. On the nominal side, prices mostly move in the same direction as quantities, as one day of extreme drought significantly increases HICP for Germany and Italy by 0.2-0.3 percent in the first 6 months, while it curbs HICP for France by 0.2 percent after 2 months, with negligible effects in Spain. When significant, extremely low precipitation tends to have a demand-side nature across countries.

Discussion. Overall, the analysis above shows that extreme weather events indeed affect overall economic activity across the largest euro area countries, but with varying magnitudes, directions, and duration, as well as their demand- or supply-side nature. In terms of magnitude and duration, the real GDP level effects are significant in several cases on impact, and they rise over time, often peaking in the second quarter (4th to 6th month) following the weather shock. In terms of nature, the results appear to consistently point to demand-driven type of effects, when significant, at least at aggregate level.[10] Looking at patterns across countries, these results further emphasise the vulnerability of the German economy to temperature extremes. They also highlight that extreme weather events of various types support economic activity in Italy as well as, to a lower extent, Germany and France. Interestingly, the economic consequences to extremely low temperature and precipitation shocks are similar in Germany and Italy, on

[10] Note that, due to the design of the empirical methodology, in the absence of sectoral prices, this analysis cannot uncover the sector-specific demand-supply nature of extreme weather event shocks, which remains an interesting avenue for future research.

Figure 8: Impact of extremely high (left panel) and low (right panel) temperature on the level of real GDP and sectoral activity
(colour based on direction and significance)



Notes: The table shows the direction and significance of the impact of an increase by one in the number of days with the considered extreme weather event in a month (i.e., days above (below) the 95th (5th) percentile of the country-specific historical distribution). The (red and green) coloured cells indicate the presence of at least one month with (negative and positive, respectively) responses within the 68 percent credibility bands. Short term (medium term) refers to the horizon between 0 and 3 (4 and 12) months ahead.

the one hand, and France and Spain, on the other hand. This result—bundling the countries with the two largest euro area manufacturing sectors on one side, and two more services-oriented economies on the other side—hints at a possible role for the production structure of the economy, especially its sectoral composition, in shaping the transmission of extreme weather event shocks to the economy. In the next section, the role of sectors in the propagation of extreme weather events is analysed.

4.2 The impact of extreme weather events across sectors

This section explores the propagation of extreme weather event shocks to overall economic activity by focussing on their impact on activity across sectors. Given the different country-specific production structure, this analysis may in turn help explain the role of the sectoral composition of the economy in propagating extreme weather event shocks. Specifically, we extend the baseline SBVAR model in Equation (3) with one of the following sector-specific activity indices at a time: the main macroeconomic sectors, i.e. mining, manufacturing, electricity and gas, construction, and (market) services, as well as five manufacturing subsectors with the largest (euro area) weights (food, pharmaceuticals, electrics, machinery and motor vehicles).

Figures 8 and 9 indicate whether shocks due to extremely high (left panels) and low (right panels) temperature and precipitation events, respectively, have a significantly positive (negative) impact on the level of real GDP or sectoral output in Germany, France Italy, and Spain with green (red) cells for both the short term (any month in the 0-to-3-month horizon) and the medium term (any month in the 4-to-12-month horizon).[11]

Extremely high temperature shocks. In Germany, the significantly negative impact of extreme heat on real GDP in the near term is mainly driven by manufacturing (reflecting food and, to a lesser extent, machinery, electrics and pharmaceuticals), mining and, after a few months, electricity and gas (which however responds positively on impact). The adverse impact from extremely high temperature shocks on German real GDP in the medium term mainly stem from electricity and gas and, to a lower extent, mining and some manufacturing subsectors (especially food), compounded by a protracted negative contribution from services. In France, the favourable effects on real GDP over the entire horizon are mainly driven by manufacturing (reflecting motor vehicles in the short term and machinery in the medium term), services and, in the near term, construction. In Italy, the negligible impact of extreme heatwaves on real GDP masks significant cross-sectoral heterogeneity, with significant contractions in construction and electricity and gas (despite an immediate increase, as in the case of Germany) and some manufacturing subsectors (food and pharmaceuticals), broadly compensated by significant increases in mining. In Spain, the positive effect on impact appears associated with activity gains in electrics, motor vehicles, electricity and gas and services, more than offsetting output losses in pharmaceuticals. In the medium term, despite the negligible effects on real GDP, extreme heatwaves induce lower production in pharmaceuticals and electricity and gas.

Overall, Germany is characterised by an immediate and persistent contraction driven primarily by energy-intensive and industrial sectors, with delayed spillovers to the services sector. France and Spain appear to benefit from production gains in manufacturing subsectors, such as motor vehicles and machinery, as well as in services, possibly in activities related to cooling and health. In between, Italy records an idiosyncratic decline in construction output amidst an exceptionally high temperature. Across countries, some sector-specific regularities emerge, as pharmaceuticals appear to consistently suffer the occurrence of extremely hot days throughout

[11] The detailed impulse response functions of sectoral output to the specific extreme weather event shocks are presented in Appendix C, while, for the sake of brevity, the main text presents a condensed version of the results.

the horizon, possibly related to the sector's dependence on transports via rivers and hence their water level (Dobson, 2021). By contrast, electricity and gas experience immediate gains, likely due to a boost in demand, but they exhibit a prolonged decline thereafter, consistent with supply disruptions or efficiency losses under extremely high temperatures.

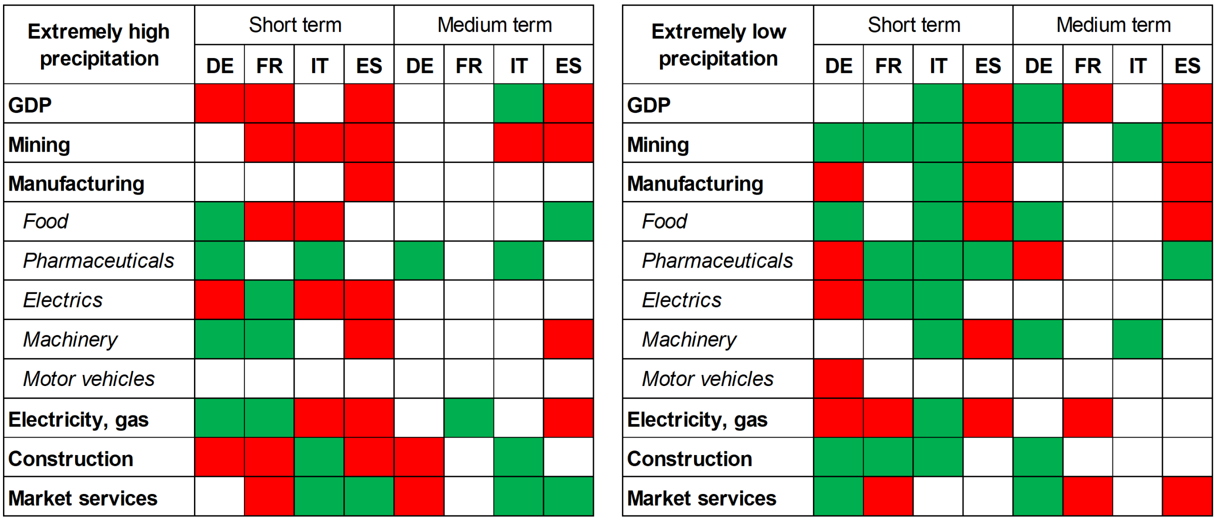
Extremely low temperature shocks. In Germany, the negative aggregate output reaction on impact stems from a broad-based contraction in mining, manufacturing (driven by electrics), construction, and services. The medium-term recovery in real GDP instead stems from manufacturing (this time driven by food and motor vehicles) and electricity and gas. In France, the negligible output effects throughout the horizon are a result of broadly compensating impacts of mining, construction and electrics, on the downside, and electricity and gas and services, on the upside. In Italy, the near-term decline and the medium-term recovery of real GDP follow a similar sectoral composition to those in Germany: drops in mining, manufacturing (driven by food and machinery), and construction prevail in the short term, while rises in manufacturing (again food, but also pharmaceuticals and motor vehicles), electricity and gas, and services. In Spain, the insignificant effect on aggregate activity conceals significant gains in output in many sectors, notably construction, electricity and gas, mining, and manufacturing (including pharmaceuticals, motor vehicles, machinery, and food).

Overall, the German and Italian economies appear to react to extreme coldwaves in a similar fashion, reflecting the relevance of input-output production linkages among their sectors. By contrast, France and Spain feature a relatively higher overall resilience to cold extremes, but many French sectors suffer, while many Spanish sectors thrive under extremely low temperatures. Across countries, sector-specific commonalities again emerge, mainly related to electricity and gas, which seems to benefit from extremely low temperature, possibly due to increased demand for heating when cold.[12]

Extremely high precipitation shocks. In Germany, the immediate negative impact on real GDP stems mainly from construction and, to some extent, electrics, partly countervailed by pharmaceuticals, food, machinery, and electricity and gas. The medium-term negligible economic impact hides a prolonged contraction in construction, broadly offset by a persistent increase in

[12]Interestingly, extremely low temperature shocks have negative effects on impact in many sectors and positive effects with a delay across many other sectors in Germany, France and Italy. Yet, impacts do not typically shift signs in a single sector over time, as this occurs only in the Italian food sector.

Figure 9: Impact of extremely high (left panel) and low (right panel) precipitation on the level of real GDP and sectoral activity
(colour based on direction and significance)



Notes: See notes to Figure 8.

pharmaceuticals, with services being only mildly depressed. In France, the short-term reduction in overall activity is brought about by a decline in construction, similarly to Germany, but also food, only partly offset by rises in electricity and gas as well as machinery and electrics. Medium-term dynamics indicate only a persistent increase in electricity and gas, similarly to Germany. In Italy, the negligible effects on real GDP in the short-term mask substantial declines in electricity and gas, mining, electrics, and food, broadly compensated by rises in services, construction, and pharmaceuticals. As the positive effects prevail later in the horizon, real GDP significantly rises in the medium term. In Spain, the output losses throughout the horizon arise are caused by declines in mining, electricity and gas, machinery, partly compensated by gains in services, with short-lived contractions in manufacturing as a whole, electrics, and construction in the near term.

Overall, Germany and France display closely aligned responses to extremely high precipitation shocks, with short-term GDP losses mainly driven by contractions in construction and, to a lesser extent, energy-related activities. Italy and Spain instead show more asymmetric dynamics: in both cases, sizeable short-run disruptions in energy, mining, and selected manufacturing branches coexist with compensating gains in services and other sectors, with Italy in particular experiencing a clear medium-term expansion in aggregate activity. Across countries, construction emerges as a systematically vulnerable sector in the short run (except in Italy), reflecting the high exposure of building activity to heavy precipitation. By contrast, pharmaceuticals often act as stabilising forces, contributing positively or remaining resilient across countries and horizons, thereby cushioning the aggregate effects of extreme precipitation shocks. Interestingly, some sectors display a dichotomy between groups of countries: in Germany and France, extreme rainfalls curb activity in services, possibly due to disruptions in transport, and support production of electricity and gas, likely due to rising demand, while the opposite holds for Italy and Spain.

Extremely low precipitation shocks. In Germany, the near-term negligible effects on real GDP are the result of substantial cross-sectoral heterogeneity, as mining, construction, and services, together with food, benefit from periods of extremely low precipitation, whereas manufacturing, including pharmaceuticals, electrics, and motor vehicles, as well as electricity and gas tend to suffer. In the medium term, however, the positive effects across sectors persist (except for the prolonged decline in pharmaceuticals), thus supporting overall activity. In France, as in the case of Germany, there are also negligible effects on real GDP in the short term, as a result of gains in mining, construction, as well as pharmaceuticals and electrics, and losses in electricity and gas and services. In contrast to Germany, the negative effects take hold of the economy, thus depressing overall activity in the medium term. In Italy, real GDP significantly rises on impact as a result of a broad-based, albeit short-lived, improvement in activity, with the most noticeable gains observed in mining, construction, electricity and gas, and manufacturing (with all subsectors, except motor vehicles). Conversely, in Spain, the adverse effect on aggregate output throughout the horizon is associated with lower output in mining and manufacturing, especially food, as well as lower activity in machinery and electricity and gas in the short term and services in the medium term.

