# The macroeconomic effects of extreme weather events in Spain: a high-frequency, regional approach

This paper quantifies the macroeconomic impact of extreme weather in Spain using high-frequency regional data and exogenous, meteorologically calibrated shocks.

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## Abstract

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**JEL codes:** C33, R11, R12, R15, Q54

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December 2025

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# 1 Introduction

With global warming already exceeding the 1.5-degree threshold, extreme weather events are becoming more frequent and more severe (IPCC, 2021).[1] But the empirical evidence on their macroeconomic effects is inconclusive. This complicates the formulation of appropriate policy responses and the development of coherent adaptation strategies. Recent disasters also underscore the macroeconomic relevance of extreme weather events. Flash flooding in Valencia in 2024, wildfires near Athens in 2023 and 2024, and floods in Germany's Ahr Valley in 2021 each caused direct damages estimated close to 1% of national GDP (BdE, 2024, World Bank, 2024, Munich Re, 2022). Indirect damages may have been multiples of that figure. Large damages reflect the significant exposure of the regions affected, where value creation, capital density or population density are high. This means that where exactly a disaster strikes will be an important factor in determining its human and economic cost.

We therefore combine the geospatially and temporally most granular macroeconomic data available, and construct exogenous extreme weather shocks – using high-resolution gridded meteorological data to measure event intensity in the region where and on the day when it hit – to trace the consequences of such events as precisely as possible. Zooming in on continental Spain, we can then explore macroeconomic dynamics where (in the NUTS-3 region) and when (from the month onwards) an event occurred. We focus on extreme weather events as manifestations of acute physical climate risk.

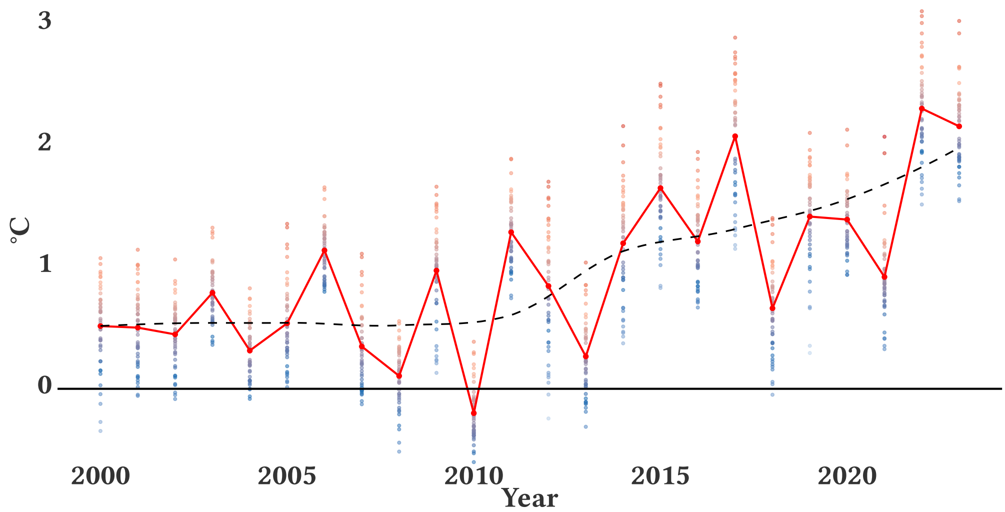
Specifically, for floods, windstorms and wildfires, we construct exogenous, intensity-weighted extreme weather shocks by matching official declarations or definitions to time an event with meteorologically derived intensity scores. We then combine monthly macroeconomic data – for Spain's 47 continental provinces from 2000 to 2022 – into a synthetic proxy for monthly regional GDP per capita.[2] This enables us to estimate the monthly output effects of different types of extreme weather events using a panel local projections framework. In state-dependent local projections, we also incorporate mediating factors at the regional level that will affect extent of damages and recovery speed, including capital density, fiscal space and insurance coverage. Previous studies have tended to focus on annual data either at the national or regional levels, or higher-frequency data at the national level, with temporal or spatial aggregation potentially obscuring effects. Existing studies also typically employ binary dummies as extreme weather shocks and, if at all, frequency metrics or direct damage estimates to calibrate event intensity, which may lower precision and create potential endogeneity concerns (Felbermayr and Gröschl, 2014).

We find that floods, windstorms and wildfires generate economically and statistically significant contractions in regional output per capita, though to differing magnitudes and degrees of persistence. The impacts of floods and windstorms both peak at about 1 percentage point decline in regional per-capita output, compared to the pre-event output level, with a faster recovery after floods than after windstorms. In both cases recovery remains incomplete after three years. Wildfires result in a short-lived, limited contraction of about 0.2 percentage points during the year after an event. All event types propagate to the economy through employment, with floods also dampening tourism and windstorms weakening new construction. We also show that regions with higher capital intensity experience more severe and persistent

[1] The 1.5-degree threshold was agreed during the 2015 UN Climate Change Conference (COP21) in Paris. It reflects the stated aim of pursuing efforts to limit the global temperature increase to 1.5°C above pre-industrial levels.

[2] Spain's provinces correspond to NUTS-3 regions. NUTS-0 corresponds to the national level (countries), NUTS-1 to major socioeconomic regions, NUTS-2 to basic regions for policy implementation, and NUTS-3 to small regions (provinces, counties or groups of municipalities), the highest level of regional economic detail in Europe.

**Figure 1: Average maximum temperature anomaly** (Continental Spain, 2000-2022)




Source: Authors' calculations based on AgERA5. Anomaly in maximum average annual temperature across regions compared to the 1979-1999 mean of maximum average annual temperatures.

output declines, and recovery is notably slower in areas with lower insurance coverage and more limited fiscal space, especially in case of floods.

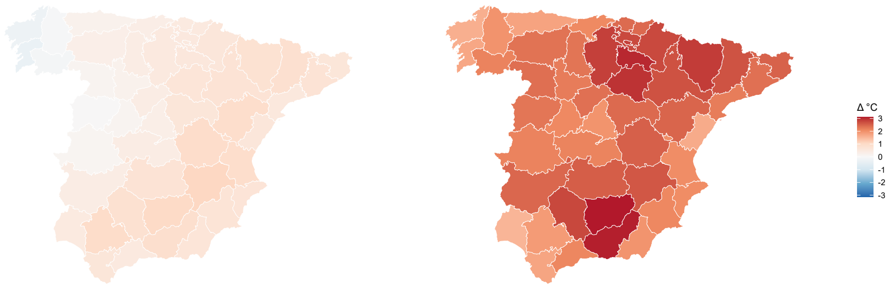
Our analysis thus fills an important gap: we jointly exploit temporal and geospatial granularity, allowing us to observe how shocks propagate precisely where and when their effects are most acutely felt. Furthermore, we construct extreme weather event shock series for floods, windstorms and wildfires that are exogenous – in terms of their timing and their intensity – to the high-frequency macroeconomic cycle and measured precisely on the day(s) on which an event occurred, in the region in which it occurred.

Spain is highly vulnerable to physical climate risk. Europe is the fastest-warming continent in the world (European Environment Agency, 2024), and Spain is one of the most vulnerable countries in Europe.[3] Spain is also one of the countries with the greatest climatic diversity in Europe (Arellano et al., 2025). These features render Spain an especially relevant setting for our analysis. Global warming is clearly apparent in Spain within our sample period (2000 to 2022), with the average maximum temperature anomaly, compared to the 1979-1999 mean, rising by more than 1.5 degrees between 2000 and 2022, as shown in Figure 1. Both the extent of warming and the exposure to extreme weather events are heterogeneous across the country, as shown in Figures 2 and 3. Spain is projected to face continued warming, increased aridity and more extreme weather events, making the policy implications of our findings highly relevant.

Insights from our analysis could inform shock and adaptation policy response and mitigate regional vulnerabilities. Our findings suggest that recovery aid may be required for a prolonged period after an event, and that increasing insurance coverage could protect growth and fiscal space. Our evidence also underscores the importance of adaptation and resilience-building to mitigate the economic costs of extreme weather events, especially for flood-prone regions, those where economic activity or capital are concentrated, and those with limited fiscal space or low insurance coverage. These steps could reduce regional macroeconomics vulnerabilities, especially those associated with the concentration of economic activity, as physical climate risk intensifies.

[3] According to the EC's INFORM index, Spain ranks 5th out of 27 EU countries in terms of natural hazard exposure.

**Figure 2: Geospatial distribution of temperature anomaly**
(Continental Spain, 2000–2022)

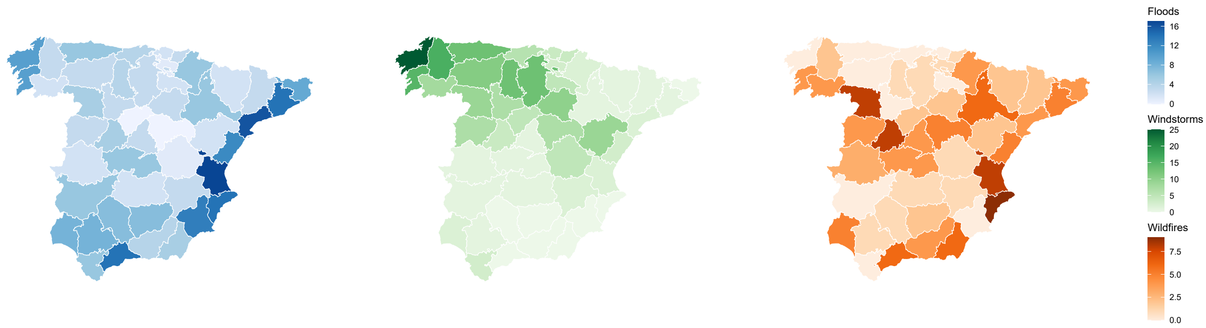



**2000** **2022**

Source: Authors' calculations based on AgERA5. Anomaly in maximum average annual temperature across regions compared to the 1979–1999 mean of maximum average annual temperatures.

**Figure 3: Geospatial distribution of main climate-related shocks**
(Frequency of extreme weather events of the type mentioned above the chart, per region, continental Spain, 2000-2022)

**Floods** **Windstorms** **Wildfires**

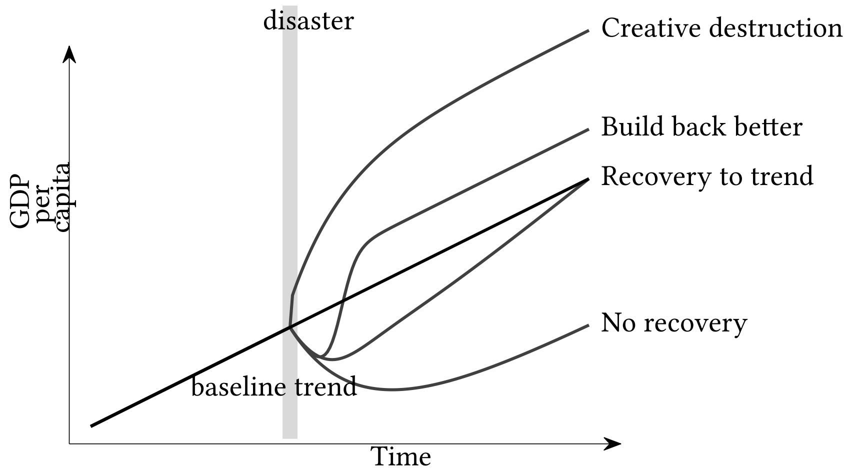



Source: Authors' calculations based on HANZE (for floods), Copernicus Climate Change Services (for windstorms) and Spain's Ministerio para la Transición Ecológica y el Reto Demográfico (for wildfires).

