Journal of Environmental Economics and Management 140 (2026) 103409

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/yjeem

The regional economic impact of weather shocks: Evidence from Portugal

Dhruv Akshay Pandit [a], Paulo M.M. Rodrigues [b,c,*], João Seixo [c]

[a] Nova Information Management School (NOVA IMS), Universidade Nova de Lisboa, Lisbon, Portugal
[b] Banco de Portugal and Nova School of Business and Economics, Lisbon, Portugal
[c] Nova School of Business and Economics, Universidade Nova de Lisboa, Campus de Carcavelos, 2775-405 Carcavelos, Lisbon, Portugal

HIGHLIGHTS

- We assess the short-term regional impact of weather variability on economic activity.
- A Panel VAR with exogenous regressors and local projections quantifies dynamic responses.
- A novel factor extraction method isolates large-scale Mediterranean climate influences on Portugal.
- Hourly rainfall volatility raises purchases and house-price growth, and lowers unemployment; responses differ across regions.

ARTICLE INFO

JEL classification:
Q54
R11
R12
C33

Keywords:
Panel VARX
Local projections
Climate change
Regional impacts

ABSTRACT

Weather extremes shape short-run economic activity through both market and nonmarket channels, yet evidence on local consumer-side activity remains limited. Using a municipality-level panel of Portuguese data (2010–2021), we estimate panel VAR and local-projection responses to weather shocks of point-of-sale purchases (a measure of merchant-location transaction activity, not resident household consumption), together with unemployment and house prices. Our central methodological finding is that hourly rather than daily measurement of rainfall variability raises the estimated semi-elasticities by an order of magnitude, suggesting that the existing climate-economy literature systematically understates the importance of high-intensity rainfall. Substantively, the local-projection responses indicate that hourly rainfall volatility raises purchases on impact and reverses the following quarter, consistent with intertemporal reallocation; temperature variability generates a sharp positive impact effect followed by a contraction; and high fire-danger days raise contemporaneous purchases. Unemployment and house prices follow the same patterns more weakly. Regional heterogeneity is substantial, with the Lisbon Metropolitan Area and the Algarve sometimes displaying effects opposite in sign to those in the North.

1. Introduction

A growing body of evidence documents the impact of weather extremes on economic activity, yet most studies focus on temperature-GDP relationships at the country level (Dell et al., 2012; Burke et al., 2015; Diffenbaugh and Burke, 2019). Two important gaps remain. First, while temperature effects on GDP growth and volatility are increasingly well understood (Natoli, 2024), and recent work has extended the analysis to precipitation (Kalkuhl and Wenz, 2020; Kotz et al., 2022; Waidelich et al., 2024), there is little

* Corresponding author at: Nova School of Business and Economics, Universidade Nova de Lisboa, Campus de Carcavelos, 2775-405 Carcavelos, Lisbon, Portugal.
Email addresses: dpandit@novaims.unl.pt (D.A. Pandit), pmrodrigues@bportugal.pt (P.M.M. Rodrigues), joao.seixo@novasbe.pt (J. Seixo).

https://doi.org/10.1016/j.jeem.2026.103409
Received 10 November 2025
Available online 21 July 2026

evidence on how weather shocks translate into local consumer-side activity, one of the channels through which climate variability shapes short-run regional economic outcomes. The impact of natural disasters and temperature on prices has received some attention (Parker, 2018; Heinen et al., 2019), but the relationship between weather variability and point-of-sales purchases remains largely unexplored, particularly within Europe. Second, most studies rely on national aggregates and mean weather measures, obscuring the sub-national heterogeneity in climate exposure and economic response that is critical for the design of spatially targeted adaptation policies (European Environment Agency, 2024).

This paper addresses both gaps by analysing the short-run impact of weather shocks on point-of-sales purchases, unemployment, and house prices across 278 Portuguese municipalities from 2010 to 2021. Portugal provides a compelling setting for this analysis. Located on the western edge of the Iberian Peninsula, within the Mediterranean climate zone (Beck et al., 2018), it faces acute exposure to droughts, wildfires, and increasingly erratic precipitation (Lima et al., 2023; Bednar-Friedl et al., 2022). Its pronounced north-south climatic gradient, from the mild, Atlantic-influenced coast to the arid, continental interior, generates substantial within-country variation in weather exposure. At the same time, the availability of municipal-level data on electronic transactions, house prices, and unemployment at quarterly frequency enables a sub-national, sub-annual analysis that is rare in the climate-economy literature.

We employ a panel vector autoregressive framework with exogenous regressors (PVARX) to model the interactions between weather variations and macroeconomic indicators, and construct impulse response functions using panel local projections. The weather variables, air temperature, total precipitation, and wildfire risk, are obtained from the ERA5 reanalysis dataset[1] and aggregated to the municipal level using area-weighted averages. Crucially, we go beyond mean weather measures to incorporate both anomalies (deviations from historical means) and intra-monthly volatility, as well as fire-risk indices.

The paper makes four contributions. First, it introduces a measure of precipitation volatility based on hourly rainfall data (millimetres per hour) rather than the daily totals conventionally used in the literature. The distinction is consequential, as hourly volatility captures the high-intensity, short-duration rainfall events that climate projections indicate will become more frequent (Lima et al., 2023) and that are most clearly associated with severe economic disruption, as illustrated by the 2024 floods in Valencia, Spain (Rombeek et al., 2025), while daily totals smooth over these episodes and yield qualitatively different results. Second, building on this measurement, it provides the first European evidence on how weather variability is associated with point-of-sales purchases, our primary outcome of interest; unemployment and house prices are included as supporting outcomes that allow cross-equation comparison of the weather signal. Third, it exploits municipal-level variation to uncover substantial heterogeneity, with effects in the Lisbon Metropolitan Area and the Algarve sometimes opposite in direction compared to northern Portugal. Fourth, it constructs a set of latent climate factors from Mediterranean-region weather data to control for cross-border climatic spillovers that may confound the identification of domestic weather effects.

Our main findings are as follows. In the contemporaneous PVARX block, no weather variable is significantly associated with purchases growth except temperature variability (+2.5 pp); the contemporaneous weather signal is concentrated in the unemployment and house-price equations. The lagged terms reveal systematic within-year adjustment, with rainfall variability and rainfall anomalies generating large and partially offsetting effects on purchases growth. The smoothed local-projection responses (Section 5) show that temperature and rainfall variability are the dominant drivers across the three outcomes, with sharp impact effects on purchases and house prices that subsequently reverse, consistent with intertemporal reallocation. The estimated semi-elasticities are robust to including disposable income, non-linear terms, longer lags, and event-count weather indicators. The regional analysis reveals that responses are markedly heterogeneous across NUTS-II aggregates, highlighting the importance of spatially disaggregated analysis for climate adaptation policy.

The remainder of this paper is structured as follows. Section 2 describes the data and variable construction. Section 3 outlines the model specification. Section 4 presents the empirical results. Section 5 presents the panel local projections. Section 6 discusses the findings in light of the existing literature. Section 7 concludes. Supplementary Appendix A provides details on the estimation strategy, Supplementary Appendix B describes the construction of uniform confidence bands, and Supplementary Appendices C–G provide additional empirical results and tables.