Overall, Germany and France display broadly similar short-term aggregate responses to extreme droughts, with negligible GDP effects reflecting strong cross-sectoral offsetting forces, but their medium-term dynamics diverge, as Germany benefits from persistent gains in construction and mining while France experiences a broad-based deterioration in activity. Italy stands out with a clear positive short-run response, driven by a widespread but temporary expansion across most sectors, whereas Spain shows a consistently adverse aggregate effect, reflecting limited offsetting forces and more pervasive sectoral losses. Across countries, mining and construction tend to benefit from extremely low precipitation, especially in Germany, France, and Italy, suggesting improved operating conditions in these activities. By contrast, electricity and gas and manufacturing subsectors—most notably food processing and, in some cases, pharmaceuticals—exhibit

Figure 10: Summary table

	Extremely high temperature		Extremely low temperature		Extremely high precipitation		Extremely low precipitation	
	Short term	Medium term	Short term	Medium term	Short term	Medium term	Short term	Medium term
DE	mining, manufacuring	mining, electricity, services	mining, manufacturing, construction, services	manufacturing, electricity	construction			mining, construction, services
FR	manufacturing, construction, services	mining, manufacturing, services			mining, construction, services			electricity, services
IT			mining, manufacturing, construction, services	manufacturing, electricity, services		construction, services	mining, manufacturing, electricity, construction	
ES	electricity, services				mining, manufacturing, electricity, construction	mining, electricity	mining, manufacturing, electricity	mining, manufacturing, construction

Notes: The table shows the significant positive (negative) impact on country-specific real GDP in green (red) cells within the 68 percent credibility bands. Short term (medium term) refers to the horizon between 0 and 3 (4 and 12) months ahead.

recurrent vulnerabilities, highlighting the dependence of energy supply and food value chains on water availability. Services generally play a secondary but non-negligible role, acting as a stabiliser in some cases and amplifying medium-term downturns in others.

4.3 Summary of results

Figure 10 summarises the estimated effects of extreme weather events across the main sectors. In the case of extremely high temperature shocks, Germany is the most affected country, with significant negative impacts on key sectors like mining, manufacturing, and services. By contrast, France and Spain see overall positive effects, especially in services. This pattern holds for the full year after such events. Among sectors, the pharmaceutical industry stands out as being negatively affected by extreme heat while benefiting from episodes of extremely high precipitation, a result that is robust across countries and horizons. Turning to extremely low temperature shocks, they are disruptive for output in Germany and Italy, in mining, manufacturing and construction in the short term. However, these adverse effects dissipate over time, and after several months the overall impact becomes neutral or mildly positive, most notably in manufacturing and electricity across countries.

Extremely high precipitation shocks generate negative short-term effects in Germany, France, and Spain, with construction and selected country-specific sectors being particularly affected. By contrast, Italy benefits from positive medium-term impacts, especially in construction and services. Across sectors extreme rainfalls tend to dampen mining, but they boost pharmaceuticals across countries and horizons. Extremely low precipitation shocks severely affect France and Spain, particularly in electricity and other sector-specific areas. However, Germany and Italy show positive outcomes, especially in mining and construction.

Finally, in a nutshell, Germany and Spain appear to be the countries with the most severe consequences from extreme temperature and precipitation events, respectively. By contrast, France and Italy are relatively less sensitive to extreme weather events, with Italy standing to benefit the most from unexpected periods of extreme temperature or precipitation.

Selected comparison with other studies. First, our results relate to the literature exploring the impact on activity across sectors in euro area countries, most notably Colombo and Ferrara (2024). Consistent with their findings, we document economically meaningful and heterogeneous short-term effects, with temperature shocks playing a central role for industrial activity and precipitation shocks disproportionately affecting construction and mining. However, our results reveal sharper cross-country asymmetries once extreme events are defined relative to the full historical distribution rather than month-specific thresholds. In particular, we find that extremely high temperature shocks induce a persistent contraction in real GDP in Germany—driven by manufacturing, mining, and services—while France and Spain exhibit neutral or positive aggregate responses, reflecting potentially gains in services and selected manufacturing subsectors. These differences are less pronounced in Colombo and Ferrara (2024), where seasonal conditioning dampens cross-country contrasts and complicates the economic interpretation of temperature extremes.

Second, our results relate to studies focussing on the effects on inflation from weather events and their overall demand or supply effects on the overall economy. Consistent with a large body of the literature (Natoli, 2023, Ciccarelli and Marotta, 2024, Ciccarelli et al., 2024, Colombo and Ferrara, 2024),[13] our results show that the aggregate responses of output and prices tend to move in the same direction, suggesting a predominantly demand-side nature of extreme weather event shocks when effects are statistically significant. However, in line with the literature, they also signal supply (or purely inflationary) effects of extreme weather event shocks in some sectors and countries. Indeed, Natoli (2023) observes that demand-side effects dominate

[13] Cevik and Gwon (2024) also focus on the impact of weather events on inflation, but their focus is the concomitant impact on supply chain disruptions, rather than activity. Hence, their study cannot capture the demand/supply nature of weather events.

in his baseline estimates of the effects of a temperature shock in the United States. Moreover, in a panel of advanced economies, Ciccarelli and Marotta (2024) conclude that physical risks (of a similar nature to the shocks in our paper) primarily operate as demand-type shocks, in contrast to environmental policies and green innovation (beyond the scope of our paper), which tend to generate adverse supply shocks. Looking at the four largest euro area economies, Ciccarelli et al. (2024) find that high temperature shocks in the summer, somewhat comparable to the extremely high temperature shocks, induce inflationary pressures, with the effects being particularly pronounced for the food component of HICP inflation. However, when looking at the effects on the broader economy, they show that supply-side effects appear to be limited to France, where also the producer price index (PPI) spikes on impact (although it then significantly declines) and the industrial production index (IPI) contracts (differently from our results, possibly due to the inclusion of construction and services in our measure of overall activity). By contrast, most HICP components, the PPI, and the IPI significantly decline in Germany (similarly to our results for real GDP and HICP), while they tend to increase in Spain (in stark contrast to our results for HICP, possibly due to the extreme nature of our shock). Their results thus mostly signal asymmetric demand-side effects across countries, especially in the months following the shock. Finally, in a similar set-up to ours, Colombo and Ferrara (2024) track the reaction of sectoral production and producer price indices. They find that, when the effects are significant, cold, heat, precipitation, and drought shocks tend to affect output and prices in the same direction, except for drought shocks in the energy sector, which induce supply-side effects.

5 Robustness checks

5.1 Extreme weather events as exogenous variables

As a first robustness check, we follow Ciccarelli et al. (2024) and consider extreme weather events as exogenous variables. Formally, we estimate the SBVAR model below:

$$\tilde{Y}_t = \tilde{C} + \sum_{p=1}^{P} \tilde{A}_p \tilde{Y}_{t-p} + \sum_{p=0}^{P} B_p W_{t-p} + \tilde{\varepsilon}_t \tag{4}$$

where $\tilde{Y}_t$ is a vector of endogenous variables in month t, W_t is a vector of exogenous variables in month t, $\tilde{A}_p$ and B_p are matrices of slope coefficients on lag p of the endogenous and exogenous variables, respectively, and $\tilde{C}$ is a vector of intercepts. The endogenous variables $\tilde{Y}_t$ in Equation

(4) include the same variables as Y_t in Equation (3), except the extreme weather event indicator, which is instead contained in W_t. The rest of the estimation proceeds as in the case of our baseline specification.

Figures D.1 and D.2 show the impact on real GDP and HICP inflation of shocks from extreme temperature and precipitation events, respectively, identified as exogenous variables in the SBVAR model. As shown in the figures, the results are quantitatively and qualitatively robust to this alternative identification strategy, including the demand-supply nature of extreme weather event shocks. The main differences relate to the significance of the IRFs, where this alternative identification strategy implies less significant responses. This observation justifies the choice of using the Cholesky identification strategy in our baseline specification, as the inclusion of extreme weather events as endogenous variables appears to remove some noise and improve the precision of our estimates.

5.2 Alternative thresholds for extreme weather events

As a second robustness check, we test for different thresholds for extreme weather events, using either less or more extreme weather events, that is, using the 10th or the 1st percentile in each tails of the country-specific historical distribution of temperature and precipitation. Figures D.3 and D.4 show the impact on real GDP and HICP inflation of shocks from extreme temperature and precipitation events, respectively, with the 10th and the 90th percentile as relevant thresholds to define extreme weather events. Figures D.5 and D.6 show the same results with the 1st and the 99th percentile as relevant thresholds to define extreme weather events. The results remain overall robust although often with less significance associated to the impacts relative to the baseline specification. This observation justifies the choice of using 5th and 95th percentile of the country-specific historical distributions in our baseline exercises.

6 Conclusions

This paper documents that extreme weather event shocks have statistically and economically significant effects on activity in the four largest euro area economies over the first year following the weather shock. These effects are highly heterogeneous across countries and sectors.

Focussing on the considered countries, the analysis points to some general results. Germany appears to be the most sensitive country to extreme temperature, as heatwaves induce a prolonged contraction in activity, whereas coldwaves bring about immediate output losses but also gains at longer horizons. In Spain, economic activity is instead found to suffer extreme precipitation, with broad-based declines throughout the first year after both extreme rainfalls and extreme dry spells. By contrast, France and Italy are relatively less sensitive to extreme weather events, with Italy standing to benefit the most from extreme temperature or precipitation.

Focussing on specific sectors, some regularities also emerge. Pharmaceuticals appear to suffer under extreme heat (and, in Germany, also under prolonged dry spells) throughout the horizon, possibly related to the sector's dependence on transports via rivers and hence their water level. By contrast, electricity and gas benefit from a boost in demand due to extreme coldwaves and, only in the near term due to extreme heatwaves, while supply disruptions or efficiency losses under extremely high temperatures curb activity at longer horizons. Moreover, mining and construction appear to be particularly vulnerable to extreme rainfalls, whereas they tend to be favoured by extreme droughts, reflecting the high exposure of their operations to precipitation extremes.

The pronounced heterogeneity of these responses across countries and sectors points to the importance of targeted policy interventions that address not only aggregate macroeconomic risks but also country- and sector-specific vulnerabilities to weather extremes. Looking ahead, the empirical framework developed in this paper can be used to inform short-term forecasts of real GDP for the largest euro area economies and the euro area as a whole. Moreover, the findings can inform the design of alternative scenarios and counterfactual analyses focusing on the macroeconomic implications of alternative combinations of extreme weather events grounded in historical experience.

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Appendix A Climate data

This appendix provides a detailed description of the climate data used in the analysis, as well as the construction of the extreme weather indicators.

A.1 Climate data

Climate data are obtained from the *Weighted Climate Dataset* developed by Gortan et al. (2024), which builds on gridded meteorological information from several sources, most notably the fifth-generation ECMWF atmospheric reanalysis (ERA5). ERA5 combines physical climate models with historical observations to ensure temporal consistency and spatial completeness, providing monthly data at a spatial resolution of $0.25° \times 0.25°$.

From this dataset, we extract monthly observations for two primary climate variables: (i) average surface temperature, measured in degrees Celsius, and (ii) total precipitation, measured in millimetres. Country-level series are constructed as population-weighted averages of the underlying grid-cell observations, using population weights based on 2015 data. This weighting scheme ensures that weather conditions are representative of the areas where economic activity and population are concentrated. [14]

The climate sample spans the period from January 1940 to December 2023. While the empirical analysis focuses on the period January 1999 to December 2023, the full historical distribution is used to define extreme weather thresholds.

A.2 Definition of extreme weather events

Extreme weather events are identified using a threshold-based approach. For each country and each climate variable, we compute the empirical distribution of daily observations over the full historical sample (1940–2023). Based on this distribution, extreme events are defined using fixed percentile thresholds.