## 2 The literature on the macroeconomic effects of extreme weather events

How economies respond to and recover from extreme weather events is a question that is settled neither theoretically nor empirically.[4] In theory, a wide range of shock recovery paths can be rationalised (cf. Hsiang and Jina, 2014, or Roth Tran and Wilson, 2024), summarised in Figure 4 and ranging from creative destruction to permanent scarring. Mirroring this, empirically, studies have concluded that extreme weather events have positive (e.g., Roth Tran and Wilson, 2024), no significant (e.g., Strobl, 2011; Cavallo et al., 2010; Ehlers et al., 2025) or negative (e.g., Felbermayr and Gröschl, 2014; Bodenstein and Scaramucci,

**Figure 4: Stylised shock recovery paths for GDP per capita**




Source: Adapted from Roth Tran and Wilson (2024), Hsiang and Jina (2014)

2025; Usman et al., 2025a) initial and subsequent consumption or output effects.

The wide range of conclusions reflects differences in data coverage, resolution and frequency, as well as type and measurement of the shock. Fundamentally, extreme weather events differ in terms of onset, duration and degree of capital destruction, and as a result also in terms of how they transmit to the economy. We focus here on sudden-onset disasters, such as floods, windstorms or wildfires, which typically cause (some) immediate destruction of physical capital (Botzen et al., 2019, Boustan et al., 2020). Comparing the direct damages typically caused by the three event types considered in our analysis, windstorms can lead to uprooting or breaking of trees and damages to overland power lines, crops, buildings (especially roofs) and transport infrastructure such as bridges or roads (Gliksman et al., 2023). Floods can cause damage to infrastructure and agriculture, but also – via water intrusion – affect buildings' foundations or cause erosion or contamination, rather than structural collapse. By contrast, wildfires primarily cause damage to forests, natural areas, soil quality and vegetation cover, but may also result in evacuations, impacts on inhabited zones and transport disruptions. Reflecting differences in typical direct damages, Von Peter et al. (2024)'s results point to most extensive long-term damages from windstorms, compared to floods for example, and significantly less severe effects of wildfires. Hsiang and Jina (2014) also identify very persistent, negative economic impacts of cyclones.

In the short run, the destruction of physical capital leads to contractions in production capacity and output. However, such events often trigger reconstruction programmes that involve new capital investment, which can generate demand in sectors like construction and manufacturing, and support growth. Consumption is hit initially because of wealth effects from capital destruction and later because of reconstruction spending (Ehlers et al., 2025). Insurance coverage and public support are therefore key to recovery speed, and there is some evidence that repeated exposure encourages adaptation (Von Peter et al., 2024,

[4] In contrast to extreme weather events, the United Nations Office for Disaster Risk Reduction (UNDRR) defines a natural disaster as a serious disruption of the functioning of a community or society, involving widespread human, material, economic, or environmental losses and impacts, which exceed the affected population's capacity to cope using its own resources. While the term "natural disaster" is often used generically, we stick to using the term "extreme weather events" instead, as based on data available to us, we cannot determine whether the shocks we study exceed a region's capacity to cope.

Roth Tran and Wilson, 2024). Overall, even when physical damage is limited, heightened uncertainty, lower confidence, and tighter financial conditions can magnify losses from extreme weather events (Eickmeier et al., 2024).

The estimated magnitude and persistence of extreme weather event impacts also depend on the resolution of the data employed. Previous studies have typically exploited either temporal or spatial granularity, but not both simultaneously. For example, Fernández-Gallardo (2025) employ weekly indicators at the US state level, units that, in terms of population and economic size, are more comparable to entire European countries than to European regions. At the other end of the spectrum, Costa and Hooley (2025) or Usman et al. (2025a) use NUTS-3 level regional data for OECD or European countries, but at annual frequency. We combine monthly frequency with NUTS-3-level coverage, allowing us to observe disaggregated regional and temporal dynamics where and when shocks occur.

Econometrically, the use of lower-frequency data may bias estimated impacts of extreme weather events towards zero or excess persistence. If the effects of shocks are relatively short-lived, a recovery within a few months after the shock may go unnoticed in yearly figures, leading to an understatement of their actual economic impact (Fernández-Gallardo, 2025). Lower-frequency data may also create a persistence bias from temporal aggregation (see Wei, 1978; Rossana and Seater, 1995 and Section 4.4).[5]

Spatial resolution is equally important. Regional studies highlight substantial heterogeneity in exposure, vulnerability, and adaptation capacity across regions (Di Marcoberardino and Cucculelli, 2024, Usman et al., 2025a). National aggregates may obscure such variation, particularly in large, advanced economies, where local losses from an extreme weather event may not translate into significant effects at the national level. However, subnational data present their own challenges, including more limited availability and potentially greater measurement error.

Beyond within-country heterogeneity, cross-country differences also shape estimated impacts. Variations in wealth, income, insurance coverage and fiscal capacity across countries studied influence both the magnitude of the initial damage and the speed of recovery. More advanced economies and, in particular, those with greater fiscal space tend to see more limited output contractions after an extreme weather event and recover more quickly (Lis and Nickel, 2009, Nguyen et al., 2025). Wealthier regions also see more limited or no impacts from some types of extreme weather, according to Usman et al. (2025a). Furthermore, insurance coverage is found to reduce the hit to GDP growth from major extreme weather events (Rousová et al., 2021, Von Peter et al., 2024).

The selection of events and the measurement of their intensity affect the precision and potential bias of impact estimates. The selection of events may – if linked to the availability of reconstruction spending – introduce bias: for example, Roth Tran and Wilson (2024) only study events that triggered federal government aid, the receipt of which reflects disaster intensity but also political dynamics. Furthermore, studies measuring event intensity with meteorological variables such as precipitation or temperature generally obtain more precise estimates than those relying on reported costs or GDP losses. This is because weather-based measures are exogenous to economic conditions, at least at short horizons, whereas monetary damages are mechanically correlated with the levels of development and exposure (Felbermayr and Gröschl, 2014). Direct cost studies typically report larger negative effects (Lazzaroni and van Bergeijk,

[5] We study extreme weather events as a manifestation of acute physical climate risk, which is possible given the high temporal and spatial resolution of our data. By contrast, distinguishing acute physical climate risk (for example, heatwaves) from chronic physical climate risk (gradual warming) based on annual data is significantly more challenging.

2014, Botzen et al., 2019), since they focus on immediate destruction of assets and infrastructure, while macroeconomic studies of indirect effects capture both destruction and reconstruction, which can offset the initial decline.

The available evidence points to the presence of non-linearities, with more extreme events typically found to have disproportionately larger impacts (Cavallo et al., 2010, Felbermayr and Gröschl, 2014, Kotz et al., 2024, Costa and Hooley, 2025). Once damages surpass an economy's absorptive capacity, the scope for substitution and resource reallocation is exhausted. Consistent with this, macro-structural modelling shows that when extreme weather shocks exceed the ability of markets to reallocate resources efficiently, the welfare costs increase non-linearly and may be amplified by fiscal and financial constraints that limit the policy response (Hallegatte et al., 2022).

**Overall, we make a timely contribution to the existing literature by using highly granular data, applying fully exogenous shocks and considering mediating factors in shock transmission.** First, we combine the highest possible temporal and spatial data resolution to study the high-frequency (monthly) response of regional (NUTS-3) economies to extreme weather events. Second, we construct exogenous, intensity-weighted extreme weather event shock series for floods, windstorms and wildfires. We time events using official declarations or definitions to ensure that we impose shocks rather than mere variation. We measure their intensity using gridded meteorological data, ensuring both exogeneity and precision. Third, we consider how mediating factors across regions – such as capital density, fiscal space and insurance coverage – affect both impact and recovery paths. Thus, we can precisely assess the dynamic impacts of extreme weather events where and when they occur.

# 3 Methodological framework

There are at least three main challenges when empirically assessing the effects of extreme weather events: the frequency and spatial resolution of the macroeconomic data, discussed in the previous section; the dating and intensity calibration of events; and the choice of empirical strategy. In what follows, we outline how we address these challenges. Section 3.1 discusses the construction of our macroeconomic dataset. Section 3.2 explains how we identify and measure the intensity of extreme weather events. Section 3.3 presents our econometric approach.

## 3.1 The macroeconomic data: granularity across time and space

We build a novel dataset comprising macroeconomic data at monthly frequency and at NUTS-3-level regional granularity for continental Spain from 2000 to 2022.[6] Each Spanish NUTS-3 region covers roughly 10,000 km$^2$ on average – about one fiftieth of Spain's total surface area. Our aim is to bridge the temporal gap in regional GDP data and enable analysis of short- and medium-term economic dynamics at the regional level following extreme weather events.

[6] We focus on continental Spain for the sake of data availability and comparability, omitting the Balearic and Canary islands as well as Ceuta and Melilla from the analysis. NUTS 1, 2 and 3 are the level of classifying sub-national regions for statistical purposes in Nomenclature of Territorial Units for Statistics (NUTS) system of the EU, designed to ensure consistency across countries. NUTS-1 regions correspond to major socio-economic regions (92 in Europe, 7 in Spain), NUTS-2 regions to basic regions for regional policies (such as EU cohesion funds; 244 in Europe, 19 in Spain) and NUTS-3 regions to small regions for specific purposes or analyses (1,165 in Europe and 59 in Spain).

**Table 1:** Description of macroeconomic series and sources

| Variable | Units | Frequency | Description | Source |
|---|---|---|---|---|
| Social security affiliations | Persons | Monthly | Proxy for income | Social Security |
| New car registrations | Units | Monthly | Proxy for consumption and industrial output | Directorate-General for Traffic, Ministry of the Interior |
| Oil consumption | Liters | Monthly | Proxy for consumption | Ministry of Transport and Sustainable Mobility |
| New construction permits | Square meters | Monthly | Proxy for construction output | Ministry of Transport and Sustainable Mobility |
| Goods exports and imports | Euros and kg | Monthly | Goods trade | Ministry of Economy, Trade and Enterprise |
| Nights spent at touristic accommodations | Number | Monthly | Proxy for services trade, consumption and services | National Statistics Institute (INE) |
| Employment (LFS) | Euros | Quarterly | Proxy for income | National Statistics Institute (INE) |
| Loans and deposits | Euros | Quarterly | Proxy for consumption and financial output | Banco de España |
| Gross domestic product | Chain linked volume | Yearly | Total production of final goods and services | Eurostat |

Official NUTS-3 level regional GDP data (production approach) is sourced from ARDECO but only available annually, which is too coarse to capture short-run macroeconomic dynamics after extreme weather events. To overcome this limitation, we develop a Monthly Synthetic Indicator of Economic Activity (MSIEA) that provides a consistent monthly proxy for regional GDP per capita. The MSIEA is built from a set of high-frequency macroeconomic indicators, as summarised in Table 1, drawn from Spanish national statistical sources, that capture or serve as a proxy for key dimensions of economic activity. We apply a two-step temporal disaggregation approach to obtain a coherent monthly GDP series. In the first step, annual GDP is converted into quarterly series using higher-frequency quarterly indicators such as Labour Force Survey (LFS) employment – which is preferred over social security affiliations for methodological consistency – and banking aggregates (loans and deposits). In the second step, quarterly GDP is further disaggregated into monthly series using the full set of monthly indicators listed above, including social security affiliation data, but excluding LFS and financial metrics. This structured approach ensures that the resulting monthly series is both consistent with annual GDP and reflects the temporal profile of high-frequency movements in underlying activity.