2. Data and variable construction

2.1. Economic variables

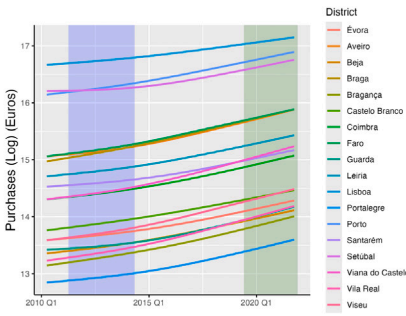
Our analysis is based on a balanced panel of 278 mainland-Portuguese municipalities observed quarterly from 2010Q1 to 2021Q4. The three endogenous variables are the value of point-of-sale (POS) purchases in euros ($pur_{i,t}$), the house price index ($hpi_{i,t}$), and the unemployment rate ($ur_{i,t}$); see Fig. 1. Purchases data are taken from Statistics Portugal (INE), reported monthly and aggregated to quarters. The unemployment rate is also provided by INE, while the house price index is compiled by *Confidencial Imobiliário* (a real estate data provider in Portugal); both are available at quarterly frequency. All series are recorded at the municipality level.

POS purchases are electronic transactions processed by SIBS[2] and reported by INE.[3] POS purchases are a measure of local transaction activity rather than total household consumption; they capture spending at the merchant location rather than at the household residence, exclude cash transactions, and are sensitive to merchant-side factors. Three implications follow. First, in tourist-intensive

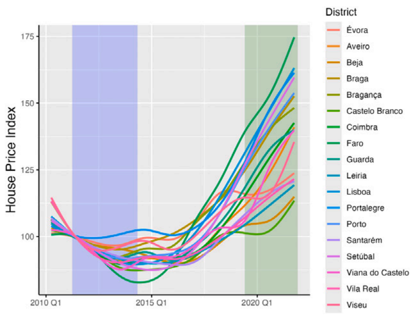
[1] https://cds.climate.copernicus.eu/.

[2] Forward Payment Solutions, SA, Portugal's main payments operator.

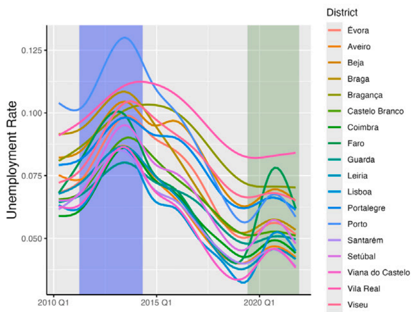
[3] https://smi.ine.pt/Indicador/Detalhes/18683.



(a) log(pur)



(b) hpi



(c) ur

Fig. 1. Plots of smoothed means of quarterly averages of total point-of-sales purchases (*pur*), house price index (*hpi*), and unemployment rates (*ur*) at the district level. *Note:* Colored periods correspond to the Sovereign Debt Crisis (*blue*) and the Portuguese Real Estate Boom (*green*). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

regions (notably the Algarve and Lisbon Metropolitan Area), a non-trivial share of recorded purchases reflects non-resident spending; the regional heterogeneity reported in Section 6.1 is consistent with this composition effect. Second, secular trends in card adoption and merchant-terminal coverage may add a slow-moving component to municipality-level purchases that the municipality-specific quadratic trend absorbs by construction, but residual measurement error of this type cannot be ruled out. Third, the rise of online retail over the sample period shifts spending from the merchant's physical location toward distribution-centre locations, which may attenuate the short-run relationship between local weather and local POS activity. We exploit this transaction-side construction deliberately, since the mobility, tourism, and retail-footfall channels through which short-run weather affects local economic activity are precisely the channels POS data captures.

We include *hpi* and *ur* to capture local economic conditions at sub-annual frequency, since key indicators such as HICP, GDP, or value added are not available at the municipality level. Conceptually, *hpi* proxies local demand pressure and wealth effects, and *ur* captures labour-market slack; together they absorb confounding business-cycle variation while preserving identification of the weather coefficients. We additionally include household disposable income as a sensitivity check, although its within-municipality variation is limited.

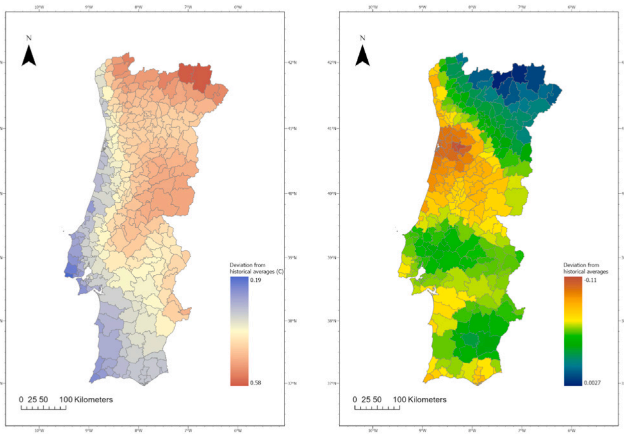
2.2. Weather variables

Weather data are obtained from the ERA5 reanalysis (Hersbach et al., 2018, 2020), which provides hourly global fields at $0.25° \times 0.25°$ resolution. We use ERA5 rather than station observations for spatial completeness and physical consistency (Linsenmeier, 2023); validation studies for Portugal confirm strong agreement with ground-station records from the Portuguese Institute for Sea and Atmosphere (IPMA), with correlations above 0.97 for temperature and close agreement for precipitation extremes.[4] This choice is consistent with prevailing approaches in climate-economics research (Kotz et al., 2021; Linsenmeier, 2023; Waidelich et al., 2024). Gridded data are aggregated to the municipal level using area-weighted averages of overlapping grid cells (Kotz et al., 2021; Dell et al., 2014).[5]

Our analysis includes six quarterly weather variables, $\boldsymbol{w}_{i,t} = \left(\tilde{T}_{i,t}, \tilde{P}_{i,t},\ \breve{T}_{i,t}, \breve{P}_{i,t}, fwi_{i,t}, hfd_{i,t}\right)'$, capturing both the mean (anomalies, denoted by tilde $\sim$) and volatility (denoted by breve $\smile$) of temperature and precipitation, as well as two fire-risk indices (the Fire

[4] See Almeida and Coelho (2023), Espinosa et al. (2023), and Espinosa et al. (2024).

[5] Implemented in Python using the xagg library (Schwarzwald and Geil, 2024).



(a) Two-metre air temperature (b) Total precipitation

Fig. 2. Average deviation from the 1961–1990 historical mean, aggregated by municipality for the period 2010–2020. Left: Two-metre air temperature (°C). Right: Total precipitation ($mm\,day^{-1}$). Positive values indicate warmer or wetter conditions relative to the baseline; negative values indicate cooler or drier conditions.