Specifically, four types of extreme weather events are considered:

- *Extremely high temperature*: number of days within a month with temperature above the 95th percentile;

[14] We use population-weighted temperature and precipitation to measure climate exposure because GDP responds to conditions experienced by firms and production rather than land area.

- *Extremely low temperature*: number of days within a month with temperature below the 5th percentile;
- *Extremely high precipitation*: number of days within a month with precipitation above the 95th percentile;
- *Extremely low precipitation*: number of days within a month with precipitation below the 5th percentile.

The resulting indicators measure the number of extreme days per month, capturing both the occurrence and the duration of extreme weather events. Using fixed thresholds based on the full historical distribution ensures that extreme events are rare, comparable over time, and naturally concentrated in the seasons in which they are economically meaningful (e.g. heatwaves in summer and coldwaves in winter).

As robustness checks, alternative thresholds based on the 10th and 90th percentiles as well as 1st and 99th percentiles are also considered. The main results are robust to these alternative definitions.

A.3 Economic data

Economic data are obtained from Eurostat and cover the four largest euro area economies—Germany, France, Italy, and Spain—over the period January 1999 to December 2023.

Sectoral activity is measured using working-day and seasonally adjusted monthly production indices for the sectors listed below, alongside total market services. Although all manufacturing sub-sectors in Table A.1 are included in the estimation, the main text focuses on those with the largest contribution to aggregate manufacturing output.

Monthly real GDP is not directly available and is therefore constructed in two steps. First, monthly market services output is estimated by interpolating quarterly real gross value added in services using monthly retail sales volumes as an indicator. Second, quarterly real GDP is interpolated to monthly frequency using the Chow and Lin (1971) procedure, with monthly industrial production (excluding construction), construction production, and the estimated services output as indicators. This approach yields a broad monthly measure of aggregate economic activity while avoiding the inclusion of climate-related variables in the interpolation step.

All real activity variables are expressed in logarithms. Inflation is measured using the harmonised index of consumer prices.

Table A.1: Sector classification

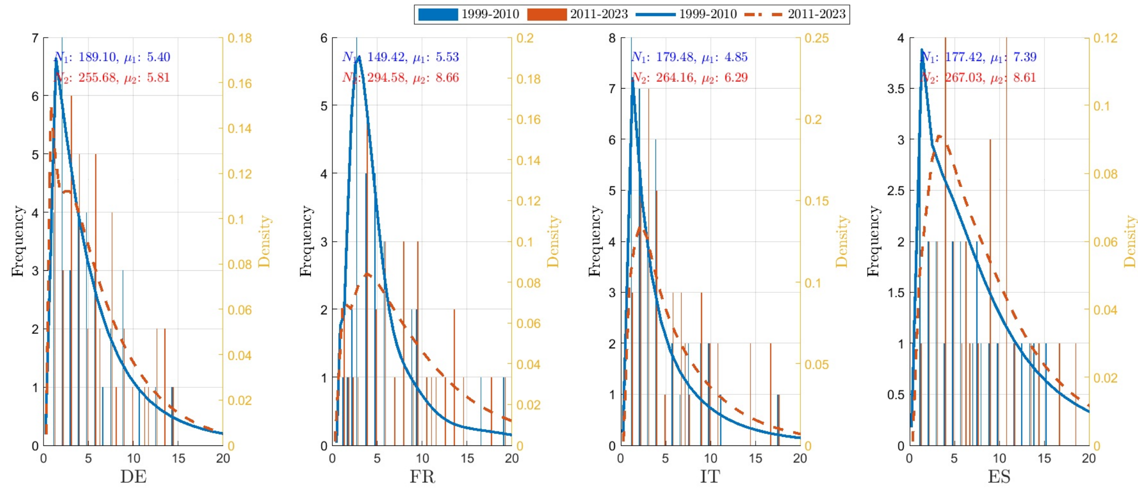
Sector code	Aggregate sector
2B00	Mining and quarrying
2C00	Manufacturing (total)
2C10	Manufacture of food products, beverages and tobacco
2C21	Manufacture of basic pharmaceutical products
2C27	Manufacture of electrical equipment
2C28	Manufacture of machinery and equipment n.e.c.
2C29	Manufacture of motor vehicles, trailers and semi-trailers
2D00	Electricity, gas, steam and air conditioning supply
2F00	Construction
2H00-2N00	Market services

Notes: Sections from NACE Rev.2.

Appendix B Conditional distributions

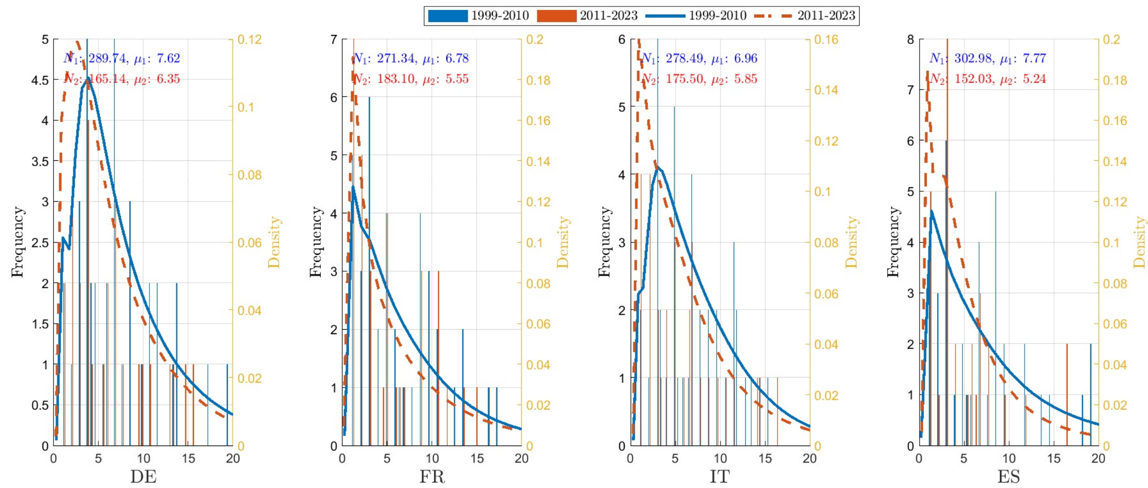
The following figures show the conditional distribution of the extreme weather events, excluding months in which weather conditions were not in the 5th or 95th percentiles of the distribution. A comparison between the periods 1999–2010 and 2011–2023 reveals a pronounced rightward shift in the distribution of extremely high temperatures across countries, indicating a rising incidence of extreme heat. Conversely, the distribution of extremely low temperatures has shifted inward, with fewer days recorded in the lower tail of the temperature distribution, consistent with a decline in extreme cold events. The number of days with extremely high and low precipitation has also increased across countries over time, signaling a higher frequency of extreme weather events. The distribution of days with high precipitation has barely changed in any of the countries between these periods, while more days of extremely low precipitation is mostly visible in Italy and Spain and to some extent in Germany.

Figure B.1: Conditional distribution of extremely high temperature (number of months, excluding months with no extreme weather events)



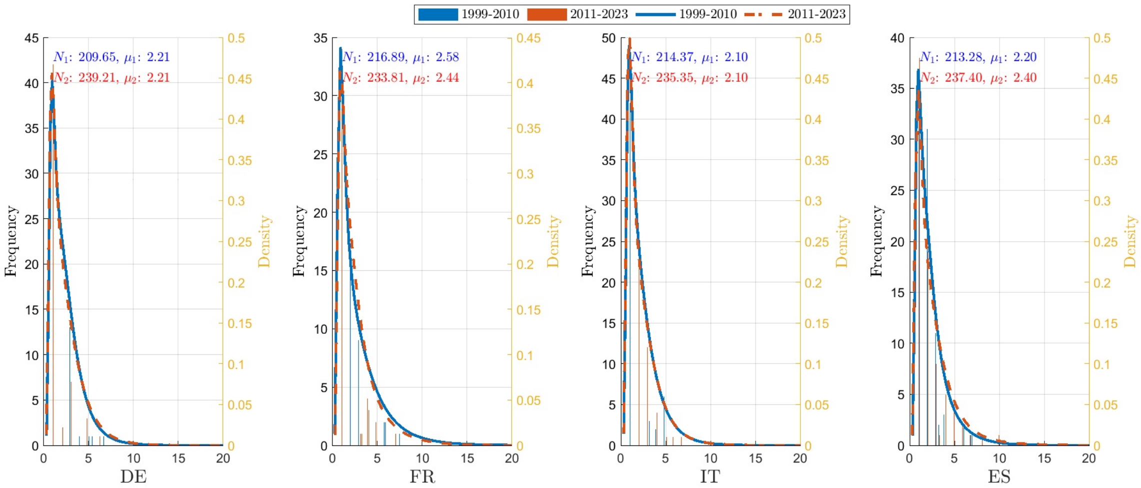
Notes: The charts show the conditional distribution of the extremely high temperatures in the respective largest euro area countries, broken down into two periods, i.e. 1999-2010 and 2011-2023.

Figure B.2: Conditional distribution of extremely low temperature (number of months, excluding months with no extreme weather events)



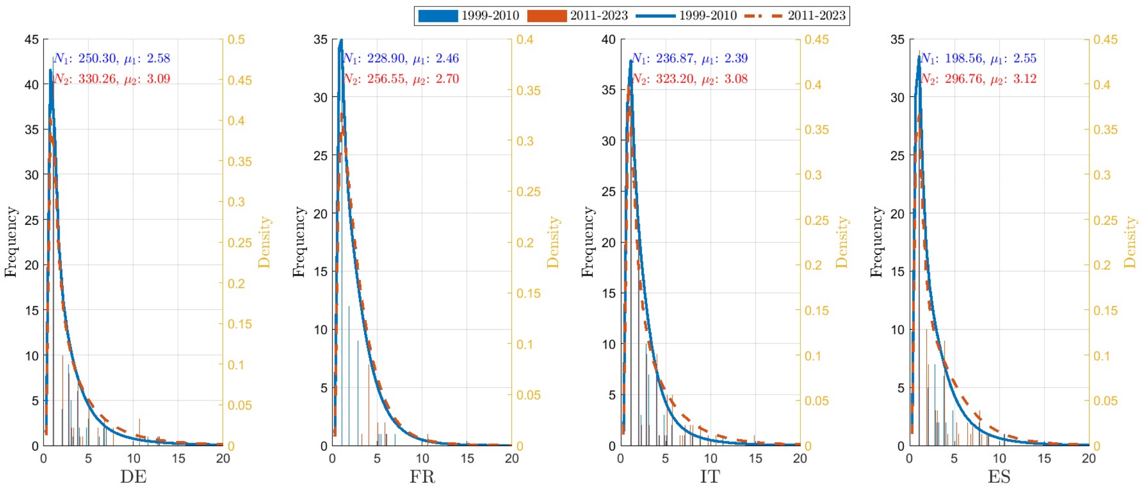
Notes: The charts show the conditional distribution of the extremely low temperatures in the respective largest euro area countries, broken down into two periods, i.e. 1999-2010 and 2011-2023.

Figure B.3: Conditional distribution of extremely high precipitation (number of months, excluding months with no extreme weather events)



Notes: The charts show the conditional distribution of the extremely high precipitation in the respective largest euro area countries, broken down into two periods, i.e. 1999-2010 and 2011-2023.