Our monthly GDP estimates rely on the Fernandez (1981) temporal disaggregation approach, which builds on the framework of Chow and Lin (1971), both of which link low-frequency aggregates to high-frequency indicators under an explicit stochastic assumption for the underlying series.[7] The key difference is that while Chow–Lin assumes autoregressive residuals, Fernández models them as a random walk. This leads to a quadratic optimisation that generates smoother disaggregated series while preserving annual totals. By penalising acceleration, it minimises artificial volatility and avoids abrupt month-to-month fluctuations, yielding smoother and more reliable monthly series. We discuss the specifics in Appendix A. 2.

[7] The IMF's Quarterly National Accounts Manual (2017) discusses benchmarking techniques for compiling quarterly national accounts (QNA), noting that regression-based temporal disaggregation methods like Chow and Lin (1971), Fernandez (1981) and Litterman (1983) are used by some countries to derive quarterly series consistent with annual benchmarks. The World Bank applies the same family of methods (Chow–Lin and Denton) in its Global Economic Monitor (GEM) and related statistical products to interpolate quarterly GDP where only annual series are available, ensuring internationally comparable high-frequency data for countries without official QNA.

Compared to more recent approaches inspired by Stock and Watson (2001) – such as Baumeister et al. (2024) and their weekly Economic Conditions Indices – our method prioritises temporal coherence with official national accounts by enforcing exact aggregation constraints. Stock–Watson-type dynamic factor models excel at summarising large national panels, but the resulting estimates would not align with annual national accounts aggregates.

The final dataset is a balanced monthly panel from January 2000 to December 2022 for 47 NUTS-3 continental Spanish provinces (12,972 observations; see Figure 5). The MSIEA provides a granular and timely measure of regional output per capita that links to observed annual GDP. It also offers the frequency needed to study dynamic regional impacts and recovery after extreme weather events. By focusing on GDP *per capita*, we indirectly capture migration flows in response to extreme weather events.

Finally, as noted at the outset, recent extreme weather events have increasingly affected areas where economic activity, capital or population are highly concentrated. An example is flash-flooding (caused by a high-altitude, low-pressure weather system) in Valencia in October 2024. We therefore also incorporate annual capital stock density (gross capital stock per person sourced from ARDECO, see Figure 10 in the Appendix) at the NUTS-3 level as one proxy for the geospatial concentration of economic activity in our dataset. Our analysis below includes this measure as a state variable in state-dependent local projections to explore its role in affecting the impact and speed of recovery after an event.

We also consider the roles of fiscal space and insurance coverage as mediating factors. We construct a NUTS-3 fiscal space indicator based on the sample period average of municipal debt per capita and revenues per capita in each region.[8] Existing literature has identified available fiscal space as one factor determining the speed of recovery (Lis and Nickel, 2009, Nguyen et al., 2025). Insurance coverage is measured as the ratio of insured physical capital to the net capital stock in real terms. Its inclusion as a potential mediating factor is motivated by the fact that insurance payouts play a key role in enabling recovery. Spain's unique public catastrophe insurance system provides data on insured physical capital and also levels the playing field across Spanish regions. The Consorcio de Compensación de Seguros (CCS) is a nationwide "last-resort" insurance scheme funded through a mandatory surcharge on private insurance policies. It automatically compensates for certain extraordinary events – including floods and windstorms, but not wildfires – without requiring an official disaster declaration.

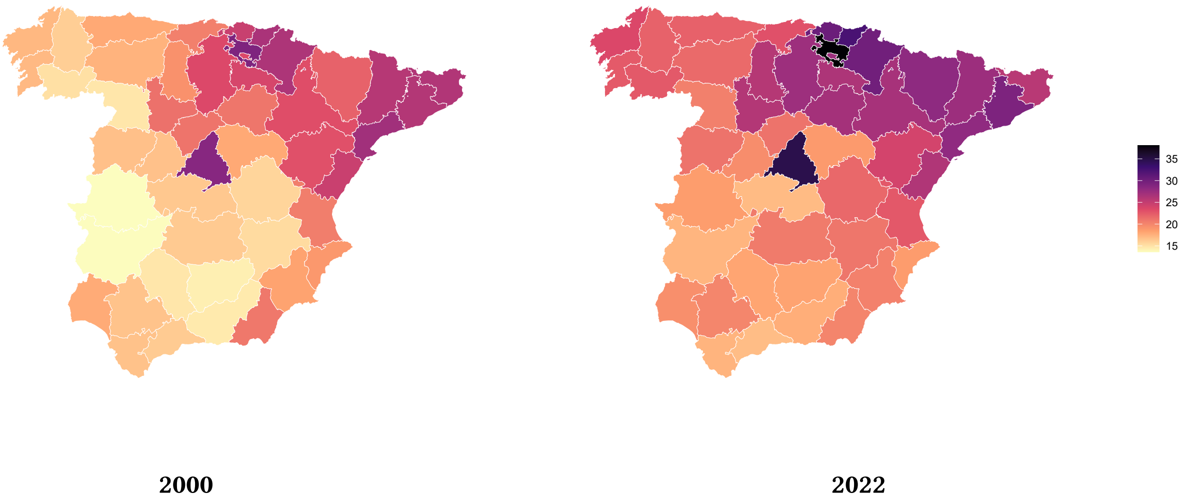
### 3.2 Extreme weather events indicators construction

We focus on floods, windstorms and wildfires as manifestations of acute physical climate risk. We do not include heatwaves and droughts, because their effects are difficult to disentangle from those of chronic physical climate risk and because they transmit to the economy primarily via productivity rather than via physical capital destruction. We do not include technological accidents, earthquakes or volcanic eruptions, as these are either human-induced or not directly linked to climate change. Event types are analysed separately to capture potential heterogeneity in their effects.[9]

To identify when extreme weather events hit and with what intensity, we merge the best of two disparate approaches taken by the literature so far. We time extreme weather events using declarations or classifications from a range of official Spanish national or European sources, detailed in Table 2. Contrary to

[8] Each province is ranked from 1 to 47, and the two ranks are summed. Provinces below the median are classified as having low fiscal space (high debt and low revenues), and those above as having high fiscal space.
[9] We focus on windstorms associated with extratropical cyclones, the most relevant type for Europe (Priestley et al., 2023).

**Figure 5: GDP per capita, 2000 and 2022**
Million 2020 Euros per person




Source: Authors' calculation based on ARDECO

much of the literature, we do not use estimates of event frequency, monetary damages or people affected provided by EM-DAT, in part because of the econometric issues created by including monetary damages, which will correlate with the level of GDP, and in part because of many missing observations. We then use meteorological and climatological indicators sourced from the AgERA5 reanalysis dataset – aggregated from highly granular 0.1° x 0.1° data to the level of NUTS-3 regions – as well as Spanish national sources to create an intensity score for each type of event.

We construct each shock as the product of an officially timed event binary (dummy) variable and a meteorologically derived intensity score, ensuring that shocks reflect both genuine events and their physical severity. In practical terms, this means multiplying an event dummy – that takes the value of 1 in the month and region in which the event occurred – by an intensity score, calibrated as summarised in Table 2 for each main extreme weather event type considered. Appendix A. 3 discusses the aggregation procedure and choice of meteorological indicators for intensity calibration in detail.

This hybrid approach addresses the two core identification problems in the literature: using meteorological indicators to calibrate intensity avoids endogeneity from damage estimates, while timing events with official declarations prevents false positives from weather anomalies without socio-economic impact. The resulting shocks are therefore exogenous to monthly GDP and reflect genuine extreme events rather than "mere" weather variation.

However, it is important to note that long-run climatic conditions have shaped where economic activity concentrates. Settlements have tended to arise in areas with (initially) manageable climatic risk, but agglomeration forces, proximity, and insurance availability may later outweigh hazard considerations (Boustan et al., 2020, Indaco and Ortega, 2024). Climate change further shifts relative risks, as illustrated by Valencia's above-average population growth despite significantly rising flood exposure. This implies that our shock series may still be endogenous to slowly evolving structural variables, such as capital density. Because income correlates with capital density and higher capital density increases gains from adaptation (Hsiang and Narita, 2012), failing to account for this could understate the role of economic geography in

**Table 2:** Overview of disaster types, intensity metric construction and sources

| Variable | N | Mean | Std. dev. | Min | Max | Identified/ classified by | Intensity calibration (source) |
|---|---|---|---|---|---|---|---|
| Floods | 268 | 44.6 | 27.5 | 1.0 | 133 | HANZE | Maximum one-day precipitation during the flood event, in millimetres (AgERA5) |
| Windstorms | 225 | 33.5 | 4.1 | 27.2 | 58.8 | Copernicus Climate Change Service | Maximum 3-second 10-m wind gust over the 72 hours centred around the footprint central time*, in metres per second (AgERA5) |
| Wildfires | 133 | 0.2 | 0.2 | 0.08 | 1.2 | Ministerio para la Transición Ecológica y el Reto Demográfico | Total surface area burned per day as a share of total region area, in square kilometres per day (Ministerio para la Transición Ecológica y el Reto Demográfico)** |

*The storm footprint is defined as the 1,000 km radius around the storm track centre. Storms are included when the region's area-weighted median 3-second 10-m wind gust, adjusted by its relative surface share within the footprint, exceeds 25 m $s^{-1}$.

**We focus on fires with burned area above 0.05% of the region's surface and, after aggregating area and duration, keep only those with intensity exceeding 0.075% of regional surface per day.

shaping impacts. To address this, we incorporate capital density as a state variable in our state-dependent local projections (Section 4.3), rather than as a direct regressor. Over our two-decade window, region fixed effects absorb unobserved, time-invariant cross-sectional differences in climatic conditions.