Weather Index, $fwi_{i,t}$, and the number of high-fire-danger days, $hfd_{i,t}$). Anomalies are computed as deviations from municipality-specific historical climatological means over the 1961–1990 reference period, the standard climatological baseline of the World Meteorological Organization (2017); see Fig. 2 for the spatial distribution of these anomalies. To examine non-linear effects, we additionally consider an interaction of temperature and precipitation anomalies ($\tilde{T} \times \tilde{P}$), as well as squared and cubed terms of $\tilde{T}_{i,t}$ and $\tilde{P}_{i,t}$ as exogenous regressors.

2.2.1. *Measuring precipitation volatility*

We deviate from the literature (Moberg et al., 2000, Kotz et al., 2021, and Waidelich et al., 2024), and measure day-to-day variability as the intra-day standard deviation of hourly rainfall, aggregated quarterly.

Hourly volatility captures the short, high-intensity rainfall projected to become more frequent (Lima et al., 2023) and is responsible for the largest disruption; 50mm falling in two hours and 50mm spread over 24 hours produce identical daily totals but very different economic effects. As Section 4 shows, the two measures yield qualitatively different results.

2.3. *Mediterranean climate factors*

To control for cross-border climatic spillovers, we construct latent climate factors from countries sharing Portugal's Mediterranean climate profile (Köppen classes *Csa* and *Csb*; Beck et al., 2018).[6] Historical weather data for precipitation (P) and temperature (T) are obtained for each country from the World Bank's Climate Change Knowledge Portal (sourced from ERA5). We compute anomalies relative to historical means and extract latent factors to construct composite indicators for temperature (η_t^T) and precipitation (η_t^P).

We decompose the $M \times 1$ vector of Mediterranean anomalies as $\boldsymbol{x}_t = \boldsymbol{\Lambda}\boldsymbol{\eta}_t + \xi_t$ (Stock and Watson, 2005), where $\boldsymbol{\eta}_t$ is the $r \times 1$ vector of latent factors and ξ_t the idiosyncratic component, and estimate the factor space by principal components (Stock and Watson, 2002; Bai and Ng, 2002). Kaiser-Meyer-Olkin statistics (0.921 for temperature, 0.788 for precipitation) and Bartlett's tests ($p < 10^{-16}$) confirm the suitability of the factor model.

2.4. *Unit root testing and variable transformations*

Logarithmic transformations are applied to purchases and the house price index; the unemployment rate is kept in levels. To assess stationarity in the presence of cross-section dependence, we employ the panel unit root tests of Demetrescu et al. (2006) and Costantini and Lupi (2013), combined with the Simes (1986) procedure for multiple testing following Hanck (2013).[7]

For the economic variables, we do not reject the unit-root null for $\log(pur_{i,t})$, $\log(hpi_{i,t})$, and $ur_{i,t}$ at the 1% level, but their first differences are stationary. The endogenous block is therefore $\boldsymbol{y}_{i,t} = (\Delta \log pur_{i,t}, \Delta \log hpi_{i,t}, \Delta ur_{i,t})'$. For the weather variables, we do not reject the unit-root null for temperature variability ($\breve{T}_{i,t}$) and $fwi_{i,t}$; these enter the model in first differences. The remaining weather variables are stationary in levels and enter the model untransformed.

[6] See Supplementary Appendix D.2 for the complete list of countries.

[7] All unit root test results are provided in Supplementary Appendix C.

3. Methodology

3.1. Model description

We employ a PVARX (Habib, 2022) to quantify how quarterly weather shocks propagate through local economic activity, with municipality fixed effects controlling for time-invariant heterogeneity.

For municipality $i = 1, \dots, 278$ and quarter $t = 1, \dots, 48$ (covering 2010Q1–2021Q4), the baseline PVARX(p,q) specification with municipality fixed effects is,

$$\boldsymbol{y}_{i,t} = \boldsymbol{\mu}_i + \boldsymbol{\theta}_{i1} t + \boldsymbol{\theta}_{i2} t^2 + \boldsymbol{\Pi} \boldsymbol{d}_{i,t} + \sum_{\ell=1}^{p} \boldsymbol{A}_{\ell} \boldsymbol{y}_{i,t-\ell} + \boldsymbol{B} \boldsymbol{w}_{i,t} + \sum_{j=1}^{q} \boldsymbol{C}_j \boldsymbol{w}_{i,t-j} + \boldsymbol{\varepsilon}_{i,t}, \tag{1}$$

where $\boldsymbol{y}_{i,t} = (\Delta \log pur_{i,t}, \Delta \log hpi_{i,t}, \Delta ur_{i,t})'$ is the 3×1 endogenous vector, $\boldsymbol{w}_{i,t}$ the 6×1 weather vector (Section 2.2), and $\boldsymbol{\mu}_i$ are municipality fixed effects. The linear and quadratic municipality-specific trends $\boldsymbol{\theta}_{i1} t$ and $\boldsymbol{\theta}_{i2} t^2$ absorb medium-run heterogeneous growth paths that could otherwise bias short-run weather coefficients (Burke et al., 2015). NUTS3-by-quarter seasonal controls, $\boldsymbol{d}_{i,t}$, interact NUTS3 region indicators with quarter-of-year dummies for $Q2, Q3, Q4$ ($Q1$ as reference); $\boldsymbol{\Pi}$ is the associated coefficient matrix.[8]

All subsequent robustness exercises (adding nonlinear weather terms, controlling for non-Portuguese weather shocks, switching to count-based hazard indices, or estimating separate regional systems), only alter the composition of $\boldsymbol{w}_{i,t}$; the dynamic structure in (1) remains unchanged. Details on the estimation strategy are provided in the Supplementary Appendix A.

3.2. Local projections

We complement the PVARX with panel local projections (Jordá, 2005), which estimate the response at each horizon h via a separate regression and are robust to dynamic misspecification (Plagborg-Møller and Wolf, 2021). Following Jordá et al. (2015), the panel local projection for each response variable $y^r_{i,t}$ $(r = 1, \dots, 3)$, is

$$y^r_{i,t+h} = \mu^h_i + \theta^h_{i1} t + \theta^h_{i2} t^2 + \boldsymbol{\Pi}^h \boldsymbol{d}_{i,t} + w^k_{i,t} \beta^h + \boldsymbol{x}'_{i,t} \boldsymbol{\Gamma}^h + \sum_{l=1}^{p} \boldsymbol{s}'_{i,t-l} \boldsymbol{\Phi}^h_l + \epsilon_{i,t+h}, \tag{2}$$

where $h = 0, 1, \dots, 12$, $w^k_{i,t}$ is the weather shock of interest, $\boldsymbol{x}_{i,t}$ is the vector of contemporaneous regressors that complements $w^k_{i,t}$ and $y^r_{i,t}$, namely the contemporaneous values of the remaining endogenous variables in $\boldsymbol{y}_{i,t}$ (excluding the response $y^r_{i,t}$) and the remaining weather variables in $\boldsymbol{w}_{i,t}$ (excluding the shock of interest $w^k_{i,t}$), and $\boldsymbol{s}_{i,t-l}$ collects the lth lag of all elements of $\boldsymbol{x}_{i,t}$ together with $y^r_{i,t-l}$ and $w^k_{i,t-l}$, with $p = 2$ in the baseline. Fixed effects, trends, and NUTS3-by-quarter controls match the PVARX specification. Pointwise 95% bands and uniform 90% (outer) and 68% (inner) sup-t bands following Montiel Olea and Plagborg-Møller (2019) (Supplementary Appendix B) are computed over 12 horizons (three years).

