

The Macroeconomic Effects of Extreme Weather Events: A Regional, High-Frequency Approach

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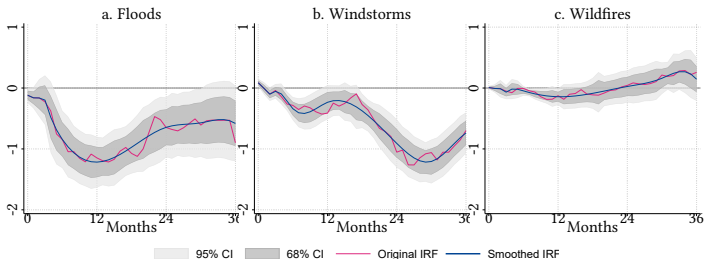
A quick summary

- How does **economic activity** respond to and recover from **extreme weather events**?
- New evidence using **geospatially** and **temporally** granular macroeconomic and weather data for Spain
 - Monthly Synthetic Indicator of Economic Activity (MSIEA) for NUTS-3 regions
 - Intensity-weighted extreme-weather shocks
- Incorporate **mediating factors** at the regional level that will affect extent of damages and recovery speed
 - Capital density, fiscal space and insurance coverage

Main takeaways

1. Floods, windstorms and wildfires initially all cause a **contraction** in regional economic output per capita, but with differing **magnitudes** and degrees of **persistence**

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

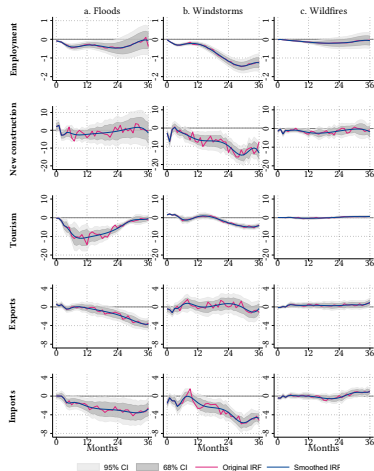


Note: graphs show impulse responses functions, derived from a panel local projections approach, in response to a median shock of the type mentioned above the chart.

Main takeaways

- For the three event types considered, **employment** is the **dominant transmission channel**, driving both the initial contraction and (part of) the subsequent recovery dynamics

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

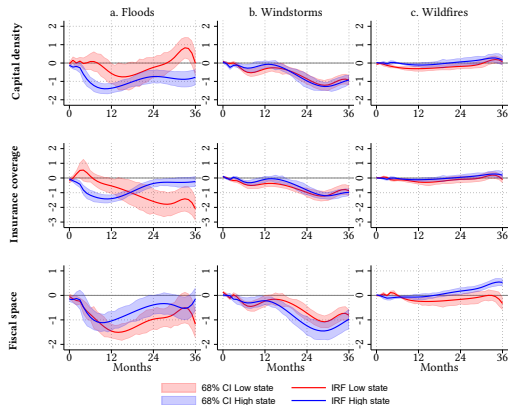


Note: graphs show impulse responses, derived from a panel local projections approach, in response to a median shock of the type mentioned above the chart. IRFs were smoothed using a cubic spline.

Main takeaways

3. Regions with **high capital density**, **limited fiscal space** or **low insurance coverage** see deeper and more persistent output declines, especially after floods

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.

- **Great paper** on a very timely and important topic!
- **Complete package** with:
 - **Novel measure** of high-frequency province-specific economic activity
 - Definition of shocks based on **meteorologically-derived** intensity score
- Important **policy implications** given interest in integrating **climate risk** into macroeconomic policy frameworks

Overview of my comments

1. **Methodology:** panel local projections vs. difference-in-differences estimators
2. **Mediating factors:** measurement, (repeated) exposure
3. **Transmission channels:** relative contributions
4. **Minor comments:** variables, specification, potential extensions

Panel local projections vs. DiD estimators

- Estimate the effects of extreme weather events using a **panel local projections** (LP) approach in the spirit of Jordà (2005)

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

- Chaisemartin and D'Haultfoeuille (2024): Local-projection regressions **do not** cleanly recover the effect at horizon h (β^h) in these designs
 - **mix together** the effects of multiple treatment changes at multiple lags
 - assign **negative weights** to some of those effects
 - can produce **sign reversals** even when all true treatment effects are positive

Panel local projections vs. DiD estimators

- When do these LP failures become particularly severe?
 1. Treatment moves up and down (**non-absorbing**)
 2. **Multiple treatment changes** for the same unit
 3. **Lagged effects** exist
 4. **Heterogeneous timing** of treatment
- **Potential solution:** Robustness checks using Chaisemartin and D'Haultfoeuille (2024) DiD estimator of intertemporal treatment effects and/or Dube, Girardi, Jordà, and Taylor (2025)'s LP-DiD approach to assess the stability of the results

Mediating factors: Measurement

- “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”
- If mediating factors respond to **past shocks** there could be some bias in interpreting the heterogeneity across regions ⚠
- Address by using **long-run (pre-sample)** mediating factors to define states
 - This removes **endogenous movements** in capital density/fiscal space/insurance coverage during the sample

Mediating factors: (Previous) exposure

Irisarri, Rábano, and Rosas (2025) explore **adaptation** mechanisms of firms in India to extreme weather shocks