### 3.3 Econometric approach

We estimate the effects of extreme weather events using a panel local projections (LP) approach in the spirit of Jordà (2005). This method is well-suited to our setting, as it allows us to trace the dynamic response of regional economies to extreme weather shocks without imposing restrictive assumptions on the underlying data-generating process. Panel LPs can also accommodate non-linearities and state dependence, both of which we explore, yield consistent Impulse Response Functions (IRFs) under weaker assumptions than VARs and have been widely used in the relevant literature (Eickmeier et al., 2024, Fernández-Gallardo, 2025, Usman et al., 2025a).[10]

Formally, for region $i$ in month $t$ at horizon $h$ ($h=0,1,\ldots,H$), we estimate:

$$\Delta^h y_{i,t+h} = \alpha_i^h + \beta^h W_{i,j,t} + \sum_{p=1}^{P} \phi_{1p}^h \Delta^h y_{i,t+h-p} + \sum_{q=0}^{Q} \phi_{2q}^h \Delta x_{i,t-q} + \gamma^h W_{i,J,t} + \varepsilon_{i,t+h} \tag{1}$$

where:

- $\Delta_h y_{i,t} = y_{i,t+h} - y_{i,t-1}$ is the $h$-period change in the logarithm of our monthly proxy for GDP per capita,
- $\alpha_i^h$ are horizon-specific (NUTS-3) region fixed effects, which capture time-invariant unobserved

[10] We considered a panel VAR approach (e.g. Sims, 1980; Kim et al., 2025) as an alternative. VARs provide a coherent approach for modelling the joint dynamics of multiple variables and are particularly useful for forecasting and structural identification. However, they require strong assumptions about the data-generating process, are sensitive to lag-length choice, and are prone to overfitting. By contrast, the LP approach offers greater robustness to misspecification at the cost of some efficiency. Importantly, our preliminary VAR estimates pointed to responses of extreme weather shocks that were similar in direction and persistence to those obtained with LPs, which reassures us that our main findings are not driven by our choice of method.

heterogeneity across regions,

- $\beta^h$ traces the impulse response at forecast horizon $h$,
- $W_{i,j,t}$ is the contemporaneous extreme weather shock of type $j$ (floods, windstorms or wildfires). It is formally defined as $W_{i,j,t} = I[w_{i,j,t} = 1] \times \iota_{i,j,t}$, where $I[w_{i,j,t} = 1]$ is an indicator (binary) variable that takes the value 1 when an event of type $j$ occurs in region $i$ and time $t$, 0 otherwise, and $\iota_{i,j,t}$ denotes the corresponding event intensity,
- $\Delta x_{i,t-q}$ is a vector of monthly contemporaneous and lagged control variables, discussed below,
- $W_{i,J,t}$ denotes the vector of contemporaneous shocks from extreme weather events other than the one under analysis $W_{i,j,t}$, and
- $\varepsilon_{i,t+h}$ is the error term.

We estimate equation (1) for each forecast horizon $h = [0, 1, \dots H]$, with horizons up to 36 months, reflecting the three-year period over which insurance payouts, investment and reconstruction efforts concentrate (Von Peter et al., 2024). We compute cluster-robust standard errors at the regional level to account for within-region serial correlation and heteroskedasticity in the residuals. Lag length for the dependent, control and shock variables is jointly determined using a LASSO procedure with cross-validation, which prevents over-parameterisation.[11]

Beyond lags of the dependent variable, the specification includes the regional price level and the unemployment rate as region-specific controls in differenced terms. To address potential cross-section dependence, we also add a set of common controls, including the first principal component of regional GDP, the short-term shadow rate, and the central government primary budget deficit, in differenced terms. We further include an indicator measuring sea surface temperature anomalies to capture El Niño Southern Oscillation (ENSO) dynamics (Rayner et al., 2003). In addition, we also include other extreme weather event types to avoid bias from concurrent events. Finally, calendar-month fixed effects are included to absorb remaining seasonality. As one of our main extensions, using state-dependent local projections, we also explore mediating factors that shape the extent and the speed of recovery from extreme weather events by focusing on three dimensions of cross-regional heterogeneity: the geospatial distributions of capital, fiscal space and insurance coverage, measured as discussed above.

Our identification strategy relies on the fact that extreme weather events are inherently exogenous to short-term regional economic dynamics. The timing and intensity of floods, windstorms, and wildfires are driven by meteorological and geophysical processes that are orthogonal to local business cycle dynamics. Moreover, the shocks are defined exclusively from physical hazard indicators – occurrence and intensity – rather than economic losses, which avoids endogeneity arising from differences in wealth, exposure, vulnerability, or reporting capacity across regions.[12] Taken together, these features ensure that variation in $W_{i,j,t}$ is plausibly as-good-as random with respect to the econometric residual, allowing us to recover the dynamic causal effects of extreme weather shocks on regional economic activity.

[11] Results are robust to alternative lag specifications on the dependent variable and the set of controls (see Section 4).

[12] For a detailed discussion of why meteorological and geophysical indicators provide plausibly exogenous variation for identifying the causal effects of natural disasters, see Hsiang and Jina (2014), who show that storm-track–based cyclone intensity is orthogonal to local economic conditions, and Strobl (2011), who uses physically modelled wind-exposure measures to address endogeneity concerns in US counties. This approach directly follows the identification logic proposed, but not implemented, by Noy (2009), who emphasised the need for disaster-intensity measures based solely on physical characteristics to overcome endogeneity in disaster–economy regressions.

# 4 Results

## 4.1 The regional macroeconomic effects of extreme weather events

We estimate the deviation of regional per-capita output from its pre-shock level in response to extreme weather events over a three-year horizon. We consider three types of events: floods, windstorms, and wildfires. Figure 6 presents the impulse response functions (IRFs) obtained from panel local projections of our proxy for real regional monthly per-capita GDP to a median shock in the extreme weather series, separately for each event type.[13] We focus on the short to medium term, under the key identifying assumption that our extreme weather event shock series, intensity-calibrated using meteorological data, are exogenous to economic activity over this horizon.

Floods, windstorms and wildfires initially all cause a contraction in regional economic output per capita, but with differing magnitudes and degrees of persistence. The impacts of floods and windstorms both peak at about 1 percentage point decline in the regional per-capita GDP level. However, peak impact of floods is reached after about half a year, whereas for windstorms impact unfolds more gradually and peaks after two years. Recovery from both floods and windstorms remains incomplete at the end of our projection horizon, with regional output per capita still about 0.5 percentage points below its pre-event level in case of floods, though only marginally significant, and about 0.9 percentage points below in case of windstorms. Wildfires cause a shorter-lived, more limited contraction of about 0.2 percentage points during the year after an event. The persistence of our identified effects is comparable to other studies relying on monthly data, such as Eickmeier et al. (2024) or Kim et al. (2025). Furthermore, the presence of longer-run negative output effects and the relatively more persistent impact of windstorms compared to floods mirror findings by Costa and Hooley (2025) and Von Peter et al. (2024).

We hypothesise that greater availability of reconstruction funding after floods, perhaps linked to greater insurance coverage of assets to flood risk, explains the somewhat more limited "permanent" (within our projection horizon) effect of floods compared to windstorms. Damages from *extraordinary* floods and windstorms (for storms with gusts above 120km/h) are covered by the CCS, for insured assets. Furthermore, floods are the most commonly funded event via European support funds (European Parliament, 2024).[14] The more limited disruption of economic activity caused by wildfires compared to floods or windstorms may reflect that rural or agricultural and generally less populated areas of Spain tend to be most affected by wildfires, as opposed to dense built environment.

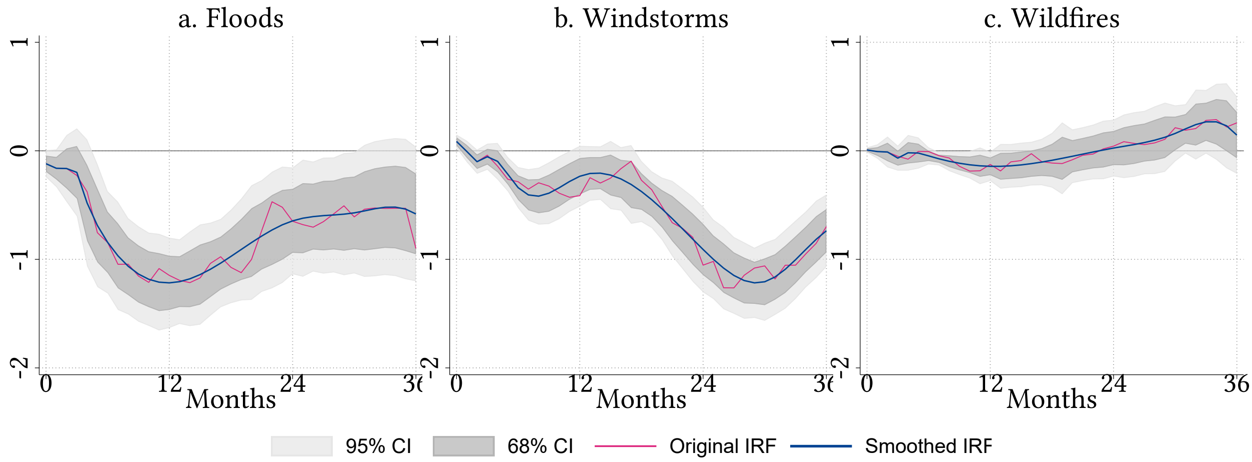
Our results are robust to various alternative specification and calibration approaches. For example, results are robust to using a range of alternative meteorological metrics to reflect the intensity of floods, windstorms and wildfires. They are also robust to different lag lengths chosen for dependent and control variables, as well as to Chow and Lin (1971), Litterman (1983) and Santos Silva and Cardoso (2001) approaches to temporal disaggregation. Finally, findings are comparable when we aggregate our shock series to quarterly and annual values and estimate equation (1) at lower frequencies (see Section 4.4).[15]

[13] We fit cubic splines to our initial estimated IRFs (pink lines in the figures) to attenuate high-frequency noise in monthly data, yielding smoothed IRFs (blue lines).

[14] About 40% of the windstorms considered in our study qualify as "extraordinary" in this sense.

[15] The temporal disaggregation procedure employed here, following Fernandez (1981), operates in first differences and thereby minimises the risk of introducing spurious persistence by interpolation.

**Figure 6: Impulse responses of per capita GDP to extreme weather events**
(Percentage points deviation from pre-shock level, panel local projections)




Note: graphs show impulse responses functions, derived from a panel local projections approach, in response to a median shock of the type mentioned above the chart. IRFs were smoothed using a cubic spline.

## 4.2 Assessing the transmission channels of extreme weather events

To examine underlying monthly dynamics, we apply equation (1) to each component of the MSIEA, sequentially treating each monthly series as the dependent variable and deriving IRFs for each extreme weather type. This sheds light on the macroeconomic transmission mechanisms of floods, windstorms and wildfires, and the drivers of the recovery.