Our identifying assumption is that, conditional on the controls, the short-run within-municipality variation in weather is uncorrelated with the contemporaneous economic shock. The municipality fixed effects absorb time-invariant cross-sectional heterogeneity, the municipality-specific linear and quadratic trends absorb slow-moving structural change, the NUTS3-by-quarter seasonal fixed effects absorb common region-by-quarter cycles, and the Mediterranean factor block absorbs cross-border atmospheric and economic spillovers. Under this design, residual within-municipality weather variation is plausibly exogenous to the contemporaneous innovation in $\boldsymbol{y}_{i,t}$ on the short, sub-annual horizon we study, since anthropogenic feedbacks on local climate operate over decades. We therefore interpret the estimated coefficients and impulse responses as conditional dynamic responses of local economic activity to realised weather deviations, not as structural climate damages or counterfactual welfare effects.

4. Empirical results

4.1. Baseline dynamic effects

Table 1 presents the coefficients from the PVARX specification with one quarterly lag. The estimation controls for municipality fixed effects, municipality-specific linear and quadratic time trends, and NUTS3-by-quarter seasonal fixed effects; for brevity, we omit these coefficients from the main tables and report the full set of estimates in Supplementary Appendix E. Because purchases and the house price index enter in first differences of natural logarithms, the reported coefficients can be interpreted as semi-elasticities of quarterly growth; i.e., a one-unit increase in the weather regressor is associated with a change of $100 \times \hat{\beta}$ in the quarterly growth rate of purchases (or house prices), in percentage points (holding other regressors fixed).

The economic block behaves as expected, i.e., purchases growth displays quarterly mean reversion, lagged unemployment changes negatively spill into purchases growth and house-price growth, and lagged house-price growth is negatively associated with the change in the unemployment rate, consistent with a short-run demand channel.[9]

[8] Nomenclature of Territorial Units for Statistics (NUTS) developed by the European Union.

[9] All magnitudes reported in this section are semi-elasticities. A coefficient of 0.015 on $\tilde{P}$, for example, corresponds to a 1.5 percentage point (pp) change in the quarterly growth rate of the dependent variable per 1 mm day^{-1} rainfall anomaly. The unemployment rate is not logged, so coefficients are interpreted directly in pp.

Table 1
Fixed-Effects PVARX(1, 1) baseline estimation results, with Conley standard errors.

Dependent Variables:	$\Delta log(pur)$	$\Delta log(hpi)$	Δur
Model:	(1)	(2)	(3)
Variables			
$\Delta log(pur)_{t-1}$	-0.1592^{*}	0.0010	0.0013
	(0.0923)	(0.0016)	(0.0015)
Δur_{t-1}	-1.033^{**}	-0.1852^{***}	-0.1047^{***}
	(0.4986)	(0.0393)	(0.0295)
$\Delta log(hpi)_{t-1}$	-0.0130	0.0092	-0.0231^{***}
	(0.0508)	(0.0326)	(0.0051)
θ_{i1t}	0.0001	0.0017^{***}	-0.0003^{***}
	(0.0006)	(0.0003)	(8.71×10^{-5})
θ_{i2t}	1.12×10^{-5}	$-1.5 \times 10^{-5***}$	$5.24 \times 10^{-6**}$
	(1.23×10^{-5})	(4.85×10^{-6})	(2.09×10^{-6})
Δfwi	0.0002	6.94×10^{-5}	0.0001
	(0.0021)	(0.0006)	(0.0002)
hfd	0.0016	-0.0005	0.0002
	(0.0027)	(0.0010)	(0.0002)
$\tilde{P}$	0.0638	0.0209	-0.0131^{***}
	(0.0403)	(0.0182)	(0.0028)
$\check{P}$	-0.0680	-0.0394	0.0235^{***}
	(0.0639)	(0.0311)	(0.0046)
$\tilde{T}$	-0.0026	0.0048^{***}	-0.0012^{***}
	(0.0041)	(0.0012)	(0.0003)
$\Delta\check{T}$	0.0254^{***}	-0.0004	-0.0013^{***}
	(0.0088)	(0.0015)	(0.0005)
Δfwi_{t-1}	0.0063^{***}	0.0011^{*}	-0.0001
	(0.0014)	(0.0006)	(9.7×10^{-5})
hfd_{t-1}	-0.0009	0.0013	-0.0002
	(0.0020)	(0.0010)	(0.0001)
$\tilde{P}_{t-1}$	-0.1232^{***}	-0.0172	0.0100^{***}
	(0.0418)	(0.0109)	(0.0020)
$\check{P}_{t-1}$	0.1460^{**}	0.0371^{**}	-0.0176^{***}
	(0.0698)	(0.0188)	(0.0032)
$\tilde{T}_{t-1}$	-0.0019	-0.0075^{***}	0.0015^{***}
	(0.0038)	(0.0013)	(0.0002)
$\Delta\check{T}_{t-1}$	-0.0568^{***}	0.0166^{***}	0.0006
	(0.0155)	(0.0032)	(0.0006)
Fixed-effects			
municipality	Yes	Yes	Yes
Observations	11,676	11,676	11,676

Notes: Sample of 278 mainland-Portuguese municipalities, 2010Q1–2021Q4 (full balanced panel $N \times T = 11{,}676$; the estimation sample reported above is reduced after first differencing and lag inclusion). All specifications include municipality fixed effects, municipality-specific linear and quadratic trends, and NUTS3-by-quarter-of-year seasonal fixed effects (full estimates in Supplementary Appendix E). Anomalies ($\tilde{T}, \tilde{P}$) are deviations from 1961 to 1990 climatological means. Standard errors are Conley spatial HAC standard errors (Conley, 1999), computed using the latitude and longitude of municipality centroids, and a 60 km distance cutoff. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Three patterns dominate the weather block. First, no contemporaneous weather variable enters significantly for purchase growth except changes in temperature variability ($\Delta\check{T}$, +2.5 pp); the contemporaneous weather signal is concentrated in the unemployment and house-price equations, where rainfall anomalies, rainfall variability, temperature anomalies, and temperature variability all enter significantly for unemployment, and temperature anomalies enter positively for house prices. Second, the lagged weather block reveals systematic within-year adjustment for purchases, lagged rainfall anomalies and lagged temperature variability are large and negative ($\tilde{P}_{t-1}$, −12.3 pp; $\Delta\check{T}_{t-1}$, −5.7 pp), while lagged rainfall variability reverses to a large positive ($\check{P}_{t-1}$, +14.6 pp). Third, for unemployment and house prices the lagged terms reverse the contemporaneous signs for rainfall and temperature anomalies, consistent with a one-quarter overshoot-and-correct dynamic. Full magnitudes and standard errors are in Table 1.