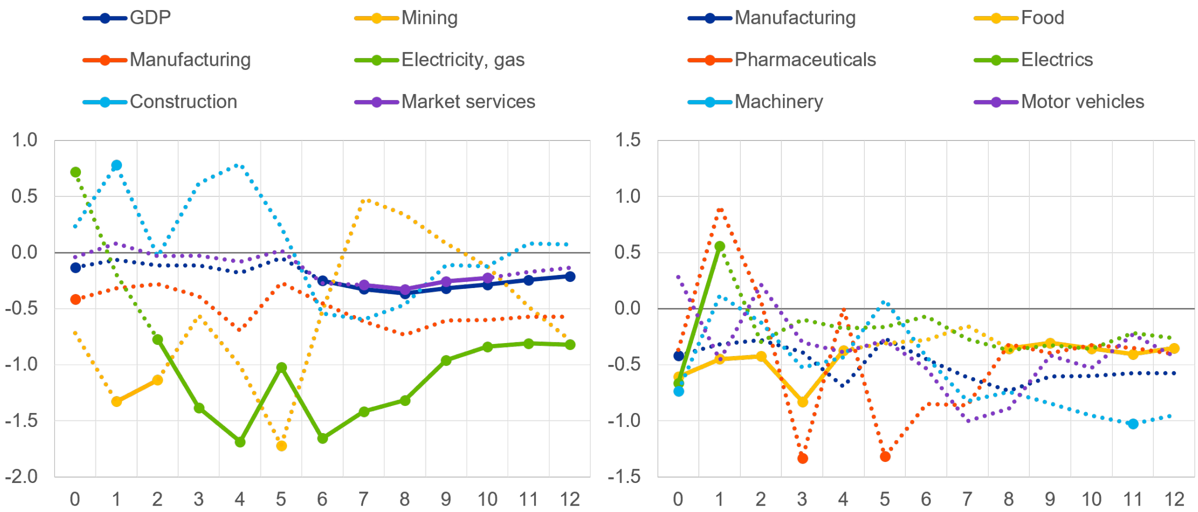
Figure B.4: Conditional distribution of extremely low precipitation (number of months, excluding months with no extreme weather events)



Notes: The charts show the conditional distribution of the extremely low precipitation in the respective largest euro area countries, broken down into two periods, i.e. 1999-2010 and 2011-2023.

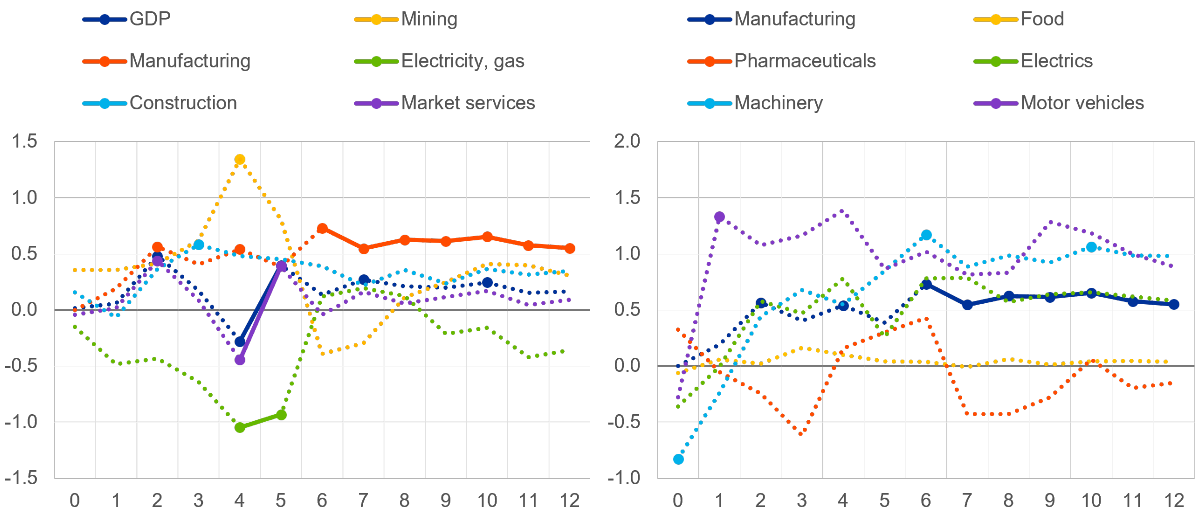
Appendix C Impulse response functions of sectoral output to the extreme weather event shocks

Figure C.1: Impact of extremely high temperature on real GDP and sectoral activity in Germany (x-axis: months; y-axis: percentage deviation from baseline level)



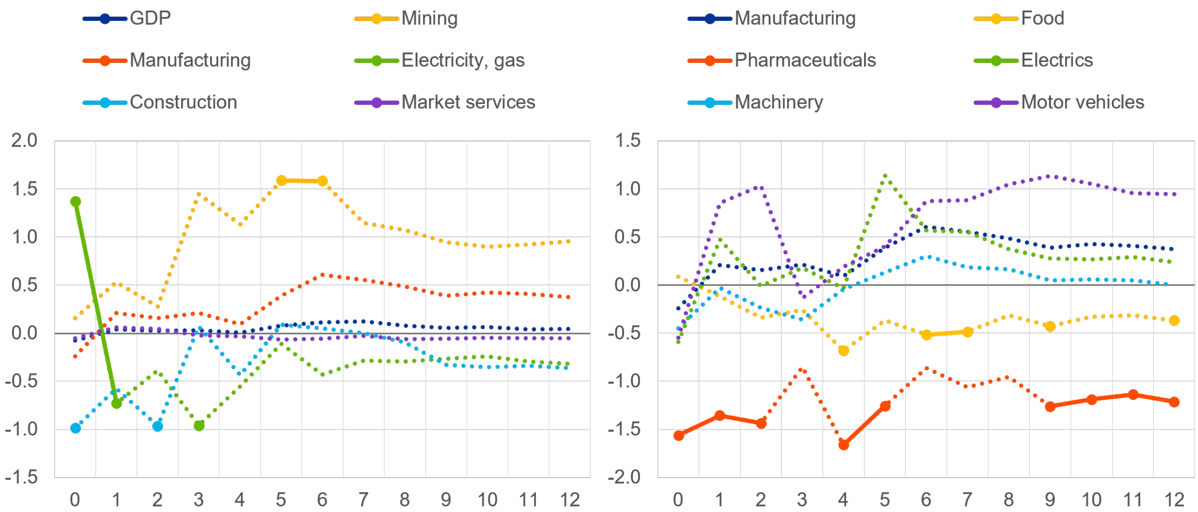
Notes: See notes to Figure 6.

Figure C.2: Impact of extremely high temperature on real GDP and sectoral activity in France (x-axis: months; y-axis: percentage deviation from baseline level)



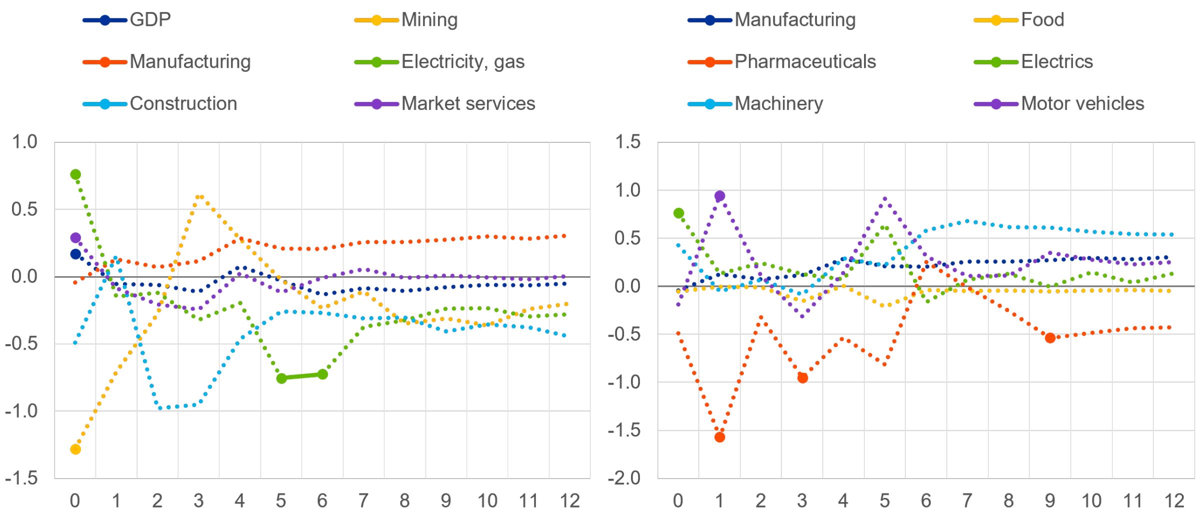
Notes: See notes to Figure 6.

Figure C.3: Impact of extremely high temperature on real GDP and sectoral activity in Italy (x-axis: months; y-axis: percentage deviation from baseline level)



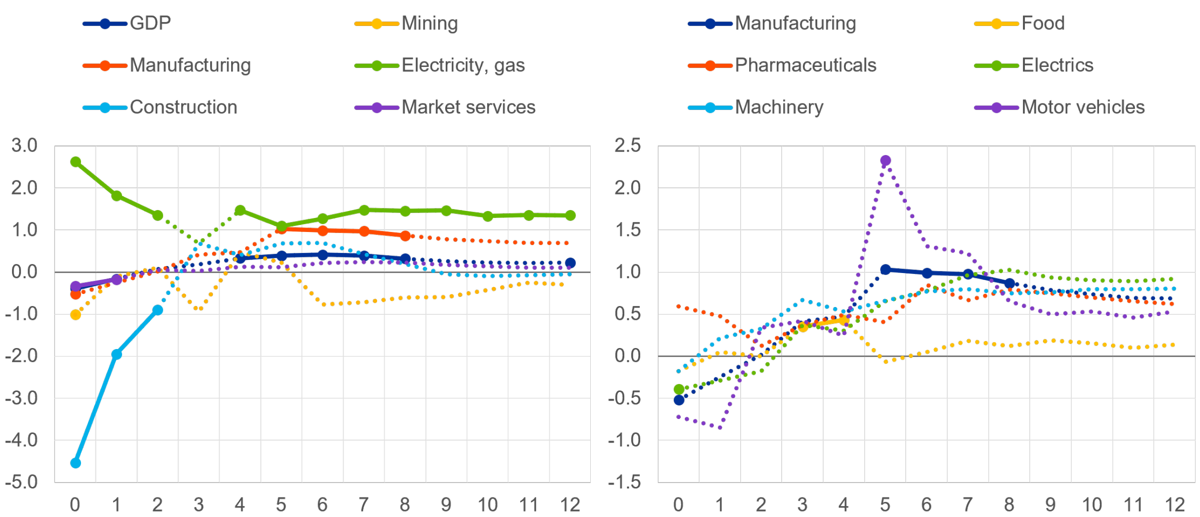
Notes: See notes to Figure 6.

Figure C.4: Impact of extremely high temperature on real GDP and sectoral activity in Spain (x-axis: months; y-axis: percentage deviation from baseline level)



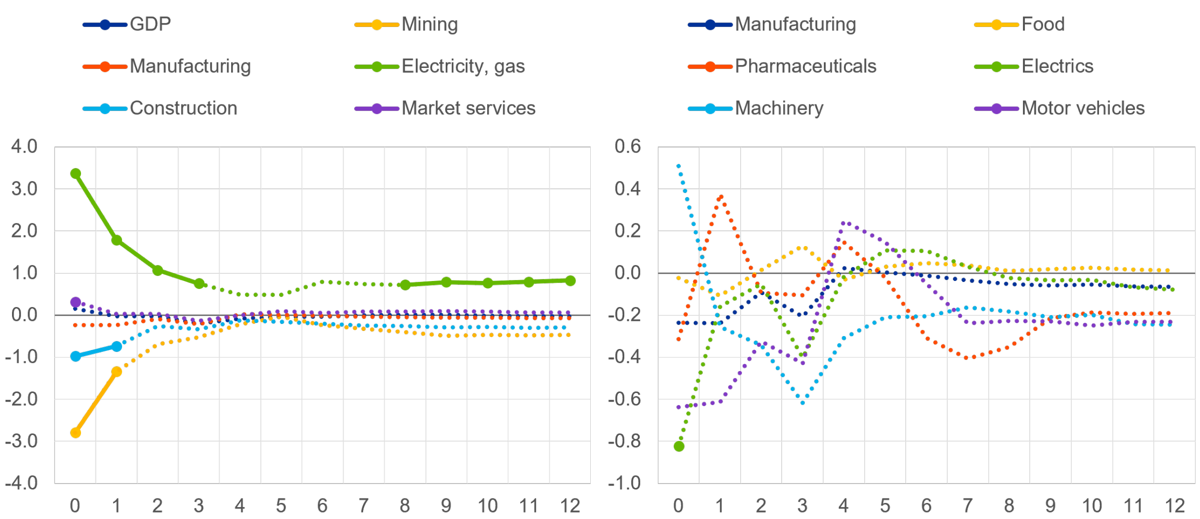
Notes: See notes to Figure 6.