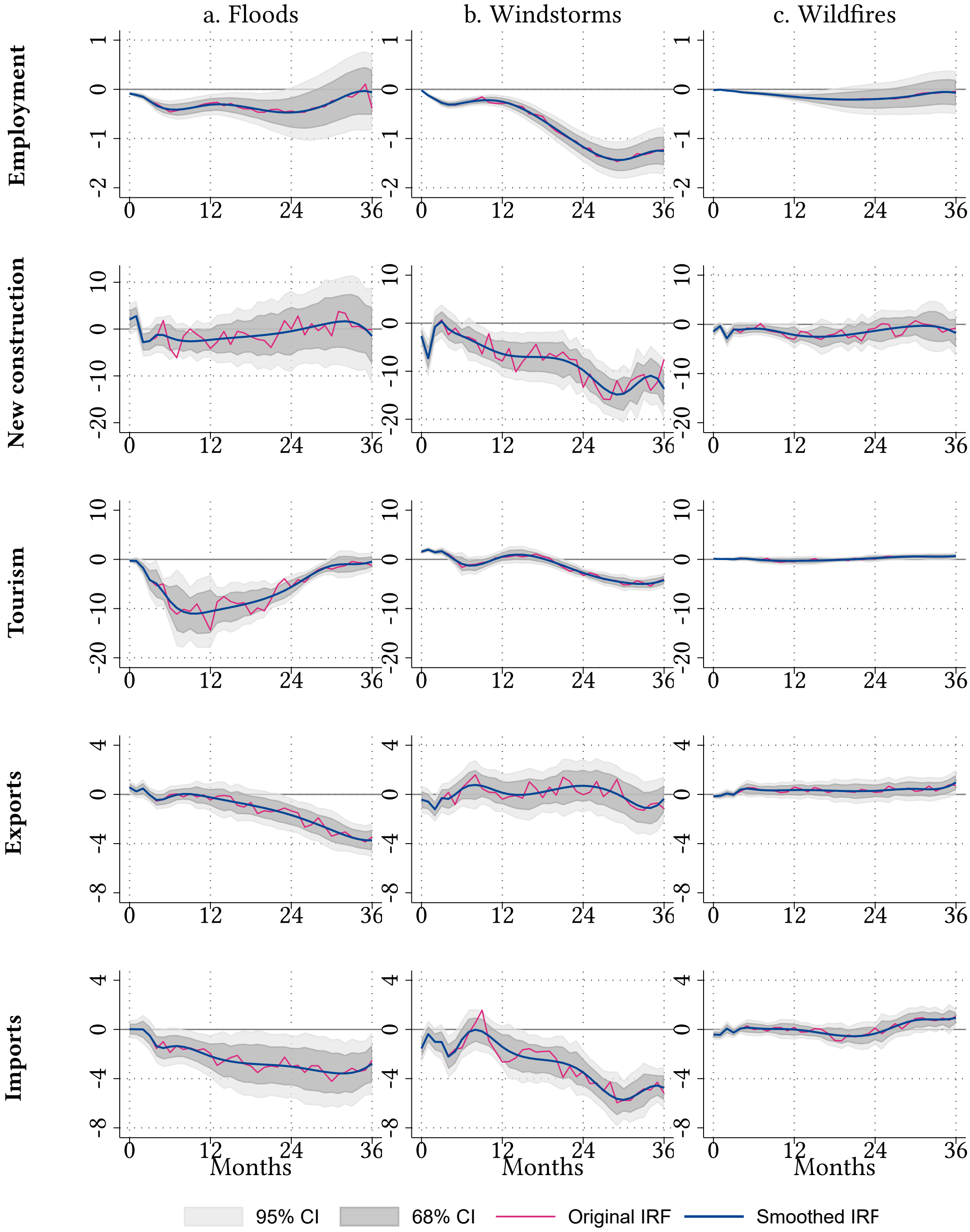
As shown in Figure 7, for the three event types considered, employment is an important transmission channel, driving both the initial contraction and (part of) the subsequent recovery dynamics. Employment moves broadly in line with per-capita GDP, albeit with smaller amplitudes. Effects on employment are particularly persistent following windstorms, where the return of employment to pre-event levels occurs beyond the three-year projection horizon, if at all. This is consistent with evidence presented in Jia et al. (2025) and Eickmeier et al. (2024), both of which document substantial persistence in post-disaster labour-market adjustments. The slow recovery in employment after windstorms may reflect longer-lasting disruptions to production capacity and local physical infrastructure.

Comparing the output and employment responses reveals several noteworthy patterns. In the case of floods, mirroring findings of Jia et al. (2025), we find that the response of output is persistent than that of employment. While employment normalises by the end of the three-year projection horizon, output remains below trend. Windstorms display a different dynamic: output recovers more quickly than employment (but more slowly than in the case of floods). These differences might be driven by greater insurance coverage and greater public fiscal support in case of floods. This would imply a greater hit to firms' cashflow from windstorms, with implications for firms' access to finance, resulting in more persistent employment effects.[16] Wildfires represent a more muted response profile, with both per-capita GDP and employment converging back to baseline after two years, indicating that neither demand- nor supply-side frictions constrain the recovery after three years.

Investment behaviour, proxied by new construction activity, also provides insight into post-event adjustment. Following windstorms, new construction falls; this is consistent with reconstruction absorbing

[16] This is consistent with more than 75% of CCS payouts over the sample period having been related to floods (and 25% to storms; for both floods and storms only to those events deemed extraordinary). Wildfire damage is generally not covered by CCS.

**Figure 7: Impulse responses of monthly raw indicators to extreme weather events**
(Percentage points deviation from pre-shock level, panel local projections)




Note: graphs show impulse responses, derived from a panel local projections approach, in response to a median shock of the type mentioned above the chart. IRFs were smoothed using a cubic spline.

resources that would otherwise finance new building activity. The weakening of new construction after windstorms may also reflect lower household income, which reduces demand for new housing. Interestingly, no event type considered exhibits a notable investment boom in its aftermath.[17] In the case of floods, the tourism sector absorbs much of the impact, with nights spent in tourist accommodation falling sharply initially and recovering slowly, reflecting the time needed to reconstruct amenities and infrastructure.

Trade flows adjust in line with the domestic supply–demand balance following an extreme weather event. For floods, supply constraints seem to weigh on export performance over the medium term, while imports decline earlier, likely reflecting lower domestic demand due to subdued labour productivity and its effect on wages. Windstorms produce a different pattern: exports are less constrained, but imports fall as employment-related income losses reduce purchasing power. As a result, net exports remain broadly unchanged after floods but improve in case of windstorms, mirroring the relative performance of employment and per-capita GDP in both cases. Overall, given Spain's reliance on tourism as a driver of growth and its historically elevated unemployment rate, the sustained impact of extreme weather events on employment, construction and tourism have important macroeconomic and policy implications.

### 4.3 The role of mediating factors: state-dependent panel local projections

Using state-dependent local projections, we explore the role of mediating factors that reflect the geospatial distribution of economic activity, including capital density, fiscal space and insurance coverage at the NUTS-3 level, in driving the recovery path after an extreme event hits.[18]

To assess the role of these mediating factors, we adapt equation (1) by introducing an interaction term between the extreme weather shock and the mediating factor, as follows:

$$\begin{aligned}\Delta^h y_{i,t+h} = \alpha_i^h + \beta_L^h \left(W_{i,j,t} \times (MF_i = 0)\right) + \beta_H^h \left(W_{i,j,t} \times (MF_i = 1)\right) + \sum_{p=1}^{P} \phi_{1,p}^h \Delta^h y_{i,t+h-p} + \\ \sum_{q=0}^{Q} \phi_{2,q}^h \Delta x_{i,t-q} + \gamma_1^h W_{i,j,t} + \nu_{i,t+h}\end{aligned} \tag{2}$$

The state-dependent model is defined by allowing the shock to interact with the mediating factor:

$$MF_i = \mathbb{I}[z_i \geq z_{p50}]$$

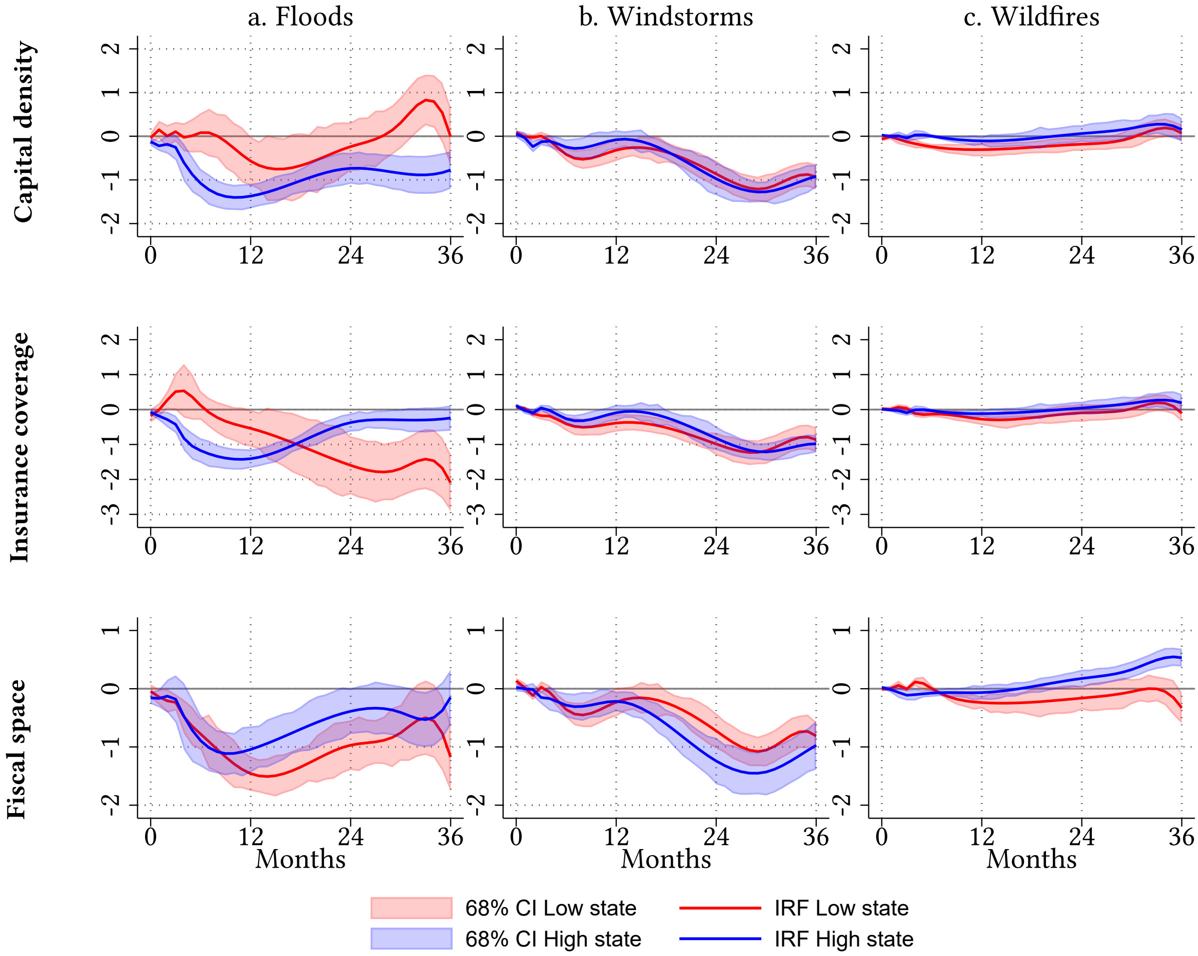
Where $\mathbb{I}[\cdot]$ is an indicator (binary) function equal to 1 when region $i$'s value of the relevant metric $z_i$ is above the median ($z_{p50}$) across NUTS-3 regions, and 0 otherwise. We estimate equation (2) separately for each state.

