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Abstract

Climate-related natural disasters, such as floods, are becoming increasingly frequent and severe. This paper proposes and validates a two-stage empirical framework to quantify their economic impact in Spain, with a particular emphasis on labor market outcomes. In the first stage, we construct a non-linear damage function to estimate flood-induced economic losses, relying on global EM-DAT data and imputing missing observations. In the second stage, we assess the effect of these shocks on monthly employment across Spanish provinces through a dynamic spatial panel model. This framework captures both the direct impacts in affected regions and the indirect spillover effects across economically interconnected areas. To validate our approach, we examine the 2024 DANA flood in Valencia and perform counterfactual simulations for alternative disaster locations. We further investigate the mitigating role of post-disaster insurance payouts. Our results underscore the non-linear nature of climate impacts, the decisive role of disaster location, and the potential of timely financial responses in accelerating labor market recovery.

Keywords: climate risk, floods, non-linear effects, labor market, spatial econometrics, disaster recovery.
JEL Classification: Q54; E24; R11; C33.

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1 Introduction

Climate-related extreme events are becoming more frequent and severe, posing growing risks to economic systems, infrastructure, and labor markets (Masson-Delmotte et al., 2021). Yet, despite this rising exposure, our ability to measure and anticipate their short-run economic consequences -particularly in real time- remains limited. Timely estimates of disaster impacts on employment are essential for effective policy response, risk management, and the design of resilience strategies (Cavallo and Noy, 2013; Deryugina et al., 2018).

This paper develops a two-stage framework to estimate the short-run employment effects of floods, combining imputed damage assessments with a spatial dynamic panel model of regional labor market dynamics. We illustrate the approach using the 2024 DANA flood in the province of Valencia, Spain, as a case study. Although our empirical focus is on Spain, the methodology is broadly applicable to other countries and climate-related disasters, such as the 2025 Texas floods in the United States.

In the first stage, we estimate the size of the disaster using a global damage function trained on historical EM-DAT data. The model predicts flood-induced economic losses as a share of GDP based on indicators such as mortality, duration, and population density, while explicitly accounting for non-linear effects. This addresses a central challenge in disaster economics: the lack of reliable damage data for a large share of recorded events (Felbermayr and Gröschl, 2018; Paprotny et al., 2018). Our imputed damages provide a consistent and scalable proxy for disaster intensity, suitable both for retrospective analysis and near-real-time estimation. In the second stage, we feed these damages into a dynamic spatial panel model of monthly employment at the NUTS-3 provincial level in Spain. This specification captures both the direct effects of local flooding and the indirect spillovers to economically connected regions through interprovincial economic linkages. We also analyze the role of post-disaster financial assistance, based on data on insurance payouts from Spain's Consorcio de Compensación de Seguros (Insurance Compensation Consortium). This enables us to assess not only the immediate disruption caused by floods but also the mitigating effect of timely recovery funding.

Our contributions are threefold. First, we develop a flexible damage imputation model that enhances incomplete disaster databases with consistent loss estimates. Second, we estimate a spatial dynamic labor model that identifies both direct and indirect employment effects nearly in real-time. Third, we quantify how recovery aid shapes the trajectory of labor market adjustment after climate shocks -an aspect often overlooked in empirical disaster research (Fakhruddin et al., 2022).

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and construction of key variables. Section 4 outlines the empirical framework. Section 5 presents the main findings, including model validation and counterfactual simulations. Section 6 illustrates the model's performance using the 2024 DANA flood in Valencia, highlighting both its predictive accuracy and its potential as a policy-relevant tool. Finally, Section 7 concludes.

2 Literature review

The economic consequences of natural disasters have been examined extensively across both macroeconomic and microeconomic dimensions, particularly with respect to output dynamics, labor markets, and reconstruction efforts. Floods, among the most frequent and costly natural hazards, have attracted growing attention as their severity and geographic scope intensify under climate change. Early macro-level studies such as Rasmussen (2004) and Noy (2009) document that disasters reduce short-run GDP growth and widen fiscal deficits, especially in low- and middle-income countries, with outcomes shaped by structural and institutional capacities. More recent contributions, including Cavallo and Noy (2013), highlight heterogeneity in post-disaster responses and the possibility of medium-term rebounds, particularly when reconstruction is supported by external financing or aid.

At the microeconomic level, disaster impacts on employment have been studied with increasing precision. Groen and Polivka (2010) analyze labor displacement after Hurricane Katrina using CPS data, finding persistent job losses in New Orleans. Deryugina et al. (2018) employ U.S. IRS and FEMA records to identify long-run declines in earnings and employment following hurricanes, while Belasen and Polachek (2014) show that labor market outcomes vary substantially across neighboring counties, reflecting complex spatial propagation mechanisms.

A growing body of work focuses specifically on floods. Strobl (2011) finds that hurricanes with inland flooding reduce short-run economic activity across U.S. counties, with stronger effects in poorer areas. Fomby et al. (2013) show that floods in developing countries depress GDP, investment, and trade in the short-term. In Europe, Paprotny et al. (2018) construct a harmonized panel of flood events and report that most damages are concentrated in a small number of severe, often underreported events. Felbermayr and Gröschl (2018) extend this analysis using EM-DAT, identifying systematic gaps in global floods loss reporting. Evidence for Spain remains scarce. García-Palomares and Moya (2020) highlights growing exposure to Mediterranean floods and stresses spatial vulnerability and the role of regional adaptation strategies. More broadly, the geographic dimension of disaster impacts has gained attention in recent years. Hsiang et al. (2017) and Kocornik-Mina et al. (2020) show that the long-run economic consequences critically depend on location, with urban hubs propagating shocks through national networks. Similarly, Ziegler and Kreft (2021) document persistent job losess in German municipalities, particularly in tradable sectors.

From a methodological perspective, spatial econometric models have been increasingly employed to capture regional spillovers and interdependencies. Elhorst (2014) provides a comprehensive treatment of spatial panel techniques, while Carvalho et al. (2016) emphasizes how local shocks propagate through production networks - mechanisms highly relevant for disaster-induced disruptions. Botzen et al. (2020) apply a spatial framework to study labor impacts of flood risk in the Netherlands, identifying cross-regional effects even in areas not directly hit. Another important strand concerns the measurement of disaster intensity. In the absence of reliable damage data, several studies employ physical proxies. For example, Jongman et al. (2012) and Kousky (2014) use precipitation and remote sensing data to estimate flood severity, while Guha-Sapir and Below (2016) highlight the limitations of EM-DAT and advocate for complementary imputation approaches.

Finally, post-disaster financial assistance plays a crucial role in shaping recovery. Raschky and Weck-Hannemann (2012) show that faster aid disbursements reduce economic losses, while Bevc et al. (2020) demonstrates that aid responsiveness influences both labor market outcomes and political trust. Deryugina et al. (2018) confirms that public transfers help mitigate household income and employment losses. Recent work by Gall and Cutter (2021) further emphasizes the role of insurance payouts in accelerating post-disaster economic normalization.

This paper contributes to these strands by jointly addressing three gaps: modeling imputed damages, accounting for spatial propagation of employment effects, and analyzing the role of financial assistance in shaping recovery. By applying a two-stage framework to the 2024 DANA flood in Spain using monthly data at the NUTS-3 level, it provides novel evidence on labor market resilience and post-disaster adjustment in the European context.

3 Data and descriptive statistics

Our analysis combines global disaster records with monthly subnational economic and climate data for Spain. The dataset is constructed to parallel the two-stage empirical strategy. In the first stage, we assemble a global panel of flood events to estimate a damage function. In the second stage, we build a monthly panel of Spanish provinces (NUTS-3 level) to quantify the labor market effects of these shocks. This section details the data sources, describes the construction of key variables, and presents summary statistics.

3.1 Climate event data: EM-DAT and climate severity

Our primary source for disaster events is the EM-DAT International Disaster Database, maintained by the Centre for Research on the Epidemiology of Disasters (CRED).[1] EM-DAT provides harmonized records of natural disasters since 1900, including event type, date, geographic location, number of affected individuals, fatalities, and -when available- estimated economic damages in constant U.S. dollars. To be included in EM-DAT, an event must satisfy at least one of the following criteria: (i) ten or more reported deaths, (ii) 100 or more people affected, (iii) a declaration of a state of emergency, or (iv) a call for international assistance.

We extract all flood events recorded between 1980 and 2025. This period strikes a balance between data reliability and alignment with auxiliary macroeconomic and climatic indicators, while earlier decades are excluded due inconsistent reporting. The resulting dataset covers 5,513 global flood events, of which only 32% report economic damages. This coverage gap that is particularly pronounced in earlier years and in lower-income countries, but it is also present in Europe. For Spain, we identify 32 flood events between 1980 and 2024, 13 of which lack damage information. To address this missingness, we estimate a global damage function that imputes losses based on observable event characteristics such as fatalities, duration, and population density.