4.2. Robustness checks

4.2.1. Controlling for cross-border weather spillovers

Including Mediterranean-wide factor variables (Supplementary Appendix D.2 lists the countries; Supplementary Appendix F.1 reports full results) leaves the domestic weather structure broadly intact for unemployment and house prices, while attenuating much of the purchases signal. In particular the contemporaneous temperature variability and the large lagged rainfall coefficients are no longer distinguishable from zero, whereas the lagged temperature variability term ($\Delta\check{T}_{t-1}$) and the lagged fire weather index remain

Table 2
Precipitation-volatility coefficients: hourly ($mm\ hour^{-1}$) versus daily ($mm\ day^{-1}$) measurement.

	Daily $\Delta\check{P}_{total}$	Hourly $\check{P}$ (baseline)
Dependent variable: $\Delta\log(pur)$		
t	0.0004**	−0.0680
$t-1$	−0.0008***	0.1460**
Dependent variable: Δur		
t	-8.33×10^{-5}***	0.0235***
$t-1$	-3.75×10^{-5}	−0.0176***
Dependent variable: $\Delta\log(hpi)$		
t	0.0001	−0.0394
$t-1$	−0.0001*	0.0371**

Notes: Coefficients are semi-elasticities; multiplying by 100 gives the percentage-point change in the quarterly growth rate of the dependent variable per one-unit change in the regressor. The two columns differ only in the construction of $\check{P}$: column (1) uses the intra-monthly standard deviation of daily totals (mm/day); column (2) uses the intra-daily standard deviation of hourly values (mm/hour). All other regressors, fixed effects, trends, and seasonal controls match the baseline PVARX(1,1) (Section 3.1). Significance: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

unaffected. The attenuation admits two complementary interpretations: (i) the common Mediterranean component may directly confound domestic coefficients by removing non-domestic atmospheric variation that coincides with favourable local conditions, or (ii) it may partly proxy for cross-border economic channels such as synchronised tourism and trade flows; the present specification cannot cleanly separate the two. The Mediterranean factors themselves enter significantly across all three equations with intuitive signs (warmer Mediterranean conditions and a positive precipitation factor are associated with higher purchases and house-price growth and lower unemployment changes).

4.2.2. Re-estimating with an alternate volatility measure ($mm\ day^{-1}$)

The literature typically measures rainfall variability as the intra-monthly standard deviation of daily totals in millimetres per day ($mm\ day^{-1}$), whereas the baseline employs the intra-daily standard deviation of hourly values in millimetres per hour ($mm\ hour^{-1}$) to capture short, intense downpours. To assess the sensitivity of the baseline findings to this choice, we recompute $\check{P}$ using the day-level unit ($\Delta\check{P}_{total}$) and re-estimate an otherwise identical specification (see Supplementary Appendix F.2 for the full results).

Switching to the daily measure alters both the sign pattern and the magnitude of the precipitation-variability coefficients; Table 2 reports the relevant coefficients side by side, drawn from the baseline PVARX(1,1) (hourly) and the otherwise identical specification with the daily measure (Supplementary Appendix F.2).

The hourly and daily coefficients in Table 2 differ in sign for every cell except lagged unemployment, indicating that the two measures capture different dimensions of rainfall exposure. The hourly coefficients are uniformly larger in absolute value; per one standard deviation of each regressor, the hourly semi-elasticities for purchases and house prices remain roughly an order of magnitude larger than their daily counterparts. Under the hourly measure, the contemporaneous purchases coefficient is large in magnitude but not statistically significant ($t\approx-1.06$); the one-quarter-lag coefficient of $\check{P}_{t-1}$ is significant at the five-percent level and reverses sign. Outside the precipitation-variability block itself, the dynamic structure of the system is stable across the two specifications. The lagged endogenous variables retain the same signs and significance under the daily measure; for example, Δur_{t-1} remains significantly negative in the house-price equation (−0.1741 versus −0.1852 in the baseline). All temperature terms (including the contemporaneous and lagged coefficients for $\Delta\check{T}$ and $\tilde{T}$), preserve their signs and significance across all three equations, and the fire-weather controls are likewise unaffected (Supplementary Appendix F.2). The one exception outside the variability block is the pair of precipitation-level variables, $\tilde{P}_t$ and $\tilde{P}_{t-1}$, which change sign in the unemployment and house-price equations. This is a collinearity effect: both $\tilde{P}$ (the rainfall anomaly) and $\check{P}$ (rainfall variability) summarise aspects of the within-quarter rainfall distribution, so switching from the hourly to the daily construction of $\check{P}$ changes how much of that joint variation is absorbed by the variability term, altering what residual variation $\tilde{P}$ is left to explain conditional on the remaining regressors. The level and variability coefficients should therefore always be read as a pair; the former has no stable interpretation independent of how the latter is constructed.

The two measures are therefore not interchangeable. The hourly construction isolates the intensity of short-duration downpours within a day, while the daily standard deviation reflects day-to-day fluctuations in total accumulation across the month. Where disruption is driven by brief, intense events, as in the Valencia flash floods, in which a large share of daily accumulation arrived within a few hours (Rombeek et al., 2025), the hourly measure captures the relevant exposure and the daily measure may smooth it away.

4.2.3. Additional robustness checks

Further robustness exercises are reported in Supplementary Appendix F. Augmenting the baseline system with municipality disposable income growth (Appendix F.3) leaves the weather coefficients with their baseline sign pattern and timing, ruling out an

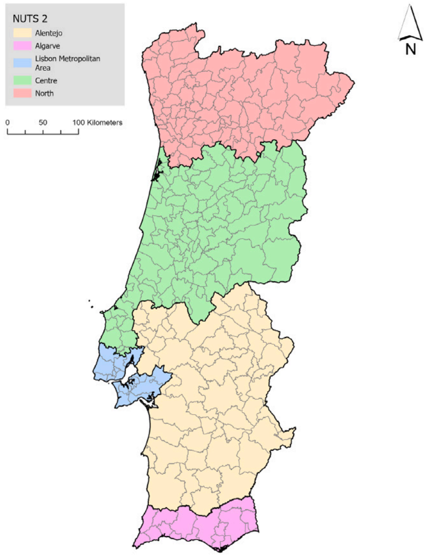


Fig. 3. Classification of municipalities into NUTS 2 categories sourced from INE.

omitted income-growth channel; lagged temperature anomalies are themselves negatively associated with income growth, suggesting an independent temperature-income channel.

Allowing non-linear weather effects (Appendix F.4) yields three messages. The compound-risk interaction $\tilde{T} \times \tilde{P}$ is significant only for purchases and indicates that jointly high temperature and precipitation anomalies are associated with lower purchase growth. Polynomial terms in temperature are significant in the unemployment and purchase equations, and a binned specification using daily-mean temperature shows lower purchase growth and house-price growth in the cold (< 0°C) and extreme-heat (> 35°C) tails. For precipitation, non-linearity is concentrated in the house-price equation.