Table 3 in the Appendix suggests that the distribution of shocks across the "high" and "low" states for each mediating factor approximates quasi-random partitions, rather than reflecting systematic sorting of shocks into structurally distinct regions. We of course still acknowledge the limitations of this approach given that the median split is observational and cannot replicate true random assignment. Regions differ in terms of a range of long-run structural characteristics, and the partitions may embed unobserved factors correlated with both exposure and recovery dynamics. However, the balance diagnostics indicate that these concerns are not first-order: the number of shocks, their average intensity and dispersion, and the underlying GDP per capita distributions are broadly comparable across the "high" and "low" states

[17] The absence of a strong rebound echoes the findings of Fernández-Gallardo (2025), who shows that reconstruction spending may not drive recovery. The muted construction response may also reflect financing constraints and insurance frictions. Note that new construction permits do not capture renovations, reconstruction, or other forms of physical capital replacement.

[18] Capital density is measured as the gross capital stock per person. The fiscal space indicator reflects municipal debt and revenues per capita. Insurance coverage is the ratio of insured physical capital to the net capital stock.

**Figure 8: Impulse responses of per-capita GDP to extreme weather events, by mediating factor**
(Percentage points deviation from pre-shock level, panel local projections)




Note: graphs show impulse responses, derived from a state-dependent panel local projections approach, in response to a median shock of the type mentioned above the chart. Regions are divided into high and low capital per worker regions based on the capital-to-worker ratio. Regions are divided into high and low fiscal space regions based on a composite indicator of regional fiscal space. Regions are divided into high and low insurance coverage based on the ratio of insured to total capital. IRFs were smoothed using a cubic spline.

for each factor. Hence, state classifications provide sufficiently balanced groups to identify meaningful heterogeneity in shock transmission.

As shown in Figure 8, we find that – especially in the case of floods – regions with above-average capital per worker experience a more persistent and more severe contraction in output after an event, with more limited recovery after three years than lower-capital regions. This result may reflect fixed assets' susceptibility to disruptions and their role in supply chains. In the case of windstorms and wildfires, higher-capital regions experience also experience a marginally more severe contraction after an event, though differences between high and low capital-density regions are only partially significant.

Greater insurance coverage is linked to less severe long-term output losses from extreme events and faster recovery, for floods, windstorms and wildfires. Our measure of insurance coverage serves as a proxy for the share of capital that would be replaced in the event of an extreme event. Especially for floods, regions with high insurance coverage experience a significantly greater degree of recovery after three years than those with low insurance coverage. For low insurance-coverage regions, output losses from floods are persistent and significantly negative until the end of the projection horizon.[19]

Finally, more limited (regional) fiscal space also appears, to some extent, to exacerbate the effects of floods and wildfires. Output losses in regions with more limited fiscal space remain significantly larger two years after an event compared to regions with greater fiscal capacity. This result is aligned with the broader empirical literature showing that countries with constrained fiscal space tend to experience more persistent output losses and slower recovery (Lis and Nickel, 2009, Nguyen et al., 2025). Regional fiscal capacity complements insurance markets by enabling timely public repairs, restoring infrastructure, and supporting households and firms during the recovery phase. However, it is worth noting that our fiscal-space measure captures only (sub-)regional components of fiscal space, namely municipal liquidity and indebtedness. This dimension is economically meaningful after an event, as municipalities may implement temporary deferrals or fractioning of local taxes (e.g., local property or council taxes, municipal road taxes), provide short-term financing of urgent repairs, or cover bridging expenditures before regional or central programmes become operational. Municipalities with stronger balance sheets can mobilise these instruments earlier and more flexibly, particularly for lower-severity events that may not trigger national support. However, our indicator does not capture the extent of central government support and thus does not reflect the full fiscal response capacity to extreme weather events.

### 4.4 The role of data frequency: quarterly and annual models

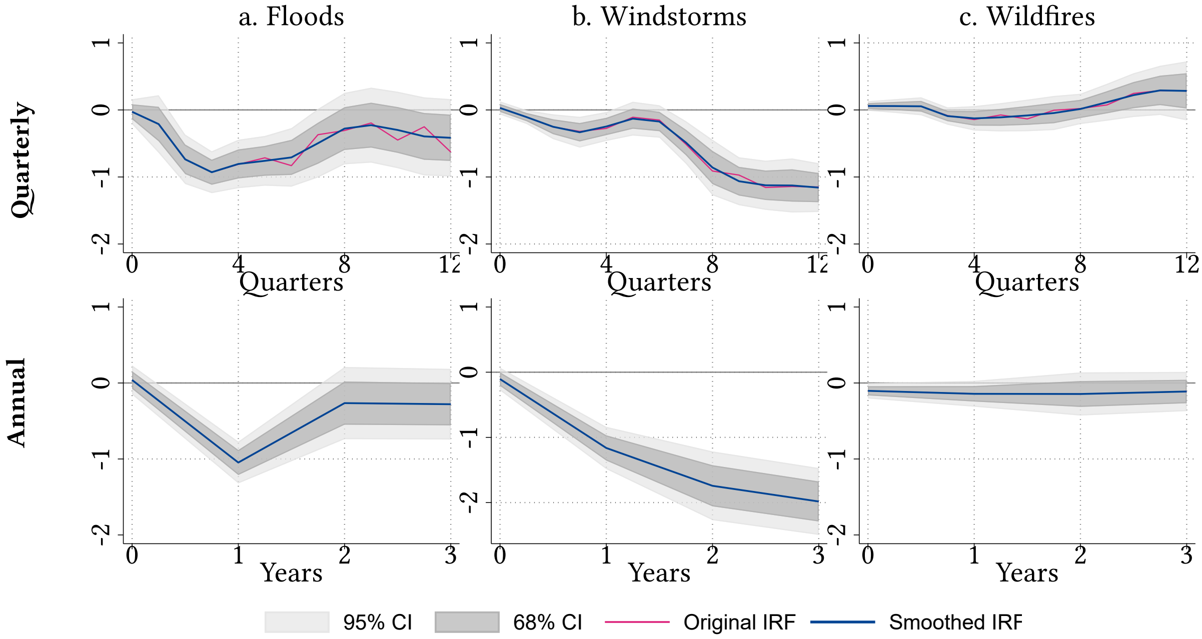
For comparability with results from the existing literature, we aggregate our extreme weather shock series and our macroeconomic series (the monthly proxy for GDP as well as all controls) to quarterly and annual frequency, and re-estimate equation (1) at these lower frequencies. Quarterly series are constructed by aggregating the monthly data, while annual series use the corresponding original annual untransformed series. Summing our monthly GDP proxy across years yields the original real regional GDP series as reported officially. The extreme weather event series are summed by event type across quarters or years.

Interestingly, results are broadly comparable in terms of direction, size and significance of effects (see Figures 6 and 9): for all three extreme event types considered, using quarterly or annual data instead of monthly data, we identify significant negative effects on regional output, with windstorms leading to the most severe and most persistent impacts. This points to the effectiveness of our extreme weather event shock series in enabling clear identification. Importantly, furthermore, there is no evidence of persistence bias introduced by our monthly disaggregation. To the contrary, it appears that the aggregation to annual frequency creates persistence towards the end of the projection horizon. Monthly data naturally also shed more light on within-year dynamics of the recovery.

In the case of floods, this means that annual-frequency results suggest a greater degree of recovery – in fact, no permanent effects – than monthly results. In our case, in the annual specification floods lead to a significant decline in regional output of about 1 percentage point in the first year, and a return close to pre-event level in the second and third years. Usman et al. (2025b) and Costa and Hooley (2025), by contrast, find persistent long-term output losses of about 2 percentage points four to five years after an event. Beyond differences in country coverage between our and existing studies, Spain's institutional

[19] Spain has a public insurer – the Consorcio de Compensación de Seguros (CCS) – that covers damages from floods, windstorms and wildfires, but only when these are deemed extraordinary. Damages from severe but below-threshold events (e.g., storms with gusts below 120km/h) are not covered. It applies as an add-on to products bought in private insurance markets, but a significant share of properties lacks private insurance. Insured sums may also be too low to rebuild or replace assets.

**Figure 9: Impulse responses of per capita GDP to extreme weather events, by frequency**
(Percentage points deviation from pre-shock level, panel local projections)




Note: graphs show impulse responses, derived from a panel local projections approach, in response to a median shock of the type mentioned above the chart. Regions are divided into high and low capital per worker regions based on the capital-to-worker ratio. Regions are divided into high and low fiscal space regions based on a composite indicator of regional fiscal space. Regions are divided into high and low insurance coverage based on the ratio of insured to total capital. IRFs were smoothed using a cubic spline.

features, such as the presence of a public insurer of last resort (CCS), may mitigate longer-term effects, as discussed in Section 4.3. How our shock variable is constructed may also play a role in driving results. In the case of windstorms, annual-frequency results suggest a permanent and continuing deterioration in output, comparable to effects identified by Costa and Hooley (2025), though potentially overstating the overall magnitude of damages: our monthly results point to an incomplete but nonetheless significant recovery towards the end of the projection horizon. For wildfires, the contrast is even clearer: the effects of wildfires appear short-lived though significant in the monthly specification, while they become marginal – in terms of both economic and econometric significance – in the annual model. This points to the additional insight using higher-frequency data can create for identifying short-term economic effects of extreme weather events.

Our findings relate to a broader discussion of the consequences of temporal aggregation in macroeconometrics. A large literature shows that moving from high- to low-frequency data alters the stochastic properties of time series and, in particular, the estimated persistence and dynamic propagation of shocks.[20] Christiano and Eichenbaum (1987) and, later, McCrorie and Chambers (2006) show that temporal aggregation can increase the moving-average order of a time series representation, which can generate spurious Granger-causal relations and apparent persistence even if the underlying process is not persistent.[21]

[20] For example, see Rossana and Seater (1995) and Marcellino (1999), who document that temporal aggregation can change autoregressive orders, bias persistence measures, and distort impulse-response functions in univariate and multivariate systems.
[21] Related work by Wei (1978) shows that temporal aggregation can bias parameter estimates in distributed-lag models, further illustrating that estimated dynamic responses at low frequency may not reflect the true short-run adjustment process. Thus, lower frequencies or the aggregation of short-run dynamics can induce apparent long memory in macroeconomic aggregates, as shown in Granger (1980) and Chambers (1998), which underscores that long-run responses inferred from low-frequency data may not map directly into the underlying higher-frequency process.

## 5 Conclusion and policy implications

**Using high-frequency regional data for Spain, we find that extreme weather events, particularly floods and windstorms, entail economically and statistically significant and persistent reductions in output per capita.** The impacts of floods and windstorms both peak at about a 1 percentage point decline in the level of output per capita, with recovery after floods quicker than after windstorms, though in both cases recovery remains incomplete. Wildfires cause a short-lived, more limited contraction of about 0.2 percentage points during the year after an event. Furthermore, regions with greater capital density, lower insurance coverage and more limited fiscal space tend to see more severe output effects and slower recoveries, especially after floods. Our findings build on a panel local projections approach and leverage exogenous, intensity-calibrated extreme weather event shocks and a new monthly macroeconomic dataset for 47 Spanish NUTS-3 regions between 2000 and 2022. Extensions to our analysis might include exploring the potential non-linearity of effects, considering spatial spillovers to neighbouring regions and inferring national-level effects, or testing for the presence of adaptation. Longer-term economic effects of the increasing frequency and severity of extreme weather events also merit analysis.