Figure C.5: Impact of extremely low temperature on real GDP and sectoral activity in Germany (x-axis: months; y-axis: percentage deviation from baseline level)



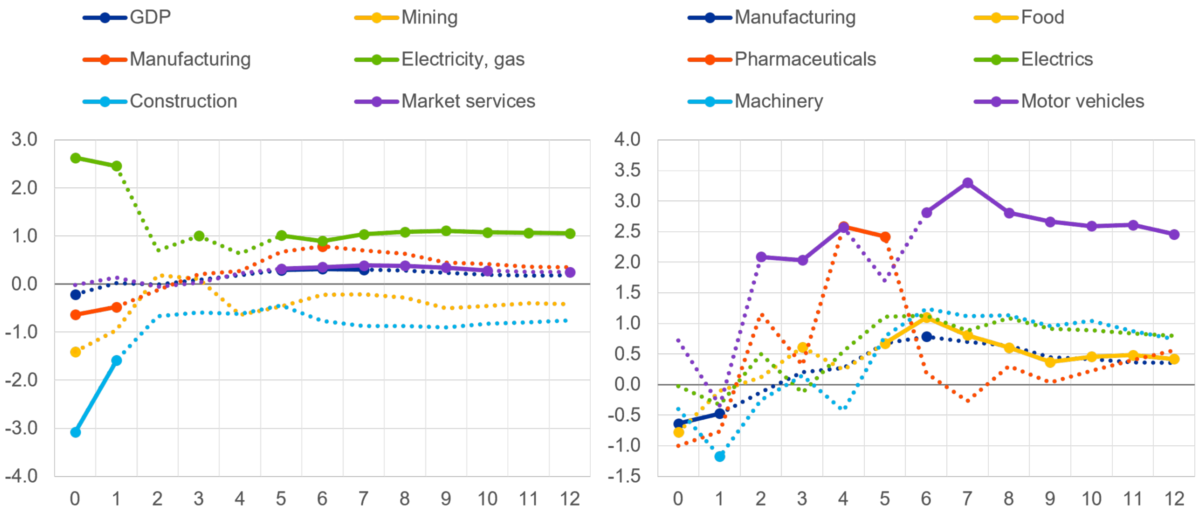
Notes: See notes to Figure 6.

Figure C.6: Impact of extremely low temperature on real GDP and sectoral activity in France (x-axis: months; y-axis: percentage deviation from baseline level)



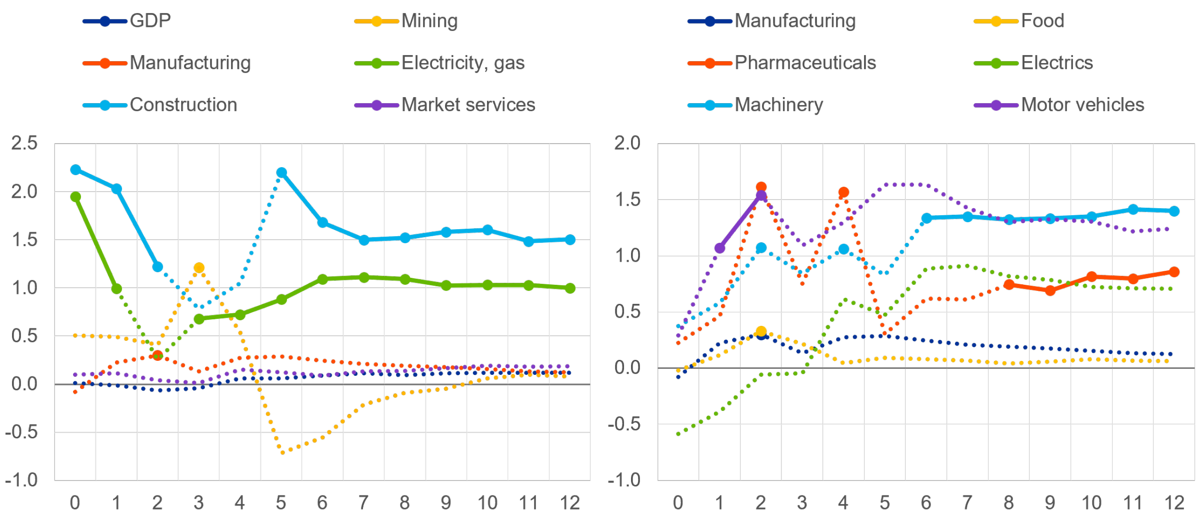
Notes: See notes to Figure 6.

Figure C.7: Impact of extremely low temperature on real GDP and sectoral activity in Italy (x-axis: months; y-axis: percentage deviation from baseline level)



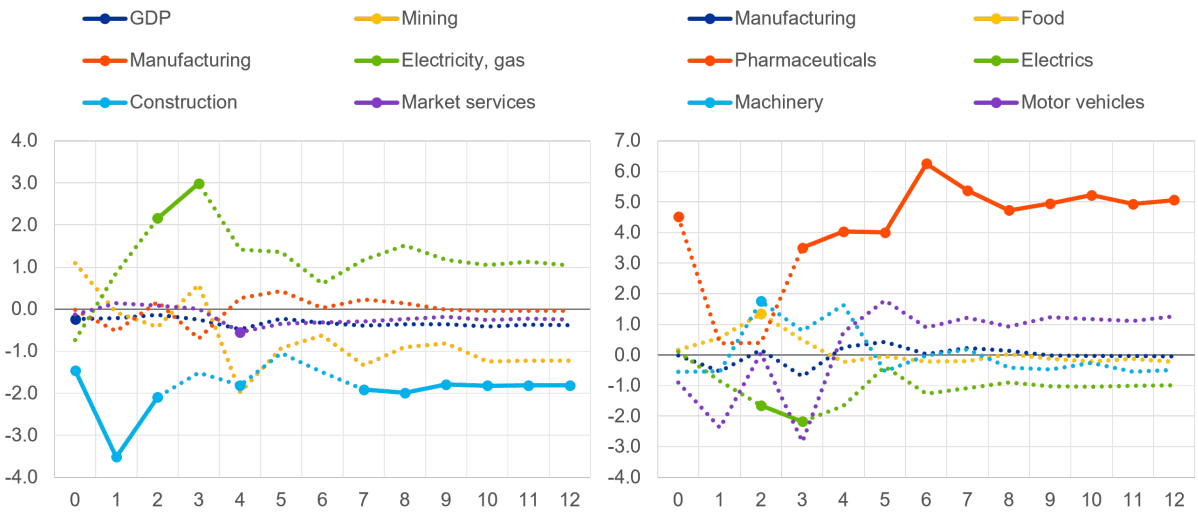
Notes: See notes to Figure 6.

Figure C.8: Impact of extremely low temperature on real GDP and sectoral activity in Spain (x-axis: months; y-axis: percentage deviation from baseline level)



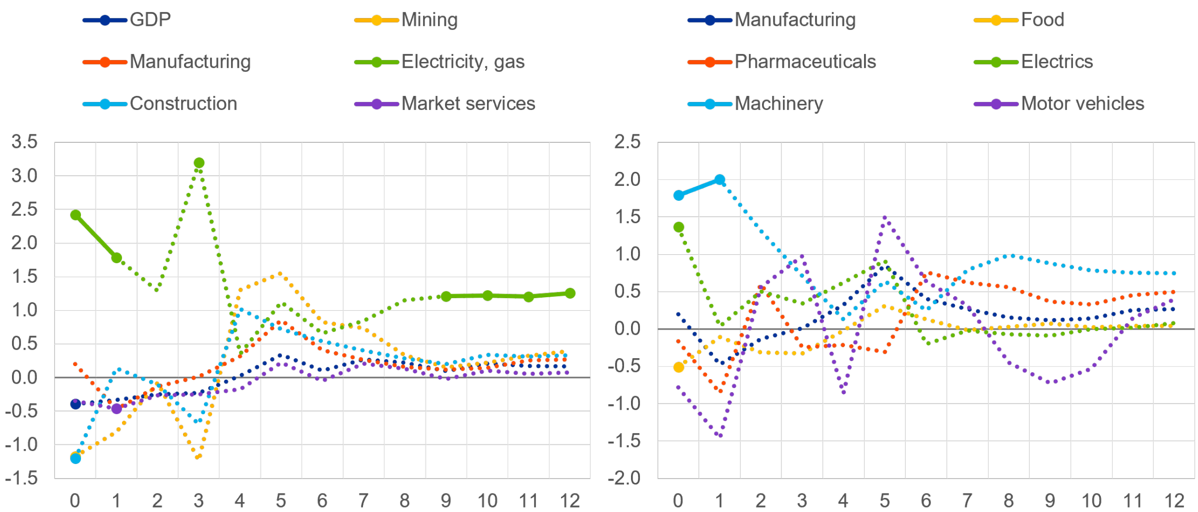
Notes: See notes to Figure 6.

Figure C.9: Impact of extremely high precipitation on real GDP and sectoral activity in Germany (x-axis: months; y-axis: percentage deviation from baseline level)



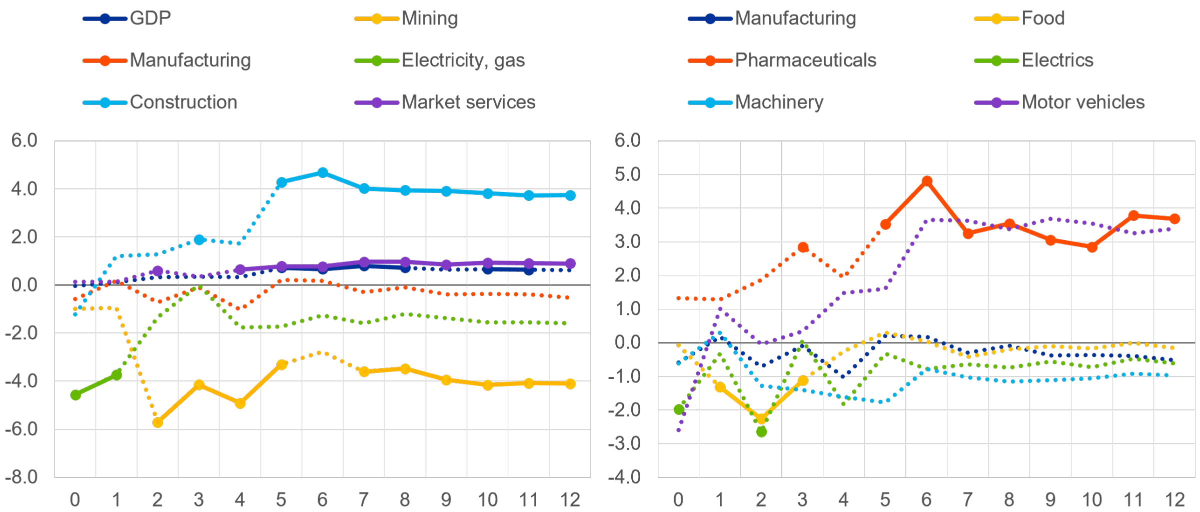
Notes: See notes to Figure 6.