Most EM-DAT flood events in Spain are georeferenced at the municipal level. We aggregate these to the provincial (NUTS-3) level to align with our economic data. When events are reported at a broader or ambiguous geographic level, we rely on official sources and media archives to allocate them to the appropriate province.

[1] https://www.emdat.be/

To enrich the disaster records with a physical measure of severity, we merge EM-DAT with monthly precipitation data from the Spanish Meteorological Agency (AEMET).[2] Using observations from more than 800 meteorological stations, we compute the standardized maximum monthly precipitation of each province. This variable serves as a proxy for the physical intensity of climate-related hazards and as a robustness check in Appendix 1.1. Because it is orthogonal to economic conditions, it provides an independent measure of shock severity.

3.2 Economic damage and exposure proxies

To estimate the economic footprint of floods, we express damages as a share of national real GDP in the year of each event, using country-level GDP data from the World Bank's World Development Indicators. Population density, obtained from UN World Population Prospects, serves as a proxy for capital stock exposure and infrastructure vulnerability.

We also compute two internal severity metrics from EM-DAT: (i) the mortality rate, measured as deaths per capita, and (ii) event duration, expressed as a fraction of the calendar year. Both indicators are available for all events in our sample and are included as covariates in the damage function.

The resulting dataset allows us to fit a global model of flood-related economic damages, which we then use to impute losses for Spanish floods without reported estimates. The same framework is generalizable: it can be applied to other countries or disaster types lacking damage estimates, or used in near real time before official assessments are published.

[2] https://opendata.aemet.es/

3.3 Employment data: Spanish provinces

For our second-stage analysis, we focus on monthly employment data at the NUTS-3 level (50 Spanish provinces). Our main source is the Social Security Affiliation Data, provided by the Ministerio de Inclusión, Seguridad Social y Migraciones. This dataset reports the stock of affiliates to the Spanish Social Security system by province. It covers both private- and public-sector employment and is released on a monthly basis. The data have been cleaned for definitional breaks and seasonally adjusted using the X-13ARIMA method implemented in Demetra+.

To ensure comparability over time, we adjust the series to account for affiliates enrolled in temporary employment protection schemes (ERTEs), which allow firms to temporarily reduce working hours or suspend contracts during economic downturns or unforeseen shocks. Specifically, we remove ERTE-affiliated workers from the series, thereby obtaining an effective measure of net employment. This adjustment is essential to avoid confounding the impact of flood events with unrelated labor market interventions.

The panel spans from January 2000 to March 2025, yielding more than 15,000 province-month observations. Employment is transformed by logarithmic differences to obtain monthly growth rates, which constitute the dependent variable in the spatial panel analysis.

3.4 Spatial interdependencies: trade-based linkages

To capture economic spillovers across provinces, we construct a spatial weight matrix based on interprovincial trade flows. The matrix W is row-normalized and excludes diagonal elements to prevent self-dependence. It is sourced from the C-Intereg project[3] and reflects trade linkages across Spanish provinces for 2019.

Although economic structures evolve over time, our robustness checks (Appendix

[3] Annual Trade Dashboard – C-INTEREG.

1) indicate that the topology of interprovincial trade networks remains relatively stable. Consistent with this evidence, our results remain materially unchanged when we replace the 2019 matrix with its historical counterpart from 1995.

3.5 Disaster relief data: public insurance payouts

Post-disaster assistance data are obtained from the Consorcio de Compensación de Seguros (CCS)[4], a public insurance mechanism in Spain that compensates for catastrophic risks typically excluded from private insurance, including floods. The CCS is funded by mandatory surcharges on most property insurance policies, which guarantees broad coverage and financial sustainability.

We collect monthly CCS indemnity payments at the provincial level and scale them by estimated damages to obtain the share of losses compensated. This variable serves as a proxy for both the scale and the timeliness of financial assistance provided after each flood event. Since indemnities are generally disbursed with a lag of several months due to administrative processing and claim verification, we incorporate this variable into our model using a distributed lag specification. This approach is supported by empirical evidence showing that indemnity payouts -consistent with their theoretical role as liquidity buffers- can significantly mitigate the adverse economic effects of disasters and accelerate recovery (Raschky and Weck-Hannemann, 2012; Gall and Cutter, 2021). Our variable reflects the actual intensity of fiscal response through a standardized, observable channel.

3.6 Summary statistics

Table 1 reports descriptive statistics for the key variables used in estimating the global flood damage function (Stage 1). The mortality rate (perpop_i), measured as the ratio of fatalities

[4] Consorcio de Seguros.

Table 1: Summary statistics (Stage 1 dataset: Global flood events)

Variable	**Mean**	**Std. Dev.**	**Min / Median / Max**
Mortality rate (perpop_i)	0.00020	0.00097	0.00000 / 0.00002 / 0.02380
Flood duration (perdur_i)	3.86	5.80	0.27 / 1.92 / 46.03
Log population density (lden_i)	4.44	1.26	0.48 / 4.72 / 8.73

Table 2: Summary statistics (Stage 2 dataset: Spanish provinces, monthly panel)

Variable	**Mean**	**Std. Dev.**	**Min / Median / Max**
Employment growth ($y_{i,t}$)	0.18	0.55	−9.66 / 0.22 / 14.44
Standardized precipitation ($\text{prestd}_{i,t}$)	0.00	1.00	−2.23 / −0.21 / 6.27
Insurance coverage ($\text{seg}_{i,t}$)	0.01	0.45	0.00 / 0.00 / 66.47
Flood damage ($s_{i,t}$)	0.00	0.01	0.00 / 0.00 / 1.56

to affected population, is highly right-skewed, with a median value close to zero and a maximum of 0.02%. Flood duration (perdur_i), expressed as a fraction of the calendar year, varies substantially across events, ranging from less than 0.3% to more than 46%. The log of population density (lden_i), employed as a proxy for economic exposure, spans from 0.48 to 8.73, with a standard deviation of 1.26.

Table 2 reports descriptive statistics for the variables used in estimating the employment impacts of floods across Spanish provinces (Stage 2). Monthly employment growth ($y_{i,t}$) has a mean of 0.18% with a standard deviation of 0.55 percentage points, and exhibits extreme values ranging from −9.66% to 14.44%. Flood-related damages ($s_{i,t}$) are zero in the vast majority of province-month observations but can reach as high as 1.56% of national GDP in extreme cases. The standardized precipitation measure ($\text{prestd}_{i,t}$) behaves as expected, centered around zero with a standard deviation close to one. Insurance payout coverage ($\text{seg}_{i,t}$), defined as the ratio of indemnities to estimated damage, displays a highly skewed distribution: while the mean is only 1%, maximum values exceed 66%, reflecting targeted post-disaster compensation in the aftermath of large-scale events.

Overall, these statistics underscores the episodic and highly skewed nature of climate-related shocks. While most province-months remain unaffected, floods events generate substantial heterogeneity in physical exposure, economic damage, and policy response. These empirical patterns motivate our modeling choices, particularly the inclusion of non-linear interactions and spatial dynamics, which are designed to capture both the intensity and propagation of disaster shocks. The next section outlines the empirical framework in detail.

4 Empirical strategy

We develop an empirical framework to identify and quantify the short-run economic impact of floods on local labor markets, with particular attention to event intensity and post-disaster policy responses. The strategy proceeds in two stages. In the first stage, we estimate a model of flood-induced economic damages using a global database of disasters, which enables us to impute missing or unreliable damage observations. In the second stage, we employ these damaged shocks to estimate their causal effects on employment dynamics across Spanish provinces using a spatial dynamic panel model. This two-stages approach builds on, and extends, earlier contributions on the economic effects of natural disasters (e.g., Strobl, 2011), while allowing us to incorporate both non-linearities in shock intensity and interregional spillovers in labor market adjustment.

4.1 Stage 1: estimating flood damages

Economic loss data from natural disasters are often missing, biased, or inconsistently reported across countries, particularly in developing regions or when damages occur outside of insured assets (Guha-Sapir and Below, 2016). To address this limitation, we estimate a damage function that relates reported economic losses to physical characteristics of floods and to proxies for exposure and vulnerability. This approach provides a consistent and harmonized measure of flood intensity, suitable for causal identification in the second stage.

Our sample is drawn from EM-DAT and includes 1,342 flood events between 1980 and 2024 with non-missing values for damage (as % of real GDP), fatalities, event duration, GDP, and population density. The dependent variable, total economic damage D_i, is expressed as a share of national real GDP, thereby capturing both direct and indirect economic losses of each event. The model specification is:

$$\begin{aligned} D_i = \alpha + \beta_1 \, \mathrm{perpop}_i + \beta_2 \, \mathrm{perdur}_i + \beta_3 \, \mathrm{lden}_i + \sum_{k=1}^{4} \theta_k \, D_{k,i} \cdot \mathrm{perpop}_i \\ + \sum_{k=1}^{4} \phi_k \, D_{k,i} \cdot \mathrm{perdur}_i + \sum_{k=1}^{4} \eta_k \, D_{k,i} \cdot \mathrm{lden}_i + \gamma_c + \varepsilon_i \end{aligned} \tag{1}$$

where:

- perpop_i: mortality rate (fatalities over affected population), proxying the event severity;
- perdur_i: flood duration as a share of the calendar year;
- $\mathrm{lden}_i = \log(\mathrm{PopDensity}_i)$: proxy for infrastructure concentration and economic exposure;
- $D_{k,i}$: dummy variables for severity bins: 80–85%, 85–90%, 90–95%, and 95–100%;
- $D_{k,i} \cdot \mathrm{perpop}_i$, $D_{k,i} \cdot \mathrm{perdur}_i$, and $D_{k,i} \cdot \mathrm{lden}_i$: interaction terms allowing the marginal effects of mortality, duration, and density to vary non-linearly with event severity;
- α: constant; γ_c: country fixed effects; ε_i: idiosyncratic error.