**Taken together, our findings imply that the impacts of extreme weather events are macroeconomically relevant** – in terms of both magnitude and persistence – and thus warrant stabilisation policies in response, especially as climate change accelerates. Therefore, integrating climate risk into macroeconomic policy frameworks is critical. To limit the expected volatility in output and associated welfare losses from extreme weather events, policy priorities that could serve as macroeconomic insurance mechanisms to such events include (i) optimally designing the recovery approach, (ii) investing in targeted adaptation measures, and (iii) taking steps to limit fiscal and financial stability spillovers from extreme weather events. We discuss these in turn.

**For designing the recovery, the persistence of our estimated effects suggests that one-off disaster relief is insufficient,** and that sustained, well-targeted recovery policies may be needed to prevent longer-term scarring. Evidence from the high-frequency indicators underlying our output proxy reinforces this conclusion: employment remains depressed well beyond two years after floods or windstorms, pointing to sluggish labour market adjustment and the need for sustained support measures. Tourism, which is central to many of Spain's regions, contracts sharply after floods and recovers only slowly, amplifying event impacts. In line with this, prior evidence points to rapid and investment-driven reconstruction as a factor that can reduce the persistence of output losses (Cavallo et al., 2010, Von Peter et al., 2024). Policy design should therefore prioritise the speed of support, focussing on productive capital and infrastructure, rather than consumption transfers, while combining support with steps to enhance resilience – a concept that could be labelled "Build Back Better 2.0" in the context of accelerating physical climate risk.

**Our findings also underscore the importance of adaptation and resilience-building to mitigate the economic costs of extreme weather events.** This is the case especially for flood-prone regions, those with concentrated economic activity or capital, and those with low insurance coverage. Adaptation spending is generally considered significantly more cost-effective than ex-post reconstruction (cf. Global Commission on Adaptation (2019)). For example, investments in flood defenses, resilient infrastructure, and early-warning systems lower direct impacts and improve recovery dynamics (Costa and Hooley, 2025). Overall, adaptation and infrastructure resilience considerations should be embedded into public investment frameworks.

**The magnitude and persistence of estimated effects points to the urgency of maintaining fiscal buffers – at the regional and national levels – to manage post-event expenditure needs.** Furthermore, the slower pace of recovery in regions with more limited insurance coverage apparent in our results suggests there is a policy case for increasing insurance coverage, to support growth and limit the fiscal impact of extreme weather shocks. An insurance gap persists even in Spain, where the CCS, the Spanish public insurer of last resort, covers damages from extraordinary climate-related events. Our findings are in line with prior evidence pointing to the macroeconomic impacts of insured losses from extreme weather events being more limited (Von Peter et al., 2024). A European backstop for natural catastrophes, set up for example as a private-sector insurance pool backstopped by a public facility (Hahn and Mayr, 2024), could be one option to absorb tail losses beyond private (re-)insurer capacity.

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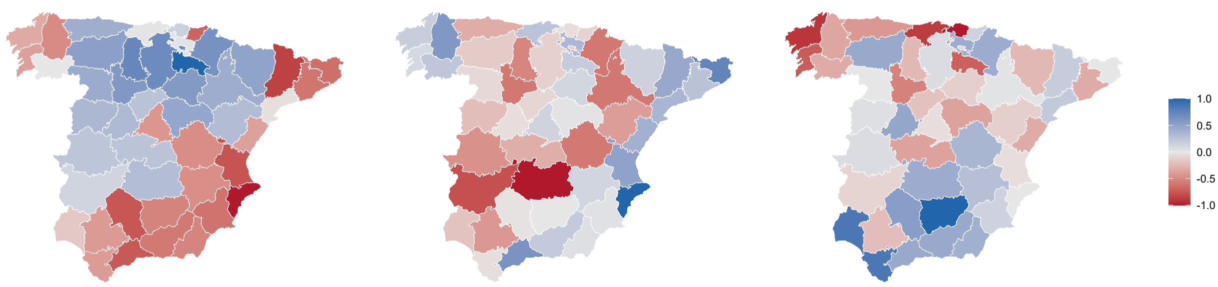
# Appendix

## A. 1 Tables and charts

**Table 3:** Comparison of "high" and "low" states

| | Capital density | | Insurance penetration | | Fiscal space | | Total |
|---|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High | |
| **Floods** | | | | | | | |
| N shocks | 192 | 76 | 104 | 164 | 119 | 149 | 268 |
| N shocks (%) | 72% | 28% | 39% | 61% | 44% | 56% | 100% |
| Average intensity | 47.9 | 36.5 | 36.0 | 50.1 | 44.5 | 44.7 | 44.6 |
| Sd intensity | 28.4 | 23.6 | 23.6 | 28.5 | 26.1 | 28.7 | 27.5 |
| **Windstorms** | | | | | | | |
| N shocks | 91 | 134 | 117 | 108 | 154 | 71 | 225 |
| N shocks (%) | 40% | 60% | 52% | 48% | 68% | 32% | 100% |
| Average intensity | 32.8 | 33.9 | 33.3 | 33.7 | 33.4 | 33.7 | 33.5 |
| Sd intensity | 4.3 | 4.0 | 4.4 | 3.9 | 4.2 | 4.0 | 4.2 |
| **Wildfires** | | | | | | | |
| N shocks | 79 | 54 | 55 | 78 | 51 | 82 | 133 |
| N shocks (%) | 59% | 41% | 41% | 59% | 38% | 62% | 100% |
| Average intensity | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |
| Sd intensity | 0.2 | 0.1 | 0.1 | 0.2 | 0.2 | 0.2 | 0.2 |
| **GDP per capita** *(thousands 2020 EUR)* | | | | | | | |
| Average | 21.4 | 22.4 | 20.9 | 23.0 | 22.5 | 21.4 | 21.9 |
| Standard deviation | 4.7 | 4.6 | 4.3 | 4.9 | 3.9 | 5.2 | 4.7 |

**Figure 10: Mediating factors**
Capital density, insurance coverage and fiscal space




**Capital density** **Insurance coverage** **Fiscal space**

Source: Authors' calculation based on ARDECO, CCS and Spanish national sources

## A. 2 Construction of monthly GDP proxy

The objective of the temporal disaggregation is to construct a coherent monthly GDP series from lower-frequency national accounts data. While annual GDP captures the total volume of economic activity, its low frequency limits its usefulness for analysing short-term macroeconomic dynamics, including the timing and propagation of shocks. Monthly indicators, by contrast, provide timely and granular information on sectoral activity but do not directly align with national accounts concepts. Temporal disaggregation provides a statistically consistent method for integrating these indicators with official aggregates, ensuring that the resulting high-frequency series both (i) preserves the annual totals published in the national accounts, and (ii) reflects the intra-year economic fluctuations embedded in the higher-frequency indicators.

This approach is used in empirical macroeconomics when monitoring economic cycles, modelling local projections with monthly data, or assessing the short-run impact of shocks that occur at sub-annual frequencies.

### A. 2.1 Methodological framework

When both low-frequency target variables and high-frequency indicators are available, different temporal disaggregation methods can be applied. Among the most widely used are Chow and Lin (1971), Fernandez (1981), Litterman (1983), Santos Silva and Cardoso (2001):

- **Chow and Lin (1971):** Assumes a linear relationship in levels between the high-frequency series and one or more indicators, with AR(1) errors governing the unobserved component. Ensures exact temporal aggregation but can transmit high-frequency noise from volatile indicators into the estimates. Works well when indicators and target series exhibit smooth co-movement, but less suitable when indicators are irregular or flow-type variables.
- **Fernandez (1981):** Reformulates the Chow–Lin model in first differences, making it appropriate for flow variables whose growth rates track underlying activity. The differenced structure filters high-frequency noise while preserving aggregation constraints, producing realistic intra-period dynamics. Performs particularly well when indicators are monthly flows that display substantial volatility.
- **Litterman (1983):** Imposes a random-walk process on the high-frequency series, generating very smooth estimates that minimise the influence of volatile indicators. This reduces noise but may over-smooth genuine economic fluctuations, especially when indicators contain meaningful high-frequency information. Best suited for target variables that evolve gradually over time.
- **Santos Silva and Cardoso (2001):** Extends the framework to a multivariate setting that efficiently combines multiple stationary indicators. Ensures aggregation consistency and improves precision when indicator information is spread across several variables but performs less well when indicators are non-stationary flows or exhibit strong short-term volatility.

Considering these statistical and econometric properties, the Fernandez (1981) method is the most appropriate choice for our temporal disaggregation because it models monthly movements through a differenced specification that links the growth rate of the target series to the growth rates of our indicators. This aligns well with the nature of our dataset, where the key predictors – such as social security affiliations, car registrations, oil consumption, construction permits, and trade flows – are volatile monthly flows that track short-term economic activity.

### A. 2.2 Our approach

We construct a monthly synthetic indicator of economic activity (MSIEA) as a proxy for real GDP per capita at the NUTS-3 region level following the approach proposed by Fernandez (1981). In this framework, the unobserved high-frequency series $y_t$ follows a regression model with random walk disturbances $u_t$, in the first step, and $v_t$, in the second step, where $x_t$ are high-frequency macroeconomic indicators. We follow a two-step algorithm:

1. **Annual to quarterly disaggregation**: estimation via maximum likelihood

$$y_t^Q = \beta x_t^Q + u_t \qquad \text{with} \qquad u_t = u_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2)$$

   subject to the aggregation constraint

$$Y_s^A = \sum_{t \in s} y_t^Q$$

   We estimate $y_t^Q$, obtaining $\hat{y}_t^Q$.

2. **Quarterly to monthly disaggregation**: estimation via maximum likelihood

$$y_t^M = \beta x_t^M + v_t \qquad \text{with} \qquad v_t = v_{t-1} + \xi_t, \text{and assuming} \quad \xi_t \sim N(0, \varpi^2)$$

   subject to the aggregation constraint

$$\hat{y}_g^Q = \sum_{t \in g} y_t^M$$

   We estimate $y_t^M$, obtaining $\hat{y}_t^M$.

This means that our monthly series are consistent with the known annual total province GDP and move smoothly and realistically within years by following the pattern of higher-frequency indicators that signal how short-term regional economic activity is evolving.