Figure C.10: Impact of extremely high precipitation on real GDP and sectoral activity in France (x-axis: months; y-axis: percentage deviation from baseline level)



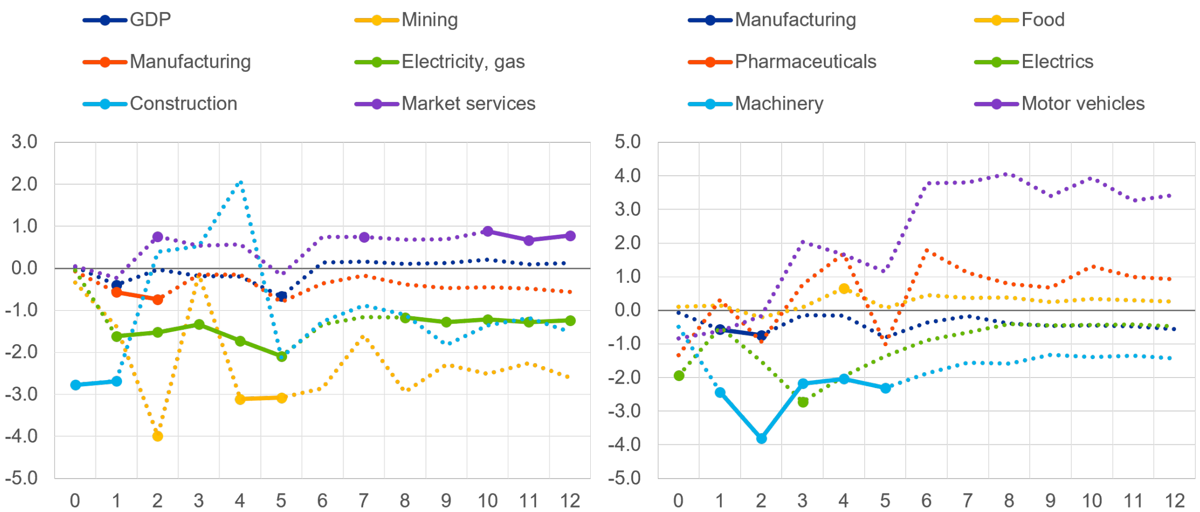
Notes: See notes to Figure 6.

Figure C.11: Impact of extremely high precipitation on real GDP and sectoral activity in Italy (x-axis: months; y-axis: percentage deviation from baseline level)



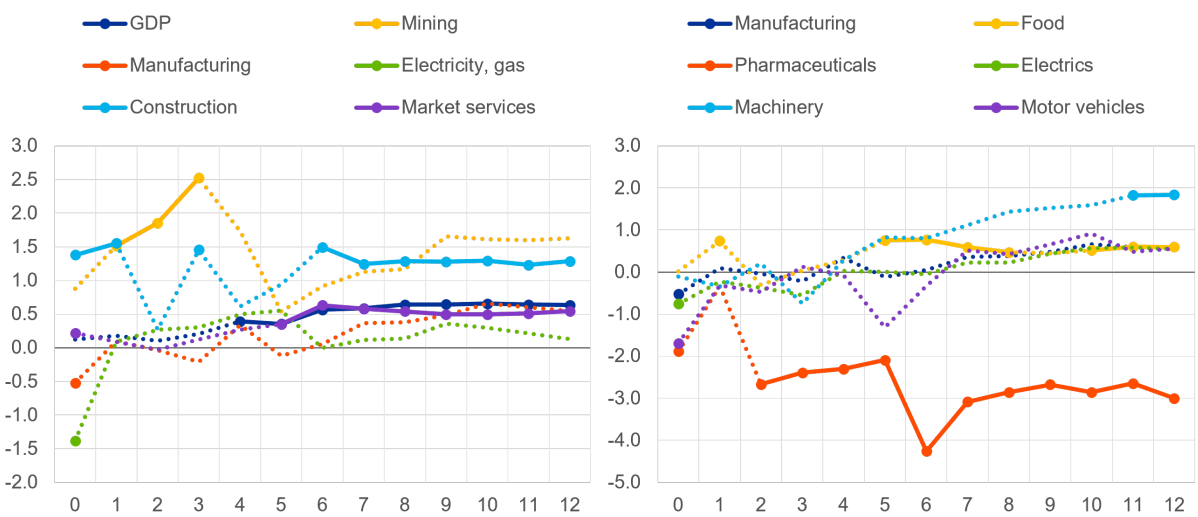
Notes: See notes to Figure 6.

Figure C.12: Impact of extremely high precipitation on real GDP and sectoral activity in Spain (x-axis: months; y-axis: percentage deviation from baseline level)



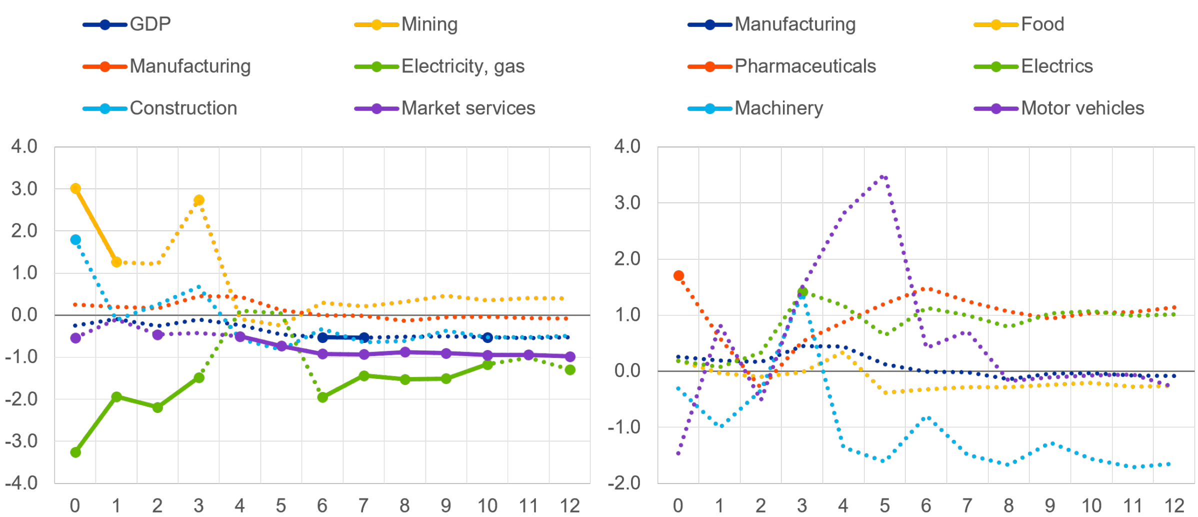
Notes: See notes to Figure 6.

Figure C.13: Impact of extremely low precipitation on real GDP and sectoral activity in Germany (x-axis: months; y-axis: percentage deviation from baseline level)



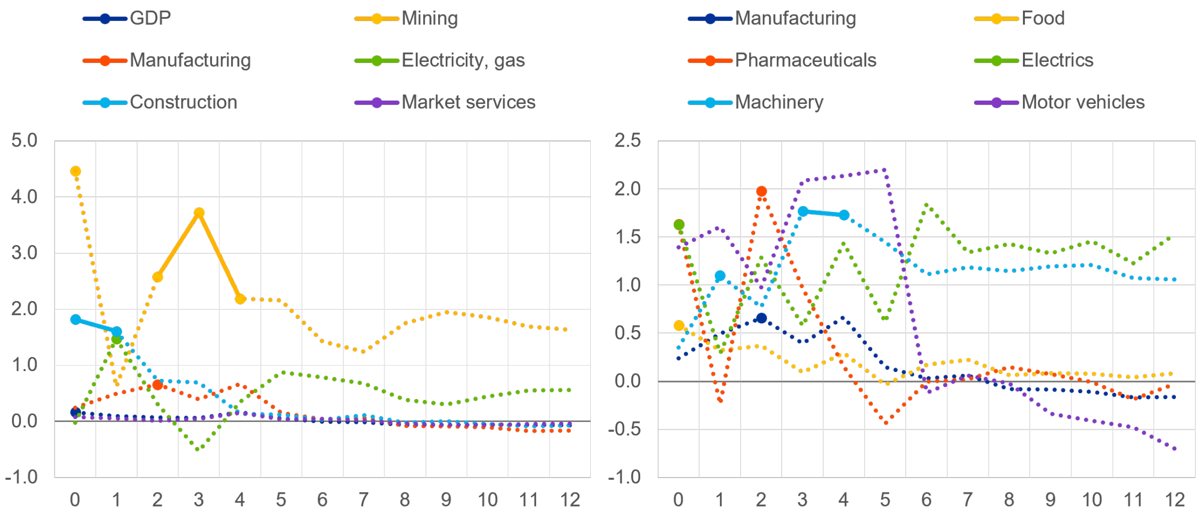
Notes: See notes to Figure 6.

Figure C.14: Impact of extremely low precipitation on real GDP and sectoral activity in France (x-axis: months; y-axis: percentage deviation from baseline level)



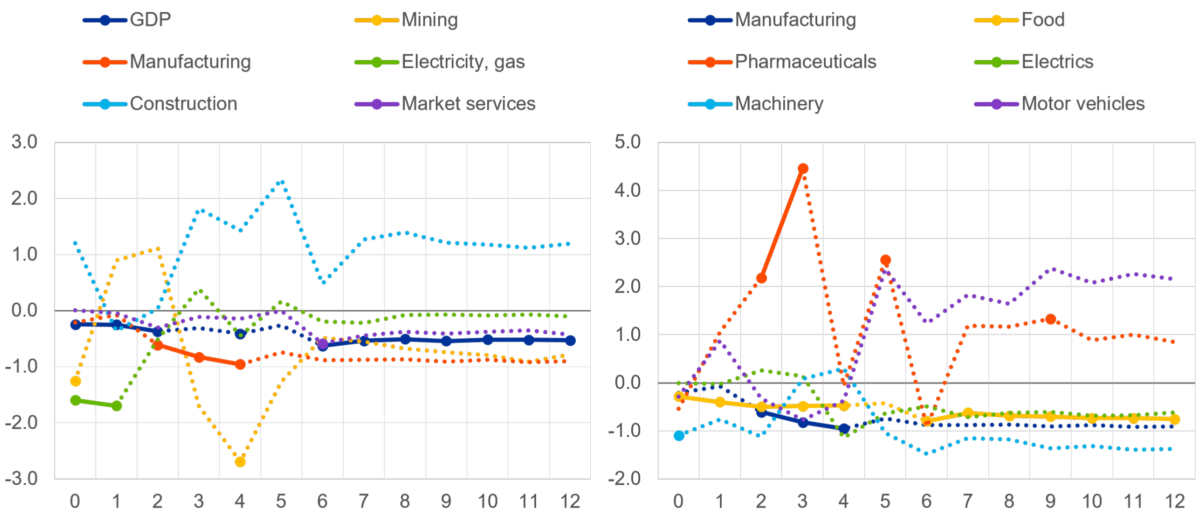
Notes: See notes to Figure 6.

Figure C.15: Impact of extremely low precipitation on real GDP and sectoral activity in Italy (x-axis: months; y-axis: percentage deviation from baseline level)



Notes: See notes to Figure 6.