The inclusion of interaction terms reflects the hypothesis that the marginal effect of physical exposure (e.g., density or fatalities) on economic losses is non-linear and contingent on event severity. This is consistent with evidence showing that moderate events are often absorbed by adaptive infrastructure and emergency protocols, whereas extreme events exceed resilience thresholds and generate cascading economic disruptions (Hallegatte et al., 2015, Noy and duPont IV, 2019).

We estimate the model using ordinary least square (OLS), which combine good performance with simplicity and interpretability. As a robustness check, we also experimented with alternative approaches such as machine learning tree models (see Appendix 1.2), but these yielded less accurate results .

4.2 Stage 2: estimating employment effects

Having constructed a harmonized measure of flood-induced damages, we turn to the analysis of their dynamic and spatial effects on labour market in Spain. Specifically, we estimate a spatial panel model of monthly employment growth at the provincial level, which allows us to capture both direct and spillover effects of flood shocks across economically interconnected regions. The specification is:

$$y_{i,t} = \sum_{k=1}^{K} \beta_{s_i}^{k} \, s_{i,t-k} + \sum_{k=1}^{K} \beta_{s_j}^{k} \, \Omega s_{j,t-k} + \lambda \, \Omega y_{i,t} + \phi_1 \, y_{i,t-1} + \phi_2 \, y_{i,t-2} + \mu_i + \eta_t + u_{i,t} \tag{2}$$

where:

- $y_{i,t}$: monthly employment growth in province i;
- $s_{i,t-k}$: flood shock in province i at lag k (measured as damage % GDP);
- $\Omega s_{j,t-k}$: spatially weighted shocks in other provinces (using a trade-based matrix Ω);
- $\Omega y_{i,t}$: contemporaneous spatial impact of employment;
- $y_{i,t-1}$, $y_{i,t-2}$: own employment lags capturing dynamic persistence;

- μ_i, η_t: province and time fixed effects;

- $u_{i,t}$: idiosyncratic error term.

This model captures three distinct mechanisms: the direct effects of flood shocks ($\beta^k_{s_i}$), the contemporaneous spatial spillovers ($\beta^k_{s_j}$) transmitted through trade-linked provinces, and the spatial dependence in employment dynamics (λ). The spatial weighting matrix Ω reflects interprovincial trade linkages, following the approach in in regional production networks (Ramondo et al., 2016; Carvalho and Tahbaz-Salehi, 2021).

To account for potential non-linearities in the response to flood events, we introduce a binary indicator I_{ext} identifying extreme shocks, defined as those above two standard deviations of the national monthly damage distribution.[5] The non-linear model becomes:

$$y_{i,t} = \sum_{k=1}^{K} (\beta^k_{s_i} + \delta^k_{s_i} I_{ext})\, s_{i,t-k} + \sum_{k=1}^{K} \beta^k_{s_j}\, \Omega s_{j,t-k} + \lambda\, \Omega y_{i,t} + \phi_1\, y_{i,t-1} + \phi_2\, y_{i,t-2} + \mu_i + \eta_t + u_{i,t} \tag{3}$$

where $\delta^k_{s_i}$ captures the additional marginal effect of extreme events.

Extension: post-disaster recovery via insurance

To capture post-disaster recovery dynamics, we extend the model by incorporating the effect of insurance payouts issued by the Spanish Consorcio de Compensación de Seguros. These indemnities are treated as ex-post financial transfers, scaled by estimated damages, and enter

[5] An indicator function classifies an event as extreme when its severity exceeds two standard deviations above the mean severity of recorded floods in the sample. For the specification based on estimated economic damages, the threshold is set, on average, at 0.46% of Spanish GDP per affected province. For the precipitation-based specification, the threshold is set, on average, at 185 millimeters per square meter per affected province. We also tested the inclusion of supplementary variables capturing events spanning one to two standard deviations (i.e. 0.25% to 0.46% of GDP), but these variables proved statistically insignificant.

the specification as a mitigating factor influencing the adjustment path of employment. The extended model is:

$$y_{i,t} = \sum_{k=1}^{K}(\beta_{s_i}^{k} + \delta_{s_i}^{k} I_{ext})\, s_{i,t-k} + \sum_{k=1}^{K}\beta_{s_j}^{k}\, \Omega s_{j,t-k} + \sum_{\ell=1}^{L}\gamma_{rrf_i}^{\ell}\, rrf_{i,t-\ell} + \sum_{\ell=1}^{L}\gamma_{rrf_j}^{\ell}\, \Omega rrf_{j,t-\ell}$$

$$+ \lambda\, \Omega y_{i,t} + \phi_1\, y_{i,t-1} + \phi_2\, y_{i,t-2} + \mu_i + \eta_t + u_{i,t} \tag{4}$$

where:

- $rrf_{i,t-\ell}$: insurance payouts in province i, lagged ℓ months;
- $\Omega rrf_{j,t-\ell}$: spatially weighted payouts in other provinces;
- $\gamma_{rrf_j}^{\ell}$: recovery coefficients at lag ℓ;
- All other terms as previously defined.

The spatial models are estimated using two-stage instrumental variables feasible generalized least squares (IV-FGLS), with standard errors robust to heteroskedasticity, autocorrelation, and cross-sectional dependence. Lagged employment terms $\Omega y_{i,t-h}$ serve as valid instrument for isolating the contemporaneous spillovers effects of employment shocks $\Omega y_{i,t}$. In all specifications, we include both regional and time fixed effects to control for unobserved heterogeneity.

Incorporating parameter and shocks uncertainty into the model

To assess the robustness of our results and to quantify the uncertainty inherent in the estimation process, we implement a Monte Carlo simulation framework that explicitly accounts for both parameter uncertainty -arising from the estimation of model coefficients- and shock uncertainty -arising from unobserved variation. The simulations build directly on the estimated dynamic spatial panel model presented in the previous subsections. Specifically, we use the estimated coefficient vector, $\hat{\boldsymbol{\beta}}$, together with its variance-covariance matrix, $\hat{\boldsymbol{V}}$, to generate simulated draws of the parameter vector:

$$\boldsymbol{\beta}^{(b)} \sim \mathcal{N}(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{V}}), \tag{5}$$

where $b = 1, \ldots, B$ indexes the simulation draws. This procedure captures the uncertainty associated with estimation error in the coefficients. In parallel, we account for shocks uncertainty by drawing additive shocks from a normal distribution with variance equal to the estimated residual variance of the model $\hat{\sigma}^2$:

$$\varepsilon_{i,t}^{(b)} \sim \mathcal{N}(0, \hat{\sigma}^2), \tag{6}$$

where i indexes provinces and t denotes time.

We run $B = 4000$ Monte Carlo simulations. In each iteration, the model is dynamically simulated forward using a combination of initial conditions, province-specific flood shocks, spatial spillovers through trade linkages, and post-disaster insurance payouts. The simulation yield a distribution of potential employment growth trajectories at the province level, from which we compute key percentiles (P5, P16, median, P84, P95) to construct confidence bands. These confidence bands provide a visual representation of the uncertainty surrounding the central scenario, reflecting both estimation and residual error.

To facilitate a clearer assessment of the medium- and long-term implications of flood-induced disruptions on regional labor markets, we also compute the cumulative effects of the simulated employment growth trajectories over time. Formally, for each simulation b and province i, the accumulated employment path is given by:

$$\tilde{y}_{i,t}^{(b)} = \sum_{\tau=t_0}^{t} y_{i,\tau}^{(b)}, \tag{7}$$

where $y_{i,\tau}^{(b)}$ denotes the simulated employment growth rate in period τ and t_0 corresponds to the period immediately preceding the shock ($t = 0$). This aggregation transforms flow effects into a stock-like measure, allowing us to track deviations from the no-shock counterfactual over time. This step is critical for two reasons. First, it captures the persistence of the shock: even modest temporary declines in employment growth can accumulate into sizable losses if not reversed quickly. Second, it provides a more policy-relevant interpretation of the shock's total economic burden, as the cumulative deviations from trend reflect forgone employment gains or slower recovery dynamics.