Two further checks confirm robustness. Four quarterly lags (Appendix F.5) redistribute adjustment across longer horizons but preserve the headline contemporaneous associations in the unemployment equation. Replacing continuous weather indices with count-based extremes (Appendix F.6) yields qualitatively similar directions and the same short-horizon reversal pattern, indicating the baseline results are not an artefact of the scaling of the weather regressors.

4.3. Heterogeneous responses across major regions

Geography, sectoral structure, and exposure to tourism differ markedly across the country, particularly between the Lisbon Metropolitan Area, the North, and the Algarve holiday coast in the south. To examine whether the headline relationships mask region-specific patterns, the panel is split into three NUTS-II aggregates (Lisbon Metropolitan Area, North, and Algarve); a map is provided in Fig. 3. Each subsample is re-estimated using the baseline one-lag specification. In these subsample regressions, the NUTS-III-by-quarter controls are replaced with quarter dummies only ($\rho_q, q \in \{2, 3, 4\}$), because each NUTS-II aggregate contains relatively few NUTS-III regions and the fully interacted set would be highly parameter-intensive, while quarter effects are sufficient to absorb common seasonality within each restricted panel. The full results, including standard errors and significance levels for all coefficients, are provided in Supplementary Appendix F.7. The coefficients reported below are statistically significant at the 5% level or better unless otherwise noted; see supplementary tables for complete inference.

In the Lisbon Metropolitan Area the weather signal does not load on purchases; no contemporaneous weather variable enters significantly at the 5% level. It loads instead on unemployment (rainfall anomalies enter positively, temperature-variability changes negatively) and on house prices (temperature anomalies enter negatively contemporaneously and positively at the lag, reversing the national sign; lagged rainfall variability is positively associated with house-price growth). The endogenous block also differs from the national panel: purchases lose mean reversion and the unemployment spillover into purchases flips sign.

In the North the baseline structure is broadly preserved and rainfall dominates the purchases equation, with large and offsetting contemporaneous and lagged associations of rainfall anomalies and rainfall variability that reverse sign at the lag; the same sign pattern holds for unemployment at smaller magnitudes. Fire-risk terms become more prominent than in the national panel and enter significantly for both unemployment and house prices.

In the Algarve, the estimated weather effects differ sharply from the rest of the country. Rainfall coefficients in the purchases equation are much larger in magnitude and reverse at the lag, contemporaneous rainfall variability is strongly positive, while its lag is strongly negative. This pattern is consistent with a small, tourism-intensive panel in which the rainfall-variability measure may capture particularly intense or localized weather dynamics. Lagged rainfall terms also enter significantly in the unemployment equation, while fire-risk and heat-related variables show more pronounced timing effects in the house-price equation, especially through contemporaneous fire weather, hazardous fire days, and lagged temperature variability.

Because the regression coefficients are expressed per unit of the regressor (mm/hour for $\breve{P}$, mm/day for $\tilde{P}$) and one-unit changes are well outside the typical in-sample range for these variables, the per-one-standard-deviation impulse responses in Section 5 should be read as the economically meaningful magnitudes for cross-region interpretation; the full coefficient table for each NUTS-II aggregate is in Supplementary Appendix F.7.

5. Economic responses to weather shocks

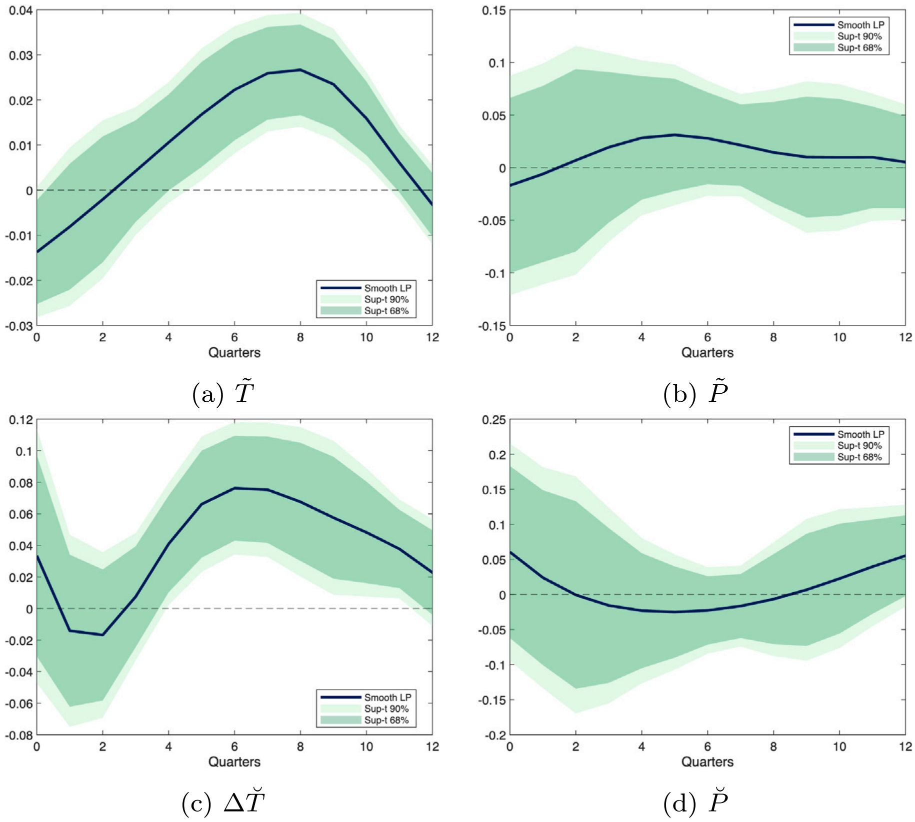
This section reports local-projection responses to one-standard-deviation shocks in temperature and precipitation conditions over twelve quarters, estimated using (2). We present the smoothed impulse responses following Barnichon and Brownlees (2019); the supplementary material reports the corresponding unsmoothed local projections, as well as responses for fire risk and Mediterranean controls. For purchases and the house-price index, the vertical axis is interpreted as percentage-point changes in quarterly growth, that is, $100 \times \hat{\beta}_h$; unemployment effects are reported in percentage points of the quarterly change in the unemployment rate. The figures plot two uniform sup-t bands: an outer 90% band and an inner 68% band; the inferential framework is described in Section 5.4.

We distinguish between (i) anomaly shocks, which are innovations to deviations from the long-run local climatology, such as unusually wet or unusually warm quarters relative to historical norms, and (ii) volatility shocks, which are innovations to mean within-day variability (capturing shifts in intra-day fluctuations).