## A. 3 Construction of extreme weather event shocks

### A. 3.1 Daily high-resolution meteorological data

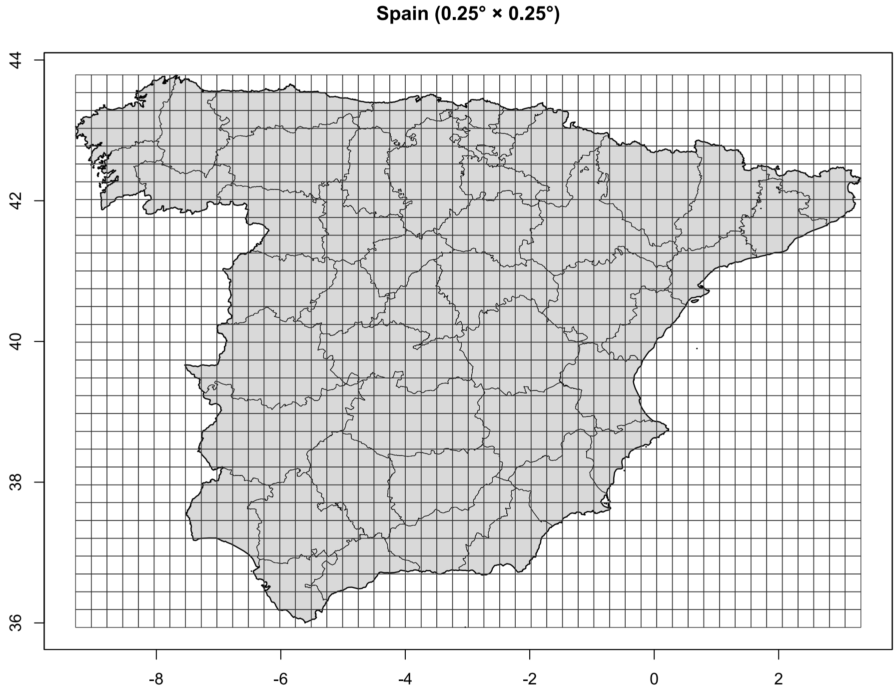
We rely on the AgERA5 Agrometeorological Indicators dataset to calibrate the intensity of extreme weather events. AgERA5 builds upon the ERA5 reanalysis dataset, the fifth-generation global climate and weather dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Copernicus Climate Change Service, 2023, Hersbach et al., 2023). Both AgERA5 and ERA5 originate from the same underlying raw data and physical modelling framework, which combine satellite and in-situ observations through a consistent global reanalysis process.[22] In practice, the reanalysis approach feeds past observations to a current weather model to deliver a complete and consistent picture of weather and climate over time.[23]

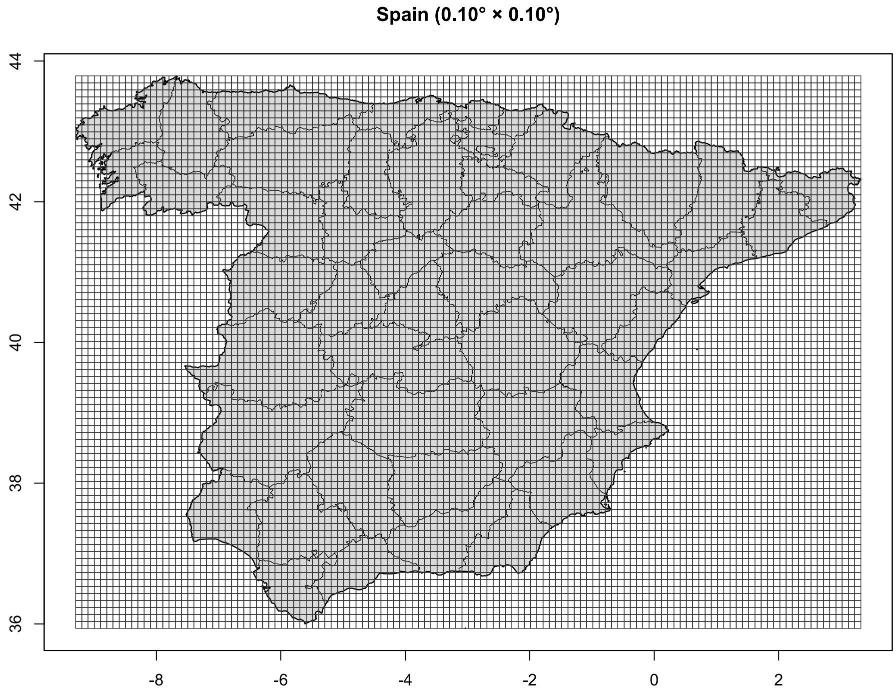
AgERA5 enhances ERA5 by (i) providing daily surface meteorological variables at a higher spatial resolution (0.10° × 0.10° compared to 0.25° × 0.25), from 1979 onwards, and by (ii) applying variable- and season-specific bias correction (Boogaard et al., 2020, Copernicus Climate Change Service, 2020). In the AgERA5 processing chain, hourly ERA5 data (native resolution of 0.28°) are first interpolated to a 0.1° grid and subsequently corrected using grid- and variable-specific regression equations calibrated through an

[22] Climate reanalysis provides a numerical reconstruction of the recent climate by assimilating historical observations into a fixed forecasting model.

[23] Weather measurements may contain gaps and overlaps, as they are retrieved from different sources such as weather stations, weather ballons, aircraft, ships, satellites, and so on. The reanalysis approach integrates and processes all these inputs through a model, blending overlapping pieces and reconstructing missing ones, thereby producing a globally consistent and gap-free datasets describing the atmosphere, land surface, and oceans over several decades (European Centre for Medium-Range Weather Forecasts (ECMWF), 2023).

**Figure 11: Meteorological grid comparison of the Spanish peninsula**




Source: Authors' calculation based on Copernicus Data Store datasets.

operational model (European Centre for Medium-Range Weather Forecasts (ECMWF), 2023). This downscaling adjustment procedure ensures that AgERA5 retains the large-scale physical consistency of ERA5, while providing a more accurate representation of local climatic conditions. These corrections are particularly relevant in mountainous and coastal areas, where standard reanalysis products tend to display systematic biases (Copernicus Climate Change Service, 2020).

For our purposes, the finer spatial granularity of AgERA5 allows for a more precise mapping between gridded meteorological data and NUTS-3 regions, capturing intra-regional heterogeneity in temperature and precipitation patterns (see Figure 11). Earlier studies (e.g., Bilal and Kanzig, 2024; Bilal and Rossi-Hansberg, 2023; Kotz et al., 2024) typically used 0.5° grids (e.g., Bilal and Kanzig, 2024; Bilal and Rossi-Hansberg, 2023; Kotz et al., 2024) or 0.25° grids (e.g., Usman et al., 2025a). The greater spatial precision used in our analysis enables a more accurate reflection of local climatic conditions. Moreover, although AgERA5 was originally developed for agricultural and environmental applications, its refinements vis-à-vis the original ERA5 data – such as a finer land-sea delineation and topography-adjusted bias corrections – enhance the accuracy of the core meteorological variables used in this study. These improvements make AgERA5 not only suitable for agro-meteorological modelling but also highly valuable for macroeconomic analyses, where spatially precise and bias-corrected meteorological data are essential for identifying local exposure to extreme weather events.

However, all these data do face an important limitation: being the result of "reanalysis", they provide model-based rather than purely observational data. This means that the values are reconstructed by assimilating station and satellite observations into a physical model, which may introduce model bias or uncertainty relative to raw station data. Yet relying exclusively on "pure" station observations would also pose challenges. Stations are unevenly distributed across space, and their data can vary in quality and temporal coverage and sometimes exhibit overlapping records. Moreover, aggregating such irregular and unevenly spaced point measurements into NUTS-3 region-level measurements would require strong spatial interpolation assumptions, potentially introducing even greater uncertainty.

Hence, for our empirical analysis, AgERA5 represents the most granular and spatially consistent source of meteorological information currently available, offering harmonised daily measures of the key variables we focus on – temperature, precipitation and wind speed – across the entire sample period and spatial coverage.

### A. 3.2 Construction of NUTS-3 level meteorological indicators

To calibrate shocks at the regional level, we construct daily meteorological series at the NUTS-3 level from the gridded AgERA5 Agrometeorological Indicators dataset.[24] The procedure consists of two steps:

1. **Spatial overlay and weighting:** The AgERA5 data are provided as daily *rasters*with a spatial resolution of 0.1° × 0.1°. Each raster cell represents a regularly spaced area on the Earth's surface, identified by its longitude and latitude coordinates. To link the meteorological data with administrative boundaries, the NUTS-3 polygons – approximating the regions' boundaries – are intersected directly with the AgERA5 raster grid to determine the share of each cell's area that lies within each region. The resulting area weights are computed with respect to the total surface of each NUTS-3 region, ensuring that all weights within a region sum to one. Three cases are considered:

   (a) If a raster cell lies **fully** within a NUTS-3 region, its weight equals the ratio of the cell's area to the region's total area.

[24] The processing is carried out in R using the terra package and Eurostat GISCO NUTS-3 boundary shapefiles, projected in the WGS 84 (EPSG:4326) coordinate system.

(b) If a raster cell **partially overlaps** a NUTS-3 region, its weight corresponds to the proportion of the cell's area contained within the region, again normalised by the region's total surface area.

(c) Raster cells that do **not intersect** any NUTS-3 region (e.g., that are entirely over sea or outside the province boundary) are excluded from the aggregation.

2. **Aggregation of raster data.** For each daily meteorological variable, AgERA5 raster values intersecting a given NUTS-3 region are matched with their area weights and aggregated to obtain regional measures. For each region and day, the area-weighted average of the variable is computed across all intersecting raster cells using the normalised weights described above. In addition, the maximum and minimum cell values within the region are recorded to capture the range of local variation; these are not weighted. Cells with missing values are excluded from the calculation, and the remaining weights are re-normalised so that they sum to one for each region and day.

The resulting database provides consistent, area-weighted daily climate indicators at the NUTS-3 level. Following Gortan et al. (2024), who proposes several weighting schemes – including population, night-time light, cropland, and area – the aggregation here is based on surface area. This best captures the de-facto, physical exposure of each region to meteorological conditions, rather than blurring the measurement of climatic conditions by including economic or demographic factors. This choice ensures that our aggregated region-level meteorological indicators reflect the spatial distribution of climate phenomena, independently of the spatial distributions of human and economic activity.

### A. 3.3 Calibrating climate shocks

In a last step, the meteorological indicators were used to calibrate the intensity of different extreme weather event types. We consider floods, windstorms and wildfires. Event dates were obtained from official sources, specifically HANZE for floods, Copernicus Climate Change Service for windstorms and Spain's Ministerio para la Transición Ecológica y el Reto Demográfico for wildfires:

- Data on flood dates were obtained from the HANZE database (2025), which compiles information on historical flood events and damages across Europe from a variety of sources.
- Data on windstorm dates were obtained from the Copernicus Climate Change Service (2025), which tracks windstorms associated with extratropical cyclones.
- Data on the wildfire dates as well as surface area burnt by wildfires were retrieved from Spain's Ministerio para la Transición Ecológica y el Reto Demográfico (2025) wildfire database. The database provides detailed statistics on the dates, cause, burned area, and type of surface vegetation affected by the fire, disaggregated by individual event, each of which is linked to a province (NUTS-3 region).

For the three types of extreme weather events, the above-mentioned sources allow us to calculate binary dummies that take the value of 1 on the day and hence the month that an event of the respective type happened, and 0 otherwise. This dummy is then multiplied by event-specific intensities sourced either from our re-processed AgERA5 meteorological indicators or from the sources mentioned above, specifically:

- For floods, we use maximum one-day precipitation during the event, in millimetres, sourced from AgERA5.

- For windstorms, we use the maximum 3-second, 10-metre (above the Earth's surface) wind gust in metres per second over the 72 hours centred around the footprint central time, sourced from AgERA5.
- For wildfires, we use the total surface area burned per day as a share of the total region area, in square kilometres, sourced from the Spanish Ministerio para la Transición Ecológica y el Reto Demográfico's wildfire database.

This means our resulting extreme event weather shocks reflect the precise meteorological conditions at the time and in the place where the event occurred.

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