Beyond the cumulative aggregates, we also conduct a structural decomposition of the simulated impacts. For each simulation and time period, we isolate the marginal contribution of three mutually exclusive transmission channels:

(i) *Direct effects* resulting from flood damages in the affected province;

(ii) *Indirect effects* generated via trade-based economic linkages with other provinces, or driven by autoregressive employment dynamics;

(iii) *Recovery effects* arising from the disbursement of public insurance payouts.

The decomposition is implemented mechanically by isolating the contribution of each term in the model's structural equation, using the simulated $\beta^{(b)}$ coefficients together with the corresponding regressors. This exercise quantifies the relative importance of each transmission channel in shaping the employment response across time and space. By combining cumulative dynamics with structural decomposition under uncertainty, this simulation-based framework provides a powerful tool: it not only delivers point estimates, but also characterizes the full distribution of potential labor market trajectories, while disentangling the underlying mechanisms.

Robustness and external validity

We conduct several robustness checks in Appendix 1:

(i) Replacing flood damages with standardized precipitation from AEMET;

(ii) Re-estimating the model using alternative spatial weight matrices (e.g., trade flows in 1995 vs. 2019);

Across specifications, the results consistently point to non-linear and spatially diffuse effects of flood shocks on employment. The proposed framework contributes to the emerging literature on climate-related transition risks and their real-time macroeconomic consequences.

5 Results on the impact of flooding on employment

5.1 First-stage estimation results: non-linear damage function

The first-stage estimation results reveal pronounced non-linearities in the relationship between flood characteristics and economic damages. As reported in Table 3, the baseline coefficients for mortality, duration, and population density are not statistically different from zero, indicating that typical flood events tend to have limited economic consequences. By contrast, the interaction terms with severity dummies (D_k) unveil strong and statistically significant effects, highlighting that extreme events generate disproportionately large economic losses.

In particular, the mortality rate emerges as a powerful predictor in the upper deciles of severity. In the 95–100th percentile, each additional fatality per 1,000 affected individuals is associated with an increase in damages of more than 328 percentage points of GDP,

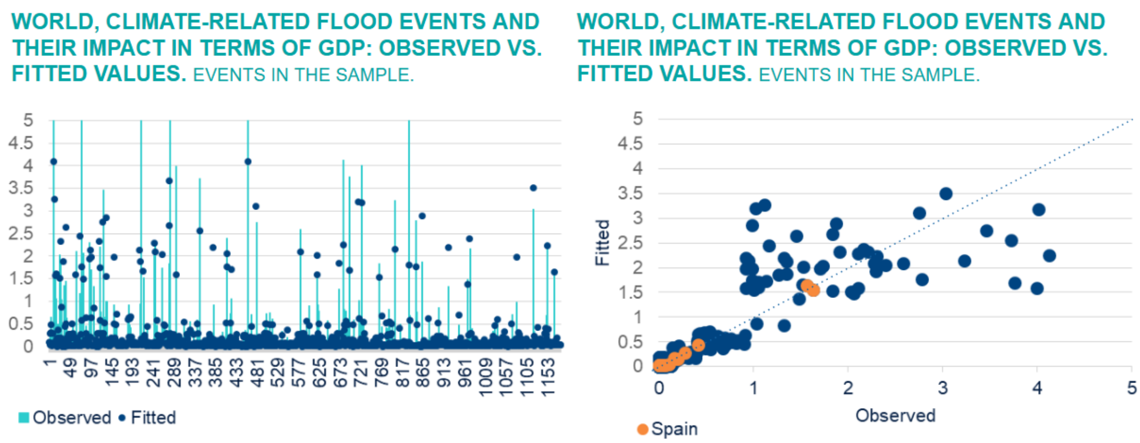

Figure 1: Observed vs. fitted values of flood damages as a share of GDP across global events.

with comparable magnitudes observed in the 90–95th percentile. Population density also becomes increasingly important as event severity rises. The interaction coefficients increase monotonically across severity bins and remain consistently significant at the 1% level. This pattern confirms that densely populated regions suffer more substantial losses during high-impact events, likely reflecting greater exposure of infrastructure and assets.

By contrast, flood duration does not exhibit statistically significant effects, even in the upper percentiles. Although theoretically relevant, its lack of significance suggests that duration alone is not a key determinant of damages once mortality and exposure are taking into account. This likely reflects the fact that, even in longer-lasting events, most of the economic impact tends to be concentrated in the immediate aftermath of the disaster.

The model's fitted values provide a strong empirical proxy for flood intensity. As illustrated in Figure 1, predicted damages closely track observed values particularly for high-loss events. The right panel, which plots fitted against observed damages, shows a correlation of 0.85. Spanish floods (in orange) align well with the 45-degree line, reinforcing the external validity of the damage function and confirming its suitability for imputing missing values in the Spanish sample.

Table 3: First-stage estimation: Global flood damage function (dependent variable: damages as % of GDP)

Variable	**Coefficient**	***p*-value**
Baseline effects		
Constant	0.230	0.366
Mortality rate (perpop$_i$)	-121.724	0.162
Duration (perdur$_i$)	0.001	0.699
Log pop. density (lden$_i$)	-0.043	0.442
Extreme event interactions (D_k)		
D_1 (95–100)×perpop	328.266***	0.009
D_1×perdur	0.055	0.141
D_1×lden	0.341***	0.000
D_2 (90–95)×perpop	335.468**	0.018
D_2×perdur	0.004	0.298
D_2×lden	0.092***	0.000
D_3 (85–90)×perpop	114.512**	0.020
D_3×perdur	-0.005	0.269
D_3×lden	0.056***	0.000
D_4 (80–85)×perpop	165.572	0.106
D_4×perdur	0.007	0.287
D_4×lden	0.025***	0.000
Adjusted R^2	0.770	

Notes: OLS regression with country fixed effects. Heteroskedasticity-robust standard errors. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

5.2 Second-stage or spatial model results: severity-dependent direct and spillover effects of floodign on employment

We now turn to the second stage of our empirical strategy, in which we estimate a spatial dynamic panel model to quantify the short-run employment effects of flood-related economic shocks. The specification incorporates local disaster intensity, interprovincial spillovers, temporal lags, and post-disaster recovery payouts, and is estimated using a two-stage IV FGLS procedure as described in Section 4.2. Table 4 reports the main results.

The model uncovers compelling evidence of non-linear employment responses to extreme climate events. Moderate floods have no discernible effect on employment, but for events classified as extreme -those exceeding two standard deviations above the mean severity distribution- the impacts are both economically large and statistically significant. In particular, the interaction between extreme flood indicators and lagged local shocks ($I_{ext} \times S_{t-1}$) yields a coefficient of -2.786 ($t = -6.39$), implying a contraction of nearly 2.8 percentage points in monthly employment growth relative to the counterfactual. Neither contemporaneous effects nor non-extreme floods exhibit statistically significant effects, underscoring the relevance of threshold-based dynamics.

While provinces not directly affected by flooding show no significant contemporaneous response to disaster shocks in neighboring regions (as indicated by the insignificant coefficients on $\Omega \times S_t$ and $\Omega \times S_{t-1}$), the model detects substantial second-order propagation through spatial economic interdependencies. The spatial lag of employment ($\Omega \times \hat{Y}_t$) is large and highly significant across all specifications (e.g., 0.964; $t = 12.27$), reflecting how disruptions in one region reverberate through trade linkages and supply chains. Employment dynamics also displays strong temporal persistence, with the first-order autoregressive term (Y_{t-1}) consistently estimated at around 0.15, highlighting the inertia in local labor market adjustments.

The results further demonstrate the critical role of public recovery funding in offsetting the adverse effects of climate shocks. Recovery payouts from Spain's insurance consortium exhibit delayed but powerful effects. Specifically, employment growth turns significantly positive starting in the third month after disbursement, with the effect peaking at month five ($\text{RF}_{t-5} = 3.513$, $t = 13.43$). This temporal pattern mirrors the typical administrative processing and liquidity deployment cycle. In addition, recovery funds generate positive spatial spillovers: payouts received in neighboring provinces significantly raise local employment ($\Omega \times \text{RF}_{t-2} = 2.160$, $t = 2.11$), consistent with cross-regional economic complementarities in reconstruction efforts.

Overall, these findings corroborate the theoretical structure of our empirical framework: climate shocks produce highly non-linear, localized labor market losses, which propagate indirectly through spatial linkages but can be mitigated -and even reversed- through timely and sizable financial interventions. The magnitude and persistence of these effects underscore the importance of both interregional economic networks and the timing of policy response in mitigating the labor market consequences of extreme weather events.