5.1. Purchases

A temperature-anomaly ($\tilde{T}$) shock reduces purchase growth on impact by roughly one percentage point (Fig. 4); the response stays negative for two quarters before reversing and tapering back to zero. Temperature variability ($\Delta\breve{T}$) generates a much larger response: a sharp positive impact effect (around four pp), a brief contraction one quarter ahead, and a sustained positive phase peaking around six quarters ahead at roughly eight pp.

Rainfall shocks are similarly large. A rainfall-anomaly ($\tilde{P}$) shock depresses purchase growth on impact by about one pp, then climbs to a peak of roughly four pp around five quarters ahead before fading. Rainfall variability ($\breve{P}$) produces a U-shape with the largest impact effects among the four shocks, a sharp + 5 pp surge on impact, a trough near −2 pp around five quarters ahead, and a return to baseline by the end of the horizon.



(a) $\tilde{T}$ (b) $\tilde{P}$

(c) $\Delta\breve{T}$ (d) $\breve{P}$

Fig. 4. Smoothed impulse responses for purchases to shocks in temperature and rain. Outer band: uniform 90% sup-t. Inner band: uniform 68% sup-t. See Section 5.4.

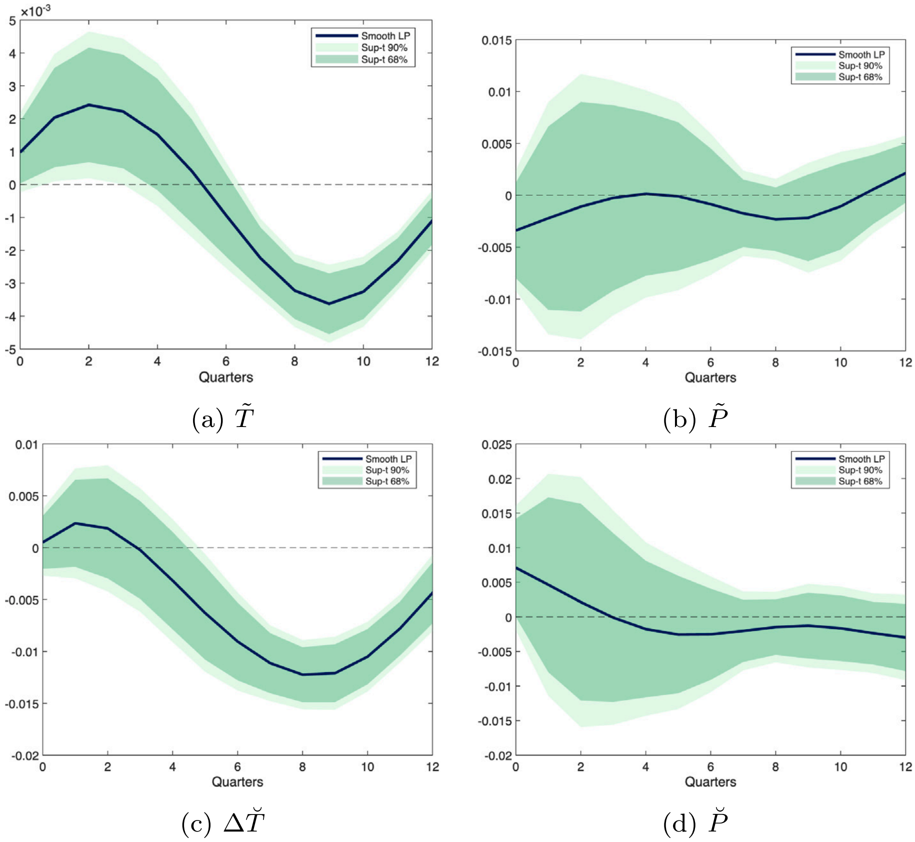


Fig. 5. Smoothed impulse responses for unemployment rate to shocks in temperature and rain. Outer band: uniform 90% sup-t. Inner band: uniform 68% sup-t. See Section 5.4.

5.2. Unemployment rate

Unemployment responses are smaller than those for purchases but more persistent (Fig. 5). Both the temperature-anomaly ($\tilde{T}$) and the temperature-variability ($\Delta\breve{T}$) shocks generate a two-phase pattern: an initial increase in the unemployment rate (peaking around 1–2 quarters ahead), followed by a deeper and more sustained negative phase whose minimum (around 8–9 quarters ahead) exceeds the initial peak in absolute value. The negative phase under temperature variability is the more pronounced of the two.

Rainfall-anomaly shocks are associated with predominantly negative unemployment responses across the horizon. Rainfall variability produces its largest effect on impact (a sharp positive spike), followed by a steady negative phase from around three quarters onward.

5.3. House price index

Fig. 6 plots quarterly house-price growth responses. Both temperature shocks generate a two-phase pattern: an initial negative phase (lasting roughly one to six quarters, with troughs near -1.25 pp under $\tilde{T}$ and -2 pp under $\Delta\breve{T}$) followed by a positive phase peaking around six to nine quarters ahead. The temperature-variability response is the sharper of the two and remains positive through the rest of the horizon.

Rainfall anomalies push house-price growth above baseline on impact (about $+1.4$ pp), peaking near +5 pp around four quarters ahead before retreating. Rainfall variability generates the largest house-price movements among the four shocks: a sharp negative impact effect (≈ -4 pp), a deeper trough near -7 pp around four quarters ahead, and a rebound to a positive peak of about +5 pp around nine quarters ahead.

5.4. Inference

The bands plotted in Figs. 4–6 are uniform 95% sup-t bands computed on the smoothed estimates (Montiel Olea and Plagborg-Møller, 2019). By construction these bands are wider than the pointwise intervals and they reflect joint uncertainty across all twelve horizons simultaneously, so an IRF segment whose band excludes zero does so with familywise rather than horizon-by-horizon coverage. Construction details, the Gaussian multiplier bootstrap algorithm, and a block-length sensitivity analysis are provided in