- Granular data for **India's manufacturing sector** firms (2000-2010)
- Focus on **most extreme floods**: recurrence interval greater than 10 years
- Classify districts based on **historical exposure** to similar events

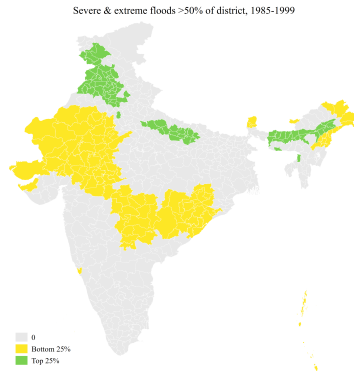
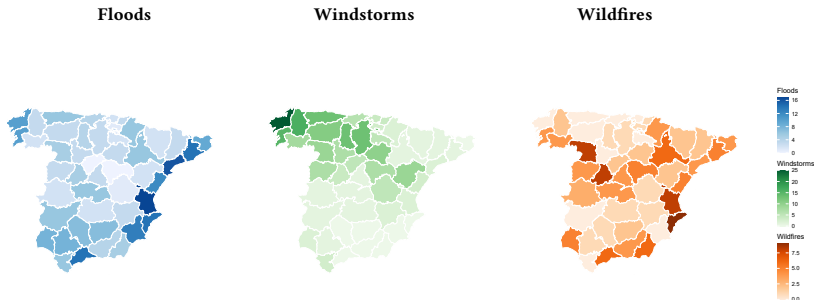


Figure 1: District-level historical flood exposure (1985-1999)

Mediating factors: (Previous) exposure

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)



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).

Mediating factors: (Previous) exposure

- What is the impact of floods on firms' **key outcomes**: output, investment?
- Do firms in **highly exposed locations** respond differently?
- Firms in **high-risk** locations show no output losses, and even increase their capital investment following floods: **“flood-preventing” capital**

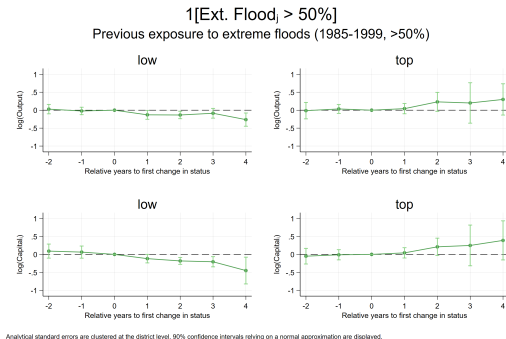


Figure 2: Dynamic effects of extreme floods on output (top) and investment (bottom), by historical exposure (low vs. high)

Channels: Relative contributions




2. For the three event types considered, **employment** is the **dominant transmission channel**, driving both the initial contraction and (part of) the subsequent recovery dynamics
 - Monthly GDP proxy is constructed via **temporal disaggregation** using a constrained, non-linear combination of multiple indicators
 - Responses of the individual indicators cannot be interpreted as **additive contributors** to the GDP response, nor can the GDP–indicator differences be viewed as evidence of **relative channel strength** ⚠
 - The channel analysis remains **informative descriptively**, but cannot support quantitative statements about the drivers or decomposition of the GDP IRFs



Minor comments: Variables, methodology, extensions

- Why keep **wildfires**? Don't seem to matter much for economic activity...
- What about **non-linear effects**? Most extreme events could have larger effects on economic activity and/or be driving the results
- Do these estimates take into account potential **spillover effects**? (e.g. tourism effects in neighboring, non-affected regions)
- **IRFs**: Barnichon and Brownlees (2019)'s Smooth Local Projections
- **Potential extensions**: effects on **prices**, regional **financial** conditions, **migration** flows, etc; other **countries**

To sum up

- Very exciting work, using novel, high-frequency, granular data to explore how **economic activity** respond to and recover from **extreme weather events**
- Very interesting empirical results
- Clear implications for stabilization policies, disaster-relief efforts and adaptation/resilience-building initiatives

-  Barnichon, Regis and Christian Brownlees (2019). **“Impulse Response Estimation by Smooth Local Projections”**. In: *The Review of Economics and Statistics* 101(3), pp. 522–530. DOI: [10.1162/rest_a_00778](https://doi.org/10.1162/rest_a_00778).
-  Chaisemartin, Clément de and Xavier D'Haultfoeuille (2024). ***Difference-in-Differences Estimators of Intertemporal Treatment Effects***. Tech. rep. SSRN Working Paper, originally written November 16, 2020. Sciences Po and CREST. DOI: [10.2139/ssrn.3731856](https://doi.org/10.2139/ssrn.3731856). URL: <https://ssrn.com/abstract=3731856>.
-  Dube, Arindrajit et al. (2025). **“A Local Projections Approach to Difference-in-Differences”**. In: *Journal of Applied Econometrics*. DOI: [10.1002/jae.70000](https://doi.org/10.1002/jae.70000).

-  Irisarri, Marko, Alejandro Rábano, and José Nicolás Rosas (2025). **“Floods and Adaptation Strategies: Evidence from Indian Manufacturing”**. In: *Working Paper*.
-  Jordà, Òscar (2005). **“Estimation and Inference of Impulse Responses by Local Projections”**. In: *American Economic Review* 95(1), pp. 161–182. DOI: [10.1257/0002828053828518](https://doi.org/10.1257/0002828053828518).