Table 4: Spatial model with panel data: Effects of flood shocks and recovery funds on monthly employment growth (dependent variable: Y_t)

	Linear	Non-linear	Non-linear (Extended)
Panel A. Flood shock effects			
Direct effects (Damaged provinces)			
S_t	−0.045	−0.157	−0.107
	(−0.38)	(0.37)	(−0.25)
S_{t-1}	−2.217***	0.136	0.181
	(−18.78)	(0.32)	(0.43)

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	Linear	Non-linear	Non-linear (Extended)
$I_{ext} \times S_t$		0.114	0.136
		(0.26)	(0.31)
$I_{ext} \times S_{t-1}$		-2.548^{***}	-2.786^{***}
		(−5.82)	(−6.39)
Direct effects (Undamaged provinces)			
$\Omega \times S_t$	−0.176	−0.162	−0.143
	(−0.45)	(−0.41)	(−0.37)
$\Omega \times S_{t-1}$	0.313	0.243	0.332
	(0.80)	(0.62)	(0.86)
Indirect or spillover effects			
$\Omega \times \hat{Y}_t$	0.916^{***}	0.914^{***}	0.964^{***}
	(11.74)	(11.73)	(12.27)
Dynamic effects			
Y_{t-1}	0.151^{***}	0.151^{***}	0.146^{***}
	(23.83)	(23.88)	(22.92)
Y_{t-2}	−0.006	−0.006	−0.004
	(−1.01)	(−1.02)	(−0.62)
Panel B. Recovery funds effects			
Direct effects (Damaged provinces)			
RF_{t-2}			0.178
			(0.65)
RF_{t-3}			2.046^{***}

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	Linear	Non-linear	Non-linear (Extended)
			(7.47)
RF_{t-4}			0.623**
			(2.31)
RF_{t-5}			3.513***
			(13.43)
Direct effects (Undamaged provinces)			
$\Omega\times RF_{t-2}$			2.160**
			(2.11)
$\Omega\times RF_{t-3}$			0.254
			(0.25)
$\Omega\times RF_{t-4}$			−1.007
			(−0.99)
$\Omega\times RF_{t-5}$			−0.784
			(−0.78)
Indirect or spillover effects			
$\Omega \times \hat{Y}_t$	0.916***	0.914***	0.964***
	(11.74)	(11.73)	(12.27)
Dynamic effects			
Y_{t-1}	0.151***	0.151***	0.146***
	(23.83)	(23.88)	(22.92)
Y_{t-2}	−0.006	−0.006	−0.004

	(-1.01)	(-1.02)		(-0.62)

Notes: All models estimated via two-stage IV FGLS. Standard errors robust to heteroskedasticity, autocorrelation, and cross-sectional dependence. Province and time fixed effects included. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

6 Case Study: The DANA Flood in Valencia

The DANA flood that struck the province of Valencia in late October 2024 serves as a timely case-based application of our two-stage framework. Using observed precipitation data and preliminary severity indicators, our model projected economic losses between 0.55% and 1.71% of Spanish GDP, depending on the assumed damage percentile. Under the central scenario, this implied an expected drop in employment of 2.2 percentage points in Valencia and 0.2 percentage points at the national level. Once official EM-DAT estimates became available (0.65% of GDP), we updated the simulation. The revised projection indicated a cumulative employment loss of 1.4 percentage points in Valencia -closely matching the observed trough of 1.5 to 1.6 percentage points.

6.1 Estimating the economic impact of the DANA

According to EM-DAT, the DANA event resulted in 232 fatalities and spanned nine days, from October 27 to November 4, 2024. However, the vast majority of physical and economic damages were concentrated on a single day, October 29, underscoring the acute nature of the shock.

Our initial damage estimates placed the DANA within either the 90–95th or 95–100th percentile of global flood events, depending on the selected classification metric. When ranked by flood-related fatalities, the event falls in the 91st percentile globally and the 100th percentile within Spain. Using physical severity instead -standardized maximum monthly

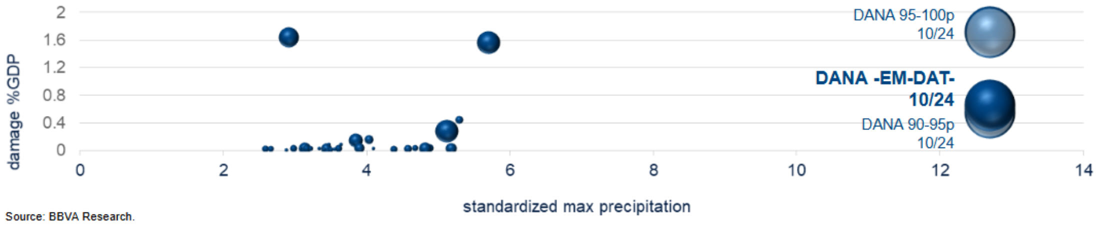

Figure 2: Spain, 1980–2024. Standardized maximum provincial precipitation (x-axis), estimated GDP losses (y-axis), and flood fatalities (bubble size).

precipitation at the provincial level- the DANA also ranks in the 100th percentile nationally. Across metrics, these indicators consistently classify the DANA as one of the most extreme flood events in Spain in recent decades, both meteorologically and in human toll.

The projected damage range of 0.55% to 1.71% of Spanish GDP is directly derived from our global damage function. Specifically, events in the 90–95th percentile group generate the lower bound (0.55%), while those in the top 5% generate the upper bound (1.71%). We maintained both estimates during the initial phase of the crisis, as contemporaneous indicators such as precipitation and fatalities provided supported either tier. Nonetheless, the global fatality percentile (91st) pointed more strongly toward the lower bound. This judgment was later confirmed when EM-DAT released its updated damage estimate of 0.65% of GDP, which aligns closely with our lower-bound projection.

Figure 2 situates the severity of the DANA flood within Spain's historical context. The event lies in the upper-right tail of the distribution of Spanish floods since 1980, as measured by standardized precipitation (x-axis), imputed or observed GDP losses (y-axis), and event lethality (bubble size). Notably, the Spanish government mobilized emergency resources equivalent to nearly 1.1% of GDP, underscoring the macroeconomic significance of the disaster beyond the direct damages recorded. Although more severe floods have occurred in Spain's history, all predate 1980 -the starting point of our sample- reflecting the lack of consistent and reliable economic data for earlier periods.

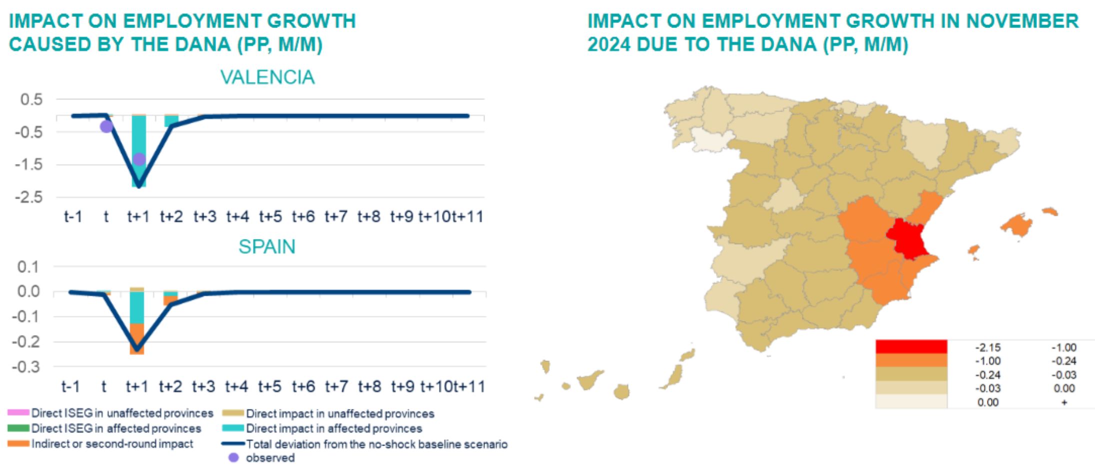

Figure 3: Impact on employment growth caused by the DANA (percentage points, month-on-month). Direct and indirect effects in Valencia and the rest of Spain.

6.2 Estimating the employment impact

As noted, in the absence of official damage figures, our baseline model projected that the DANA event would generate economic losses between 0.55% and 1.71% of Spain's GDP, with a central estimate of 1.1%. Under this scenario, we estimated a cumulative employment decline of roughly 2.1 percentage points in the province of Valencia and 0.2 percentage points at the national level. Figure 3 shows that about half of the nationwide effect is attributable to direct losses in the affected province, while the other half arises from indirect spillovers to economically linked regions. These spillovers operate through interregional trade channels, as captured by the spatial weight matrix.

Once EM-DAT released official damage estimates -placing total economic losses at 0.65% of GDP, near the lower bound of our projection interval- we revised the corresponding employment impact. The updated estimate yielded a cumulative decline of approximately 1.4 percentage points in Valencia, closely matching the observed trough of 1.6 percentage points. This 0.2 percentage points discrepancy is concentrated in the initial month of the shock (period t), as illustrated in Figure 4.