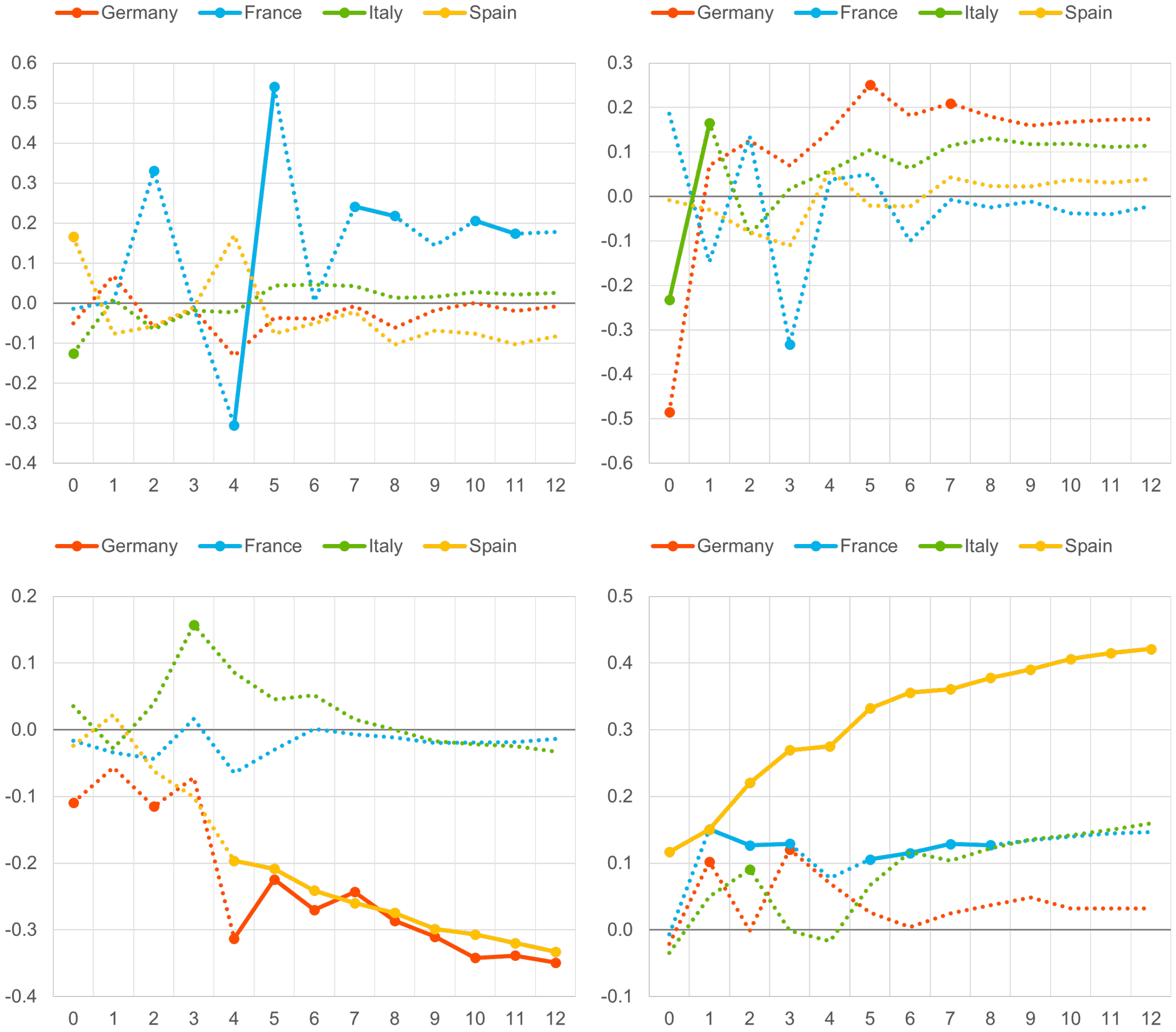
Figure C.16: Impact of extremely low precipitation on real GDP and sectoral activity in Spain (x-axis: months; y-axis: percentage deviation from baseline level)



Notes: See notes to Figure 6.

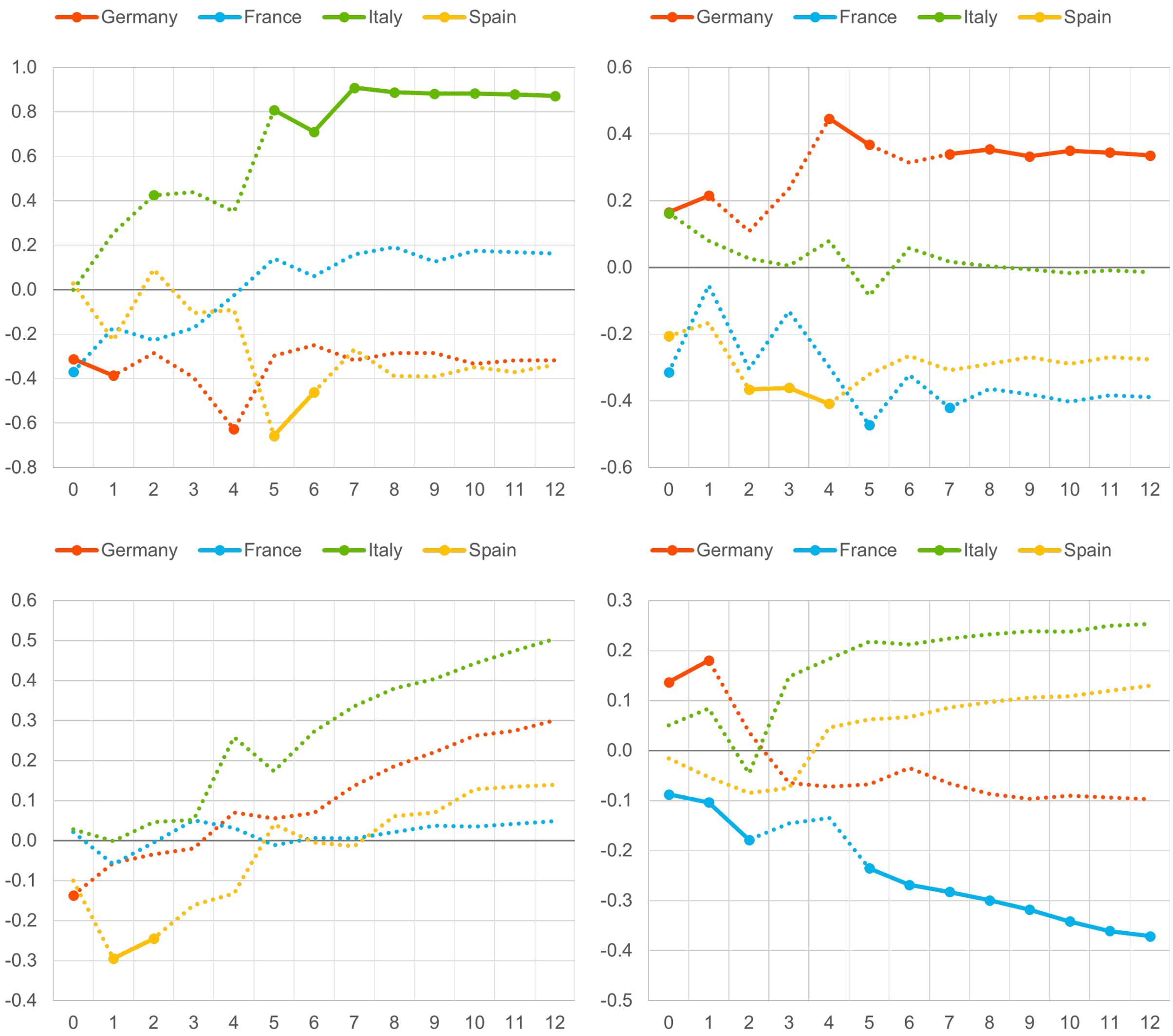
Appendix D Impulse response functions in robustness exercises

Figure D.1: Impact of extremely high (left panels) and low (right panels) temperature on the level of real GDP (upper panels) and HICP (lower panels) with exogenous extreme weather events
(x-axis: months; y-axis: percentage deviation from baseline level)



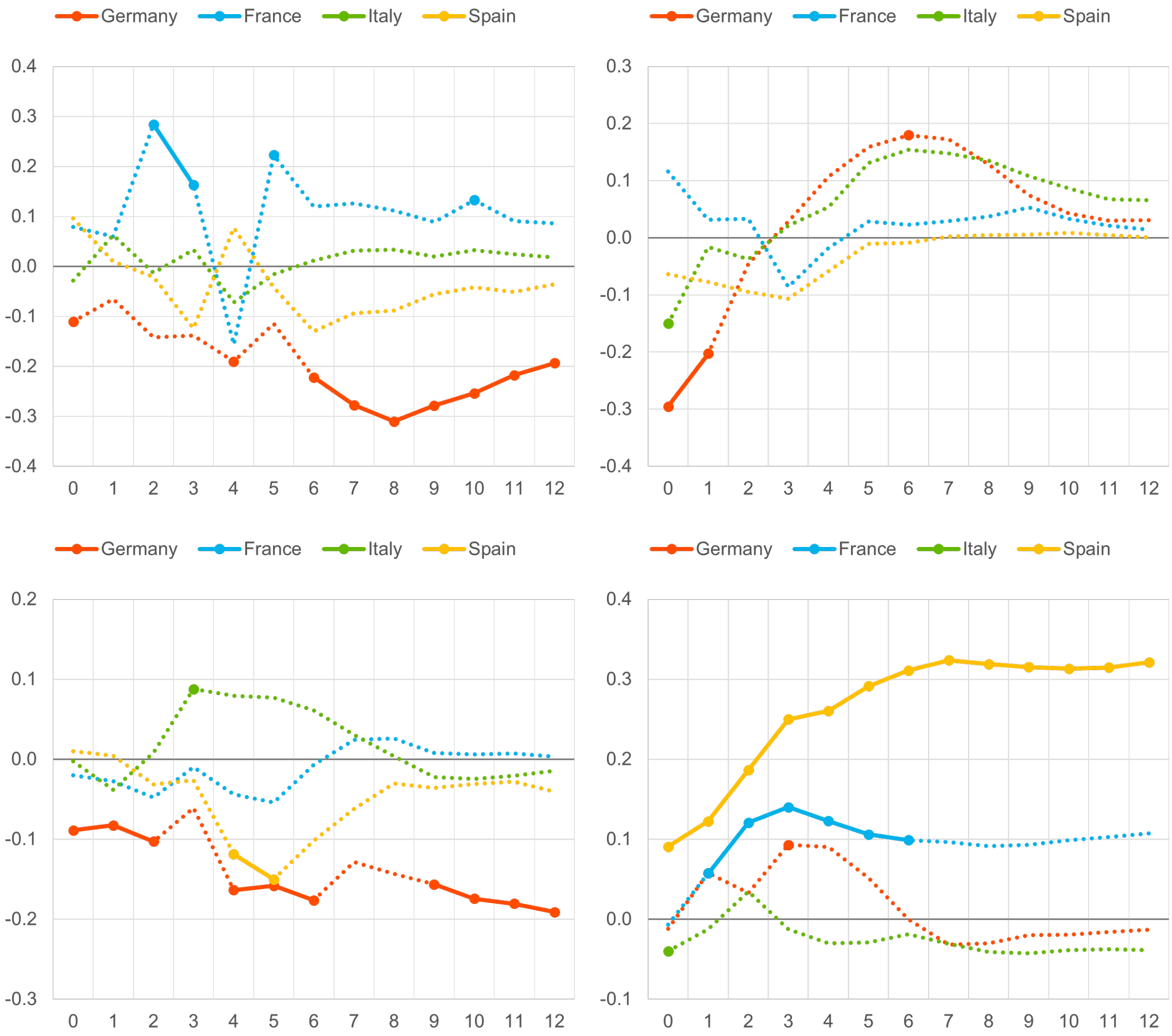
Notes: See notes to Figure 6.