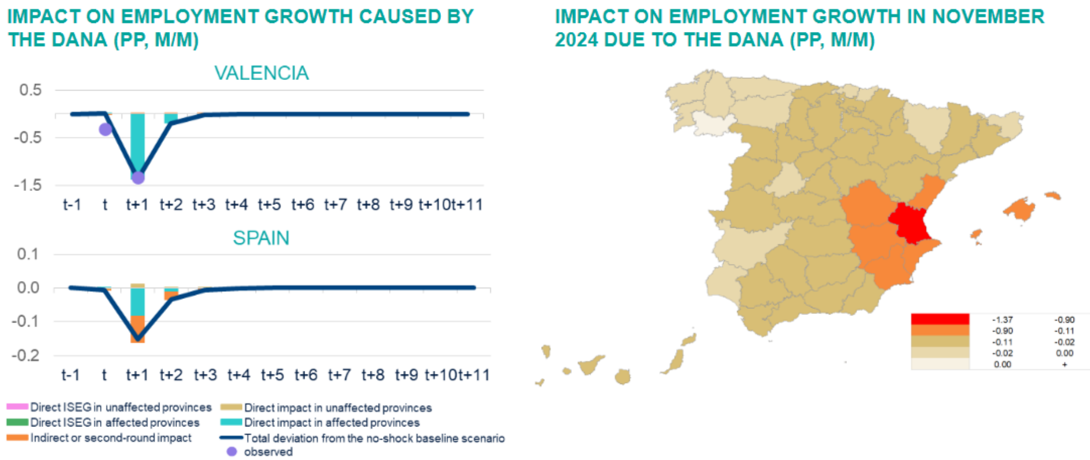

Figure 4: Observed and simulated employment growth in Valencia and Spain.

The close alignment between our simulated employment impacts and the realized labor market dynamics in the aftermath of the DANA provides compelling validation for the empirical framework developed in this paper. Despite relying only on early-stage information -such as event duration and preliminary fatality counts- the model accurately anticipated both the magnitude and timing of employment disruptions at the provincial and national levels. This degree of predictive accuracy in near real-time highlights the framework's potential as a robust tool for disaster impact assessment. Importantly, it enables policymakers to gauge the economic consequences of climate-related shocks even before official data are released, thereby facilitating for faster response planning, more targeted resource allocation, and better-informed recovery strategies. As extreme weather events become more frequent and spatially uneven, analytical tools that integrate physical indicators, imputation models, and spatially disaggregated labor economic data will become increasingly essential for managing climate-related economic risk.

6.3 Counterfactual simulations: the importance of location

Our model indicates that the aggregate labor market impact of a climate-related disaster depends not only on the magnitude of the shock but also critically on its geographic location. Regional differences in economic weight and the strength of interprovincial trade linkages shape how a localized event propagates across the national economy, amplifying or dampening its systemic footprint.

To explore this dimension, we simulate a counterfactual scenario in which a DANA-like flood -identical in terms of economic damage as a share of national GDP (0.65%)- strikes not Valencia, but the province of Barcelona. As shown in Figure 5, the employment losses in Barcelona would closely resemble those observed in Valencia, with a cumulative decline of approximately 1.4 percentage points. At the national level, however, the employment drop would reach 0.3 percentage points, nearly 50% larger than in the actual DANA event. This difference is driven entirely by Barcelona's greater economic weight and stronger interregional linkages. In this simulation, roughly two-thirds of the total national impact arises from direct effects in the affected province, while the remaining third reflects indirect spillovers transmitted through the spatial trade network.

This counterfactual underscores a key insight of our framework: geographic exposure is not neutral in determining the aggregate consequences of climate shocks. Identical damage magnitudes can produce markedly different labor market effects depending on where the event occurs. Regions with greater economic centrality act as amplifiers of systemic risk, even when the shock itself is localized.

More broadly, this simulation reveals a critical asymmetry between physical severity and economic consequences. In highly interconnected regions such as Barcelona, a less physically intense flood could generate employment disruptions comparable to those observed in Valencia -and even greater macroeconomic repercussions- owing to the region's structural

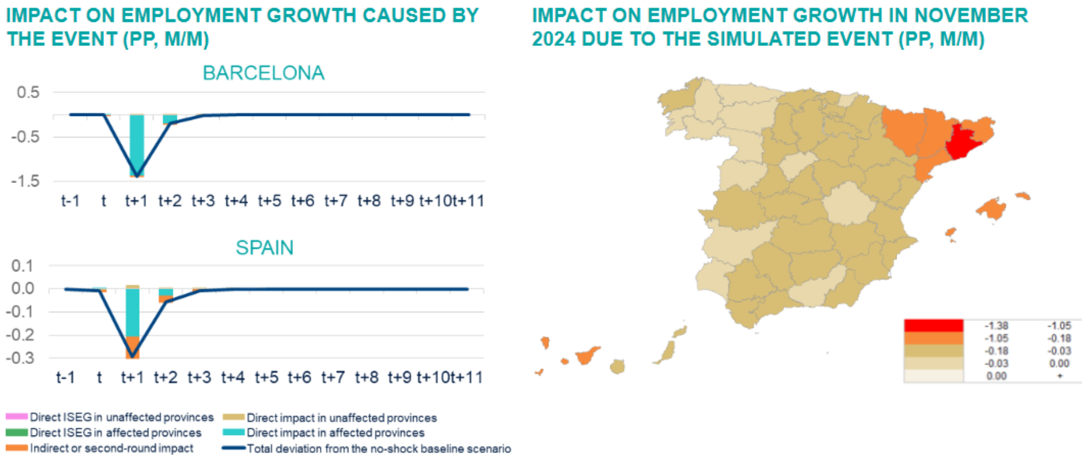

Figure 5: Simulated employment impact of a DANA-like flood in Barcelona, with identical national GDP damage (0.65%).

position within national supply and demand networks. In other words, identical aggregate losses at the national level may stem from very different physical events depending on their point of impact. Recognizing this asymmetry is essential for anticipating where relatively moderate shocks may still yield outsized economic consequences, and for designing spatially targeted adaptation and resilience policies.

6.4 Recovery and the role of financial assistance

Following the DANA flood, the employment decline in the province of Valencia was milder than initially projected, and the recovery unfolded more rapidly than in comparable historical episodes. As shown in Figure 6, social security affiliation dropped sharply in the immediate aftermath of the shock but began to rebound by December. By March 2025, the observed employment level had already surpassed the counterfactual trajectory -normalized to 100 to represent the no-disaster scenario- reaching a value of 100.6. This pattern suggests that, beyond fully offsetting the immediate losses, the recovery process temporarily lifted employment above its expected pre-disaster path.

A key feature of our framework is the explicit integration of post-disaster financial

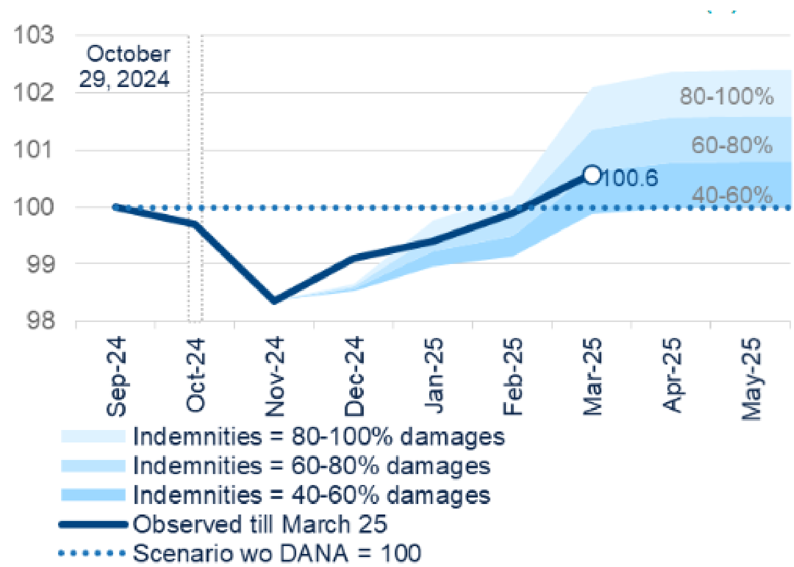

Figure 6: Social security affiliation in Valencia and model-implied recovery paths under varying levels of insurance payout coverage.

assistance, modeled using actual indemnity data from the CCS. By simulating different levels of compensation coverage, the model generates a fan chart of expected employment recovery trajectories conditional on the proportion of damages compensated. The three shaded bands in Figure 6 illustrate recovery paths under indemnity coverage of 40–60%, 60–80%, and 80–100% of total estimated damages. The observed trajectory lies well within the 60–80% band, aligning closely with the observed employment data. This coverage level is not only higher than in previous flood episodes but was also disbursed at a faster pace.

The figure further plots a counterfactual employment path for Valencia in the absence of the DANA (i.e., a continuation of the pre-event trend). By early 2025, employment had not only returned to its baseline but also exceeded the no-disaster trajectory. This suggests that financial assistance was effective not only in stabilizing employment but also in stimulating short-run labor demand through reconstruction activity. A plausible explanation for part of the rebound is forward-looking behaviour by economic agents in anticipation of the announced policy support. While this channel is difficult to quantify directly, the timing of the turnaround is consistent with such mechanisms.

It is important to underscore, however, that the DANA event entailed substantial destruction of the capital stock. Accordingly, the observed recovery in employment should not be interpreted as evidence of a full restoration of productive capacity. Achieving a complete recovery of the capital stock requires sustained economic activity above trend. In this regard, employment must remain elevated over an extended period to facilitate the reconstruction of lost assets.

Our estimates also shed light on the fiscal effectiveness of post-disaster aid. Employment appears more responsive to indemnities than to damages: the estimated fiscal multiplier of aid on employment is roughly 2.5 times larger than the damage multiplier. In practical terms, this implies that compensating 40% of the losses through insurance payouts may be potentially sufficient to bring provincial GDP-level employment back to its pre-disaster trend, even if the capital stock remains below its pre-disaster level. These dynamics highlight the powerful stabilizing role of targeted financial assistance in the aftermath of extreme weather events.

Taken together, the case of Valencia illustrates that incorporating real-time data on recovery efforts materially enhances the model's capacity to capture the rebound in economic activity. Moreover, this framework enables policymakers to assess the expected range of labor market outcomes under different aid scenarios, offering a valuable ex ante tool for designing and calibrating fiscal responses to climate-related shocks.

6.5 Confidence bands for the DANA employment impact

While our point estimates closely track the observed employment dynamics during the DANA flood, it is important to assess the robustness of these results to estimation and model uncertainty. To this end, we simulate 4,000 trajectories from our structural model using Monte Carlo draws from the estimated parameter variance-covariance matrix and the residual variance, as outlined in Section 4.

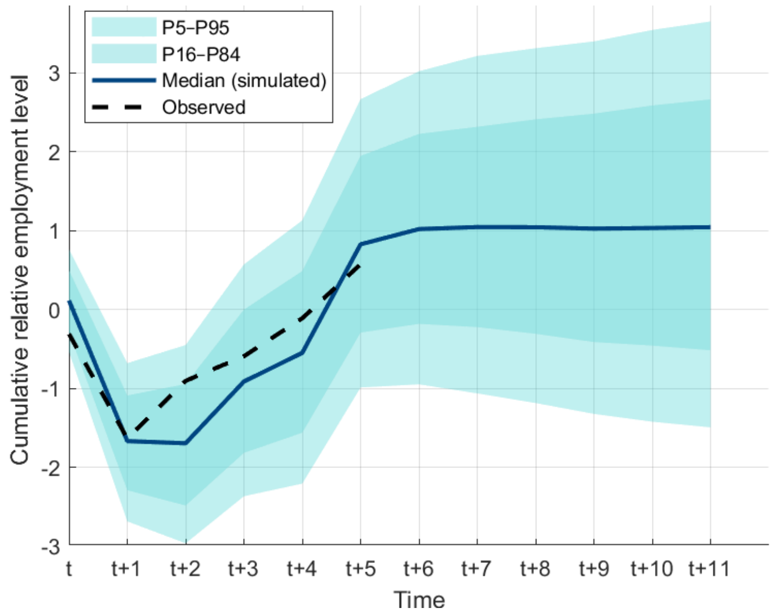

Figure 7: Simulated cumulative employment impact of the DANA flood in Valencia, including confidence bands from 4,000 Monte Carlo draws.

Figure 7 presents the resulting fan chart for cumulative employment levels in the province of Valencia. The dark blue line depicts the median simulated trajectory, while the shaded areas represent the 16th–84th percentile (light blue) and the 5th–95th percentile (lighter blue) confidence bands. The dashed black line shows the actual observed employment path. The simulations incorporate a recovery payout equivalent to 60% of estimated flood damages, consistent with the calibration outlined in Section 6.4.

The figure shows that the observed employment trajectory lies well within the model's predicted uncertainty envelope throughout both the shock and recovery phases. In fact, the realized data not only remains within the 16–84 percentile band but also closely tracks the median trajectory. This alignment suggests that our model accurately captures both the depth of the initial contraction and the pace of the subsequent recovery, conditional on observed aid disbursements. Such validation reinforces confidence in the model's predictive performance, particularly in its ability to anticipate not just point estimates but also a realistic distribution of potential outcomes. Crucially, the explicit incorporation of parameter and shock uncertainty provides policymakers with a more comprehensive view of the risks associated with extreme events, enabling forward-looking assessments that account for both central scenarios and tail risks.

7 Conclusion

This paper develops and validates a two-stage framework to quantify the short-run labor market effects of flood events, combining a non-linear global damage model with a dynamic spatial employment equation for Spanish provinces. The methodology is designed to operate under data limitations -a frequent challenge in disaster economics- by imputing missing damages and integrating spatial linkages and policy responses into the estimation of employment impacts.

Our contribution is threefold. First, we construct a global damage function that allows for non-linearities in the way mortality, duration, and exposure translate into economic losses. This provides a scalable and harmonized proxy for disaster severity, which can be applied even before official damage assessments become available. Second, we build a dynamic spatial panel model of employment that captures both direct impacts in affected provinces and indirect spillovers across interlinked regions. The model distinguishes between moderate and extreme events, revealing sizable and nonlinear employment effects only once flood intensity surpasses critical thresholds. Third, we explicitly incorporate the role of financial assistance in disaster recovery, using insurance payout data from Spain's public system. Our results demonstrate that timely aid substantially accelerates labor market recovery, with fiscal multipliers exceeding those of the shock itself.

The empirical validation using the 2024 DANA flood in Valencia illustrates the predictive accuracy of our framework. Despite relying on early-stage data, the model closely reproduced both the magnitude and timing of observed employment losses, while also capturing the subsequent rebound triggered by rapid and substantial public indemnity payouts. Counterfactual simulations further demonstrated that identical flood damage can produce very different national consequences depending on location, with economically central regions amplifying systemic labor market risk. These insights reinforce the importance of spatially explicit models in climate risk assessment. Robustness checks confirm that our findings are not sensitive to the choice of severity proxy (damages vs. precipitation) or spatial weighting scheme. The underlying mechanisms reflect structural features of Spain's economic geography and vulnerability profile.

More broadly, the framework provides a blueprint for real-time economic damage assessment in future climate events. Its modular structure and reliance on observable inputs mean that it can be extended to other countries, hazards, and outcomes -such as GDP, wages, or sectoral indicators- where data are available. As climate-related shocks become more frequent and severe, tools that integrate early damage estimation, spatial spillover modeling, and recovery calibration will be increasingly essential for timely and targeted policy response. This paper offers one such tool.

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Appendix 1 Robustness checks

Appendix 1.1 Alternative severity measures and spatial linkages

We assess the robustness of our results by re-estimating the non-linear baseline model under two alternative specifications: (i) replacing the damage-based severity proxy with precipitation-based measures, and (ii) using a historical spatial weight matrix from 1995 instead of 2019 to capture interprovincial trade linkages. These tests are conducted in a simplified specification excluding recovery aid to isolate the core shock propagation mechanism.

Table 5 reports the results using the original damage-based severity indicator, expressed as losses over GDP, for both the 1995 and 2019 matrices. Table 6 replicates the same nonlinear specification using standardized maximum precipitation per province as an alternative shock proxy.

Overall, the estimates remain highly consistent across specifications. While some coefficients differ slightly in magnitude, the core results are robust: the magnitude and statistical significance of the key parameters are preserved, particularly those capturing the non-linear impact of shocks. Using precipitation as the severity proxy produce somewhat larger estimated effects overall, but the nonlinear structure of the model remains clearly evident. The most relevant coefficient -the direct effect of the shock at lag one- remains strongly negative and highly significant across both specifications. The threshold for classifying an event as severe is set, on average, at 185 millimeters of rainfall per square meter per affected province. Thus together, Tables 5 and 6 confirm that the model's results are robust to alternative proxies of flood severity.

Regarding the stability of results across spatial weighting schemes, this consistency is to be expected given the relatively stable structure of economic interdependencies across Spanish

Table 5: Estimated effects using damage-based severity measures

	1995 matrix	2019 matrix
S_t	-0.167	-0.157
	(0.40)	(0.37)
S_{t-1}	0.132	0.136
	(0.31)	(0.32)
$I_{ext} \times S_t$	0.104	0.114
	(0.24)	(0.26)
$I_{ext} \times S_{t-1}$	-2.546	-2.548
	(-5.84)***	(-5.82)***
$\Omega \times S_t$	-0.346	-0.162
	(-0.75)	(-0.41)
$\Omega \times S_{t-1}$	0.239	0.243
	(0.52)	(0.62)
$\Omega \times \hat{Y}_t$	0.899	0.914
	(10.83)***	(11.73)***
Y_{t-1}	0.152	0.151
	(24.01)***	(23.88)***
Y_{t-2}	-0.005	-0.006
	(-0.76)	(-1.02)

Table 6: Estimated effects using precipitation-based severity measures

	1995 matrix	2019 matrix
S_t	0.004	0.003
	(0.35)	(0.30)
S_{t-1}	-0.001	-0.002
	(-0.12)	(-0.16)
$I_{ext} \times S_t$	-0.024	-0.022
	(-1.00)	(-0.90)
$I_{ext} \times S_{t-1}$	-0.267	-0.266
	(-10.98)***	(-10.90)***
$\Omega \times S_t$	-0.029	-0.035
	(-0.86)	(-1.05)
$\Omega \times S_{t-1}$	0.043	0.030
	(1.25)	(0.90)
$\Omega \times \hat{Y}_t$	0.901	0.921
	(10.83)***	(11.79)***
Y_{t-1}	0.150	0.149
	(23.68)***	(23.55)***
Y_{t-2}	-0.004	-0.006
	(-0.65)	(-0.91)

provinces. Figure 8 displays the cell-by-cell differences (in percentage points) between the 1995 and 2019 interprovincial trade matrices. The distribution is tightly centered around zero, with only a handful of moderate deviations. This visual evidence confirms that the topology of Spain's interregional economic flows has remained broadly unchanged over the past two decades. Such stability is consistent with the nature of domestic supply chains and trade relationships, which tend to evolve gradually -particularly in geographically proximate economies with entrenched regional linkages. Consequently, replacing the 2019 matrix with its 1995 counterpart yields nearly identical model estimates.