Figure D.2: Impact of extremely high (left panels) and low (right panels) precipitation on the level of real GDP (upper panels) and HICP (lower panels) with exogenous extreme weather events
(x-axis: months; y-axis: percentage deviation from baseline level)



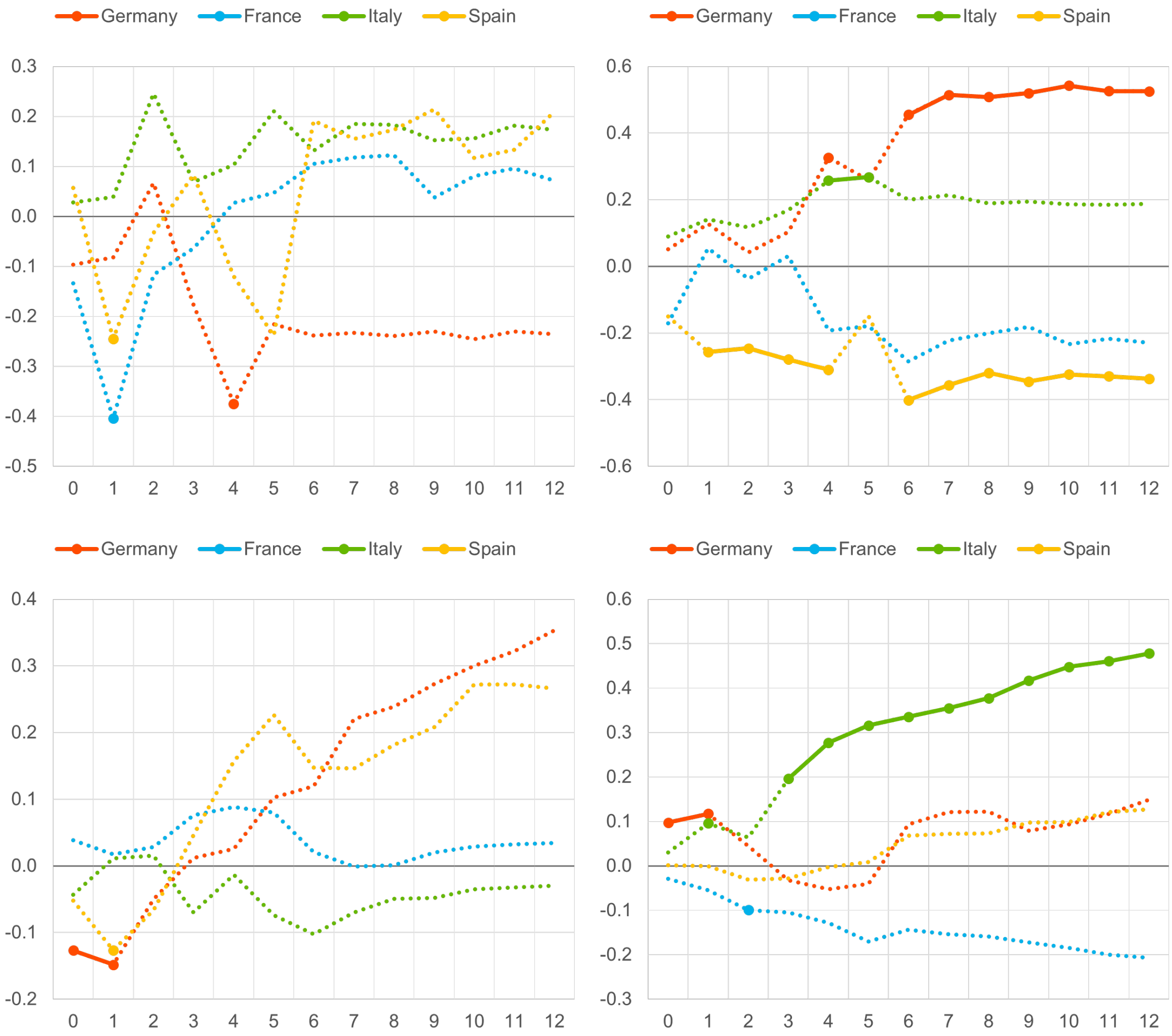
Notes: See notes to Figure 6.

Figure D.3: Impact of extremely high (left panels) and low (right panels) temperature on the level of real GDP (upper panels) and HICP (lower panels) with less extreme weather events (x-axis: months; y-axis: percentage deviation from baseline level)



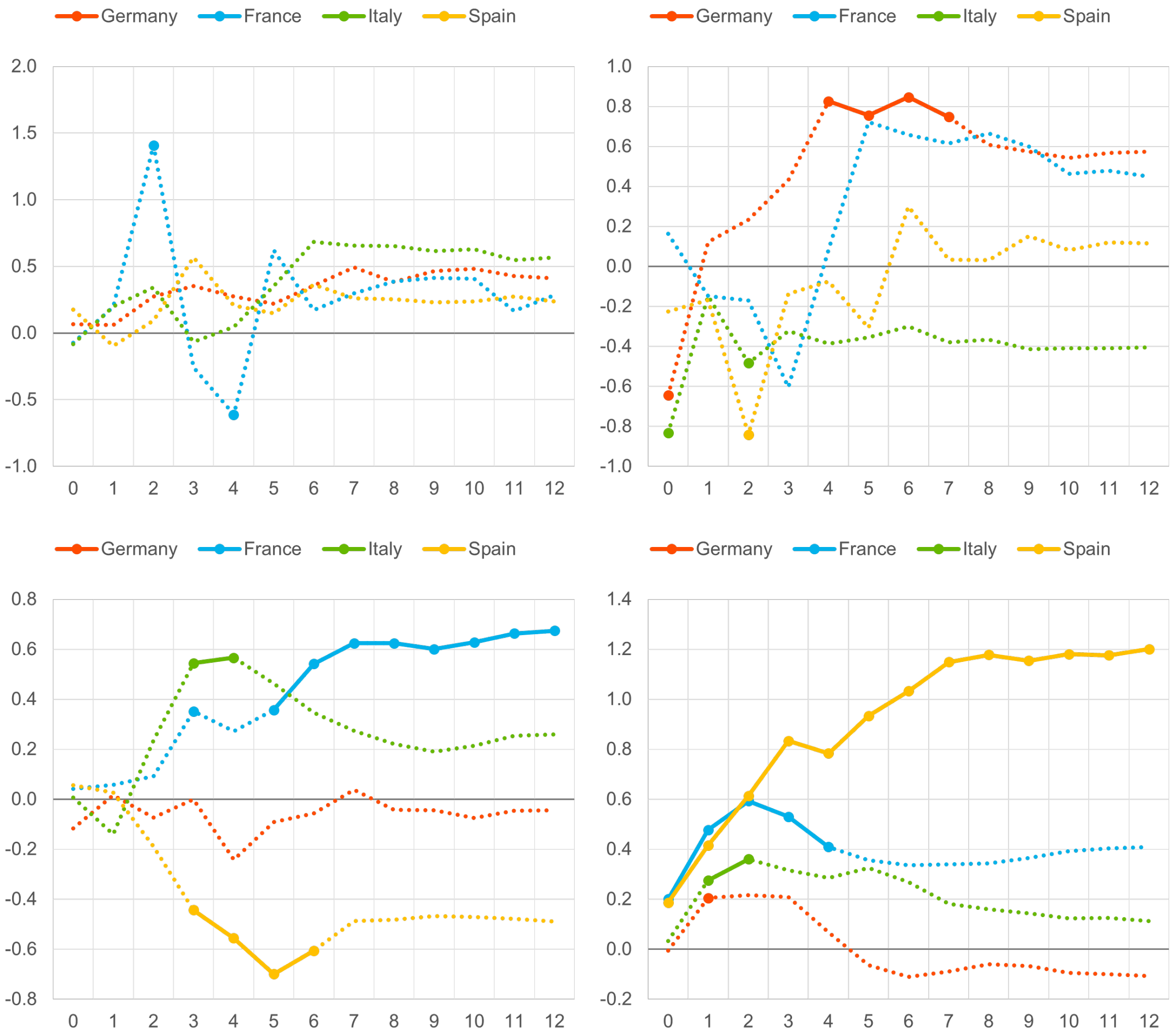
Notes: See notes to Figure 6, except for the thresholds used to define extreme weather events (below the 10th and above the 90th percentile of the country-specific historical distribution).

Figure D.4: Impact of extremely high (left panels) and low (right panels) precipitation on the level of real GDP (upper panels) and HICP (lower panels) with less extreme weather events (x-axis: months; y-axis: percentage deviation from baseline level)



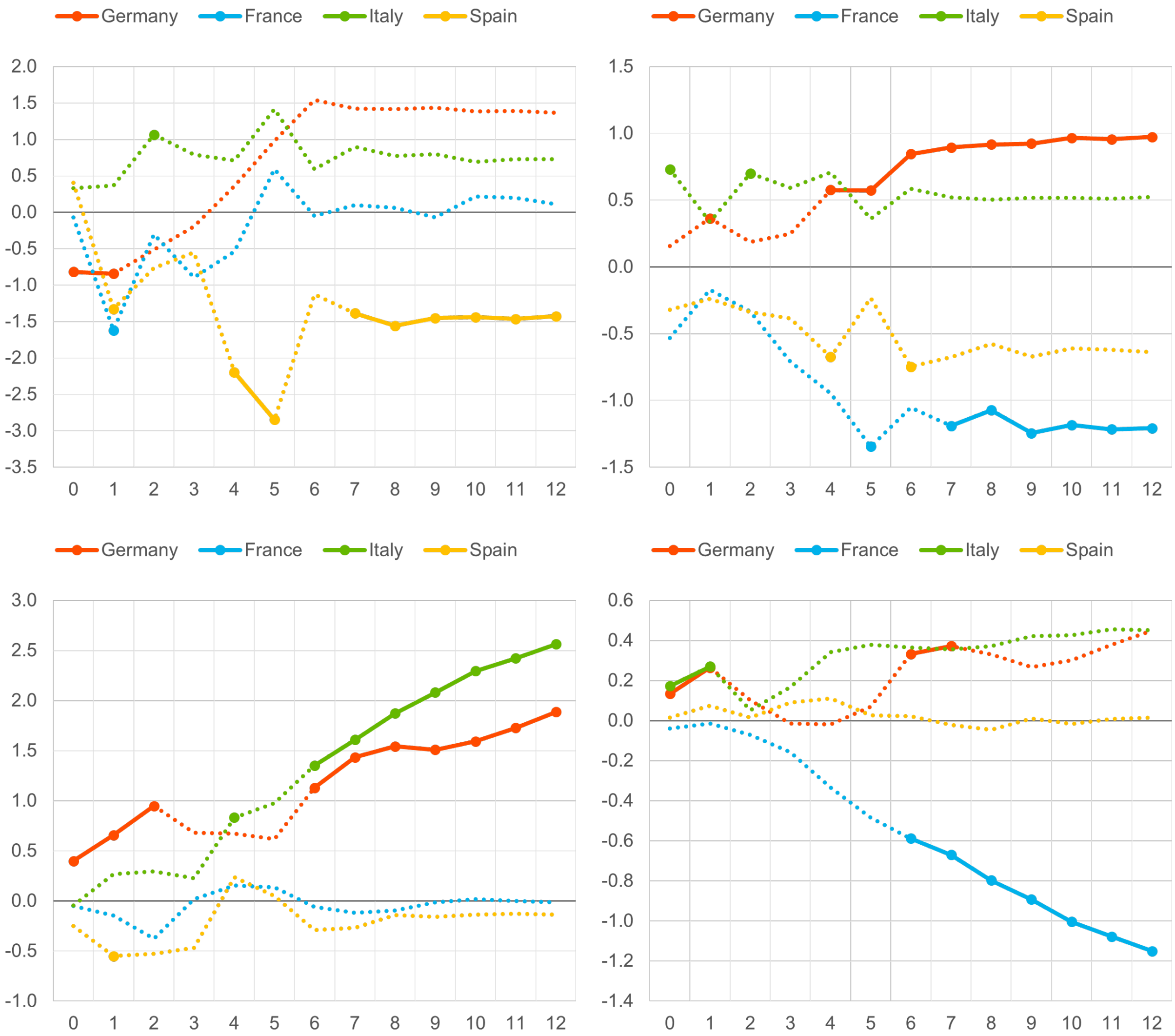
Notes: See notes to Figure 6, except for the thresholds used to define extreme weather events (below the 10th and above the 90th percentile of the country-specific historical distribution).

Figure D.5: Impact of extremely high (left panels) and low (right panels) temperature on the level of real GDP (upper panels) and HICP (lower panels) with more extreme weather events (x-axis: months; y-axis: percentage deviation from baseline level)



Notes: See notes to Figure 6, except for the thresholds used to define extreme weather events (below the 1st and above the 99th percentile of the country-specific historical distribution).

Figure D.6: Impact of extremely high (left panels) and low (right panels) precipitation on the level of real GDP (upper panels) and HICP (lower panels) with more extreme weather events (x-axis: months; y-axis: percentage deviation from baseline level)



Notes: See notes to Figure 6, except for the thresholds used to define extreme weather events (below the 1st and above the 99th percentile of the country-specific historical distribution).

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The views expressed in this paper are those of the authors and do not necessarily represent those of the European Central Bank.

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