Taken together, these robustness checks confirm that the estimated labor market impacts of flood shocks are not artifacts of the specific severity proxy or spatial weight matrix used. Rather, they reflect persistent structural features of Spain's economic geography and climate vulnerability, which remain robust across a wide range of plausible specifications.

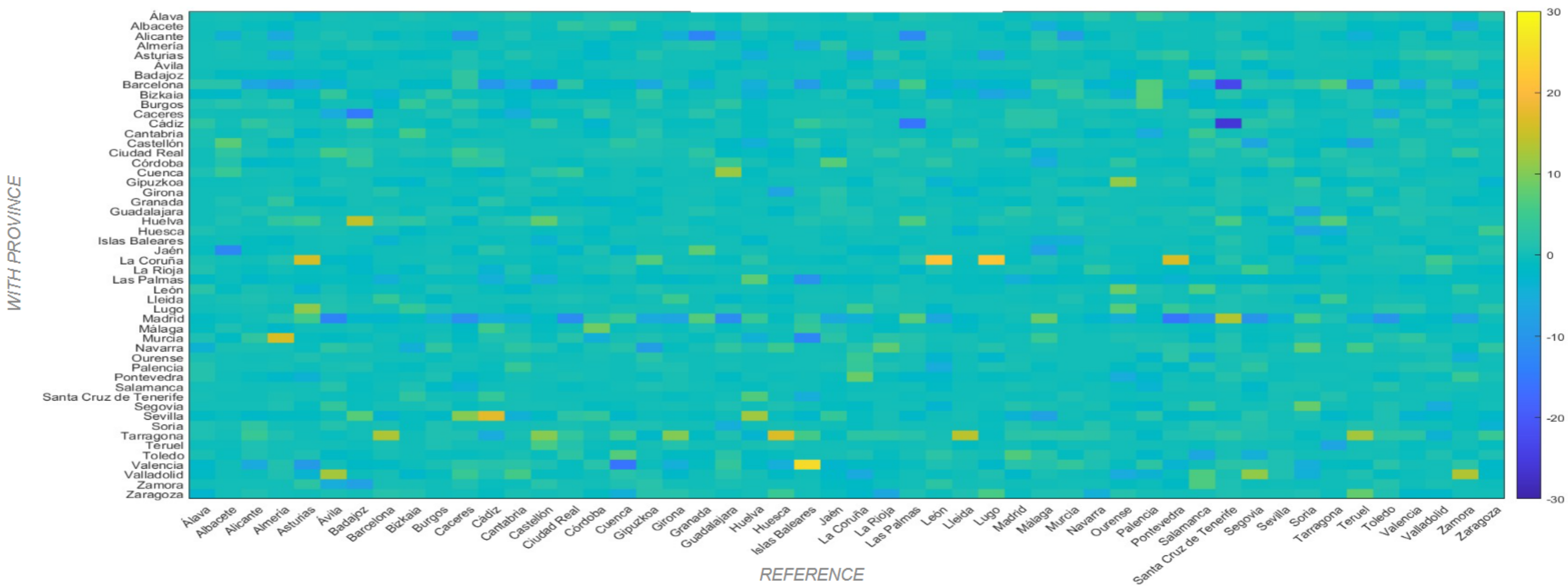

Figure 8: Differences in interprovincial trade shares between the 2019 and 1995 spatial weight matrices (percentage points).

Appendix 1.2 Tree-based model as a robustness check for damage estimation

As a robustness exercise, we estimate a regression tree (CART) to model flood-induced economic damages as a share of GDP. This approach provides a non-parametric alternative to the baseline specification presented in Section 4.1, where damages are estimated via OLS with non-linear interaction terms.

The regression tree is trained on the same EM-DAT-based dataset, using four covariates: mortality rate (m_pop), log population density (l_densi), log flood duration (ydur1), and log fatalities (l_death). These variables mirror those used in the main model. To balance complexity and interpretability, we set the complexity parameter at $cp = 0.001$, yielding a tree with 20 terminal nodes.

Figure 9 displays the resulting tree structure. Splits are based on variable thresholds selected to minimize within-node variance, with mortality rate consistently appearing at the top, underscoring its predictive strength. Deeper partitions involve flood duration, population density, and fatalities, capturing more localized interactions. Despite its intuitive appeal, the tree-based model underperforms relative to the OLS specification in terms of explanatory power. The adjusted R^2 is 0.516, compared to 0.770 in the baseline model. Moreover, trees produce discontinuous, piecewise-constant predictions, which reduce interpretability and are sensitive to small data perturbations. While the resulting decision rules are locally interpretable, they lack the clarity of marginal effects or elasticity interpretations typically provided by linear models.

Due to these limitations -namely, lower fit and reduced transparency- we exclude the regression tree from the main body of the paper. Nonetheless, the results reinforce our key findings: mortality rate is the most important predictor of flood damages, and the relationship is highly non-linear. These conclusions are consistent with those drawn from the OLS

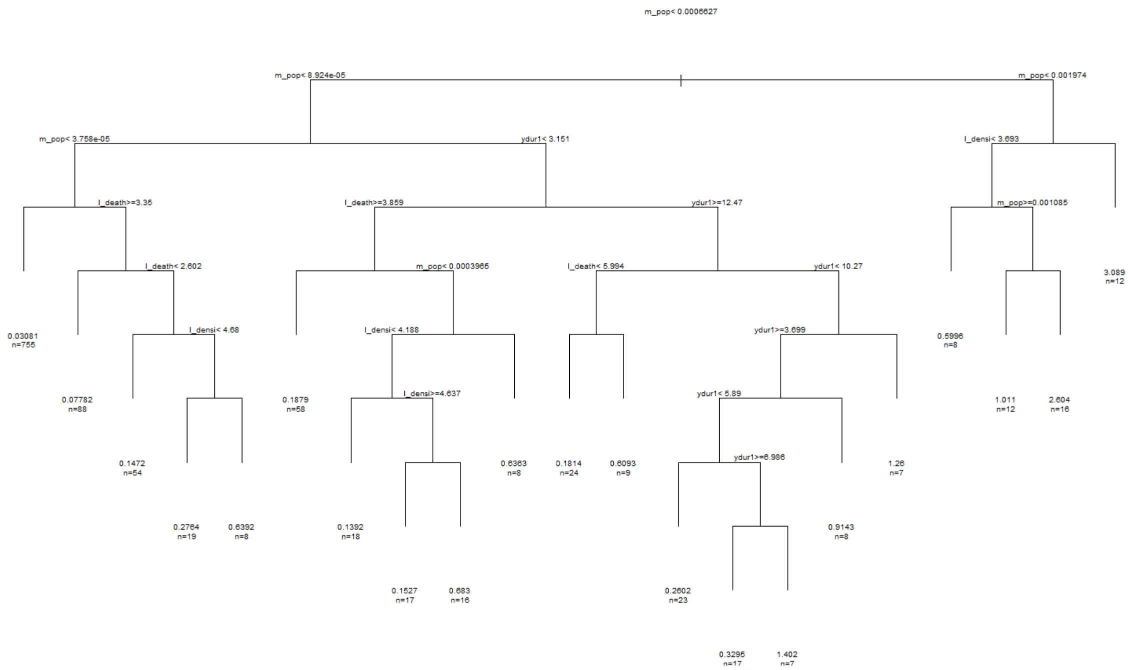

Figure 9: Regression tree model for flood damage estimation.

model in Section 5.1. Additionally, the structure of the tree validates the threshold-based logic embedded in the parametric specification. Terminal nodes that predict high damages correspond to combinations of extreme mortality, long durations, and high population density. In contrast, low-mortality, short-duration events are classified into nodes with near-zero damages -mirroring the flat baseline effects found in the OLS results.

In summary, while the regression tree confirms the robustness of our main conclusions regarding variable importance and non-linearity, its lower statistical performance and limited interpretability justify our choice to retain the OLS specification in the main analysis.

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