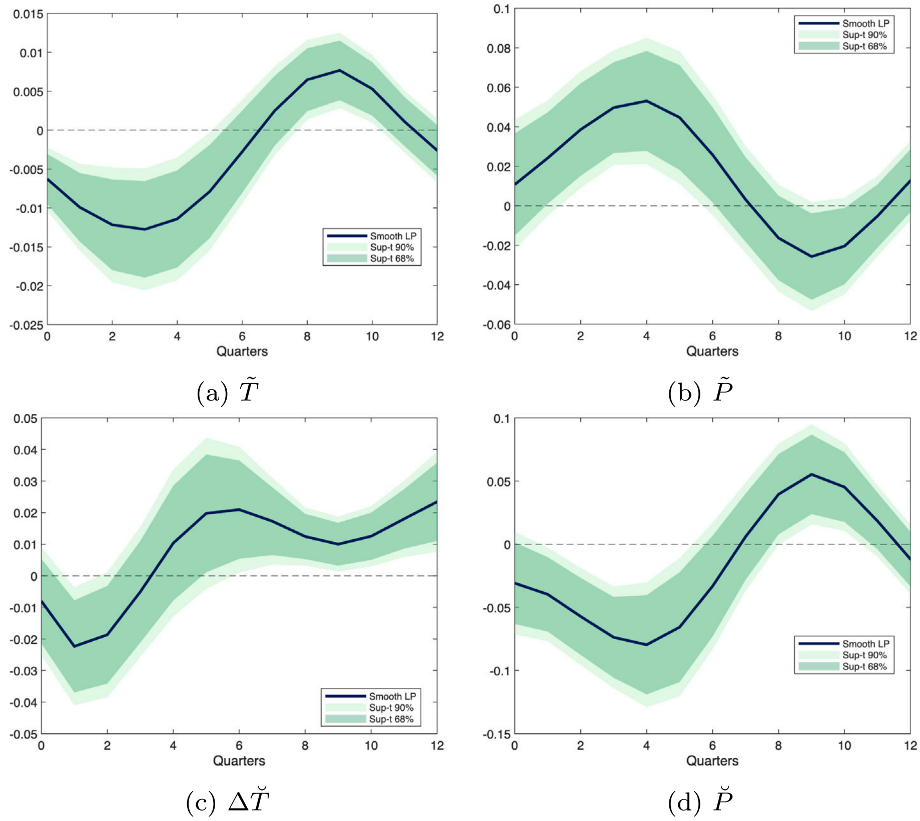


Fig. 6. Smoothed impulse responses for house price index to shocks in temperature and rain. Outer band: uniform 90% sup-t. Inner band: uniform 68% sup-t. See Section 5.4.

Supplementary Appendix B. Pointwise intervals and the unsmoothed LP responses are also reported in the supplementary material for comparison.

6. Discussion

The discussion that follows interprets the dynamic patterns documented in Sections 4 and 5 through the lens of channels emphasised in the literature on weather, retail activity, labour markets, and housing. We do not directly identify these mechanisms; the regressions report reduced-form associations between weather realisations and the three economic outcomes. Channel-specific terms (such as “access channel”, “thermal-comfort channel”, “insurance-funded renovation”) are used as shorthand for patterns consistent with prior evidence rather than as a claim of mechanism identification. Heterogeneity exercises that would pin down individual mechanisms (such as interactions with municipality-level tourism intensity, sectoral employment shares, or flood/fire exposure) are left for future work.

6.1. Weather and purchases

The literature identifies four principal channels through which weather shapes consumer spending: (i) a physical access channel, where adverse conditions reduce foot traffic to brick-and-mortar retailers (Martínez-de Albéniz and Belkaid, 2021; Badorf and Hoberg, 2020); (ii) a mood channel, where sunlight and temperature shape affect and willingness to spend (Murray et al., 2010; Buchheim and Kolaska, 2017); (iii) a thermal comfort channel, where extremes drive shoppers into climate-controlled retail environments and generate a U-shape relationship between temperature and sales (Yoo et al., 2024); and (iv) a product desirability channel, where weather alters demand for specific goods (Bertrand et al., 2015).

The impulse responses for purchases reveal a short-run contraction in response to a temperature-anomaly shock, followed by a positive rebound over the medium horizon. The initial decline is consistent with the access channel, as unusually warm conditions discourage outdoor shopping activity (Martínez-de Albéniz and Belkaid, 2021); the subsequent recovery aligns with the thermal-comfort and product-desirability channels, as consumers shift toward climate-controlled retail environments and increase demand for cooling equipment and seasonal goods (Yoo et al., 2024). Temperature variability generates the largest and most sustained purchase responses among the four weather dimensions. The sharp positive impact effect, followed by a brief contraction and a prolonged positive phase, is consistent with within-day fluctuations triggering immediate compensatory and impulsive purchases

(Buchheim and Kolaska, 2017); the sustained positive phase that follows reflects replacement demand and adaptation investments (Badorf and Hoberg, 2020; Bertrand et al., 2015).

The rainfall-anomaly response is consistent with the access channel operating through intertemporal reallocation. Rain initially depresses purchases as adverse conditions reduce foot traffic and shopping activity; the gradual positive rebound over subsequent quarters reflects deferred spending being caught up rather than permanently lost (Starr-McCluer, 2000). Rainfall variability produces a U-shaped response with the largest impact effects among the four shocks. The positive contemporaneous surge is consistent with compensatory purchasing and stockpiling behaviour during intense rainfall episodes; the mid-horizon decline and subsequent recovery align with inventory adjustments and delayed replacement of weather-damaged goods (Starr-McCluer, 2000; Bertrand et al., 2015). The disruption channel is plausibly amplified by the brief, high-intensity downpours that the hourly variability measure isolates.

Two design features mitigate the concern that within-year reversals reflect residual seasonality. First, anomalies remove the seasonal component by construction, and NUTS-III-by-quarter fixed effects absorb region-specific seasonality. Second, conditioning on the Mediterranean factors attenuates contemporaneous responses but preserves the lagged precipitation-variability terms with the same sign pattern, indicating that the surviving lagged effects reflect Portugal-specific deviations from the broad atmospheric state.

The NUTS-II subsample analysis maps onto these channels. In Lisbon, where retail is predominantly urban and indoor, the purchase signals shift from variability to precipitation levels, consistent with rain differentially affecting street-facing versus mall-based stores (Martínez-de Albéniz and Belkaid, 2021). In the North, precipitation variability remains dominant, consistent with greater Atlantic exposure and dispersed retail geography. In the Algarve, the precipitation-anomaly profile reverses; rainfall reduces contemporaneous purchase growth, consistent with the product-desirability channel operating through tourism.

6.2. Weather and the unemployment rate

The unemployment rate responds with smaller magnitudes than purchases but greater sign persistence. The literature identifies three principal channels: a labour-productivity channel, where adverse conditions reduce output per worker in outdoor, physically intensive occupations (Dasgupta et al., 2021; Higa, 2025); a sectoral reallocation channel, where weather contractions in exposed sectors release labour absorbed elsewhere (Colmer, 2021; Xie, 2024); and an event-driven disruption channel that captures acute episodes damaging capital and triggering recovery hiring (Gray et al., 2023).

The short-run increase observed in Fig. 5(a) aligns with the broader literature, where heat reduces labour productivity and raises absenteeism (Xie, 2024; Higa, 2025); however, the larger subsequent decline is consistent with Portugal's sectoral composition, where services account for approximately 70 percent of total employment and agriculture for roughly 3 percent. In a tourism-intensive economy, warm conditions plausibly stimulate labour demand in hospitality and recreation with a lag, more than offsetting the initial productivity losses concentrated in the small outdoor-exposed share of the workforce (Colmer, 2021). Temperature variability traces a similar two-phase pattern; the initial unemployment increase is sharper but peaks earlier, and the subsequent negative phase is deeper and more sustained, consistent with within-day fluctuations initially disrupting activity before services-sector demand absorbs the displaced labour.

Rainfall anomalies are associated with a predominantly negative unemployment response over the horizon. The pattern is consistent with the demand-stimulus channel dominating the disruption channel in an economy where construction accounts for roughly 7 percent of employment; wetter conditions may support indoor services and retail activity rather than acting primarily as an impediment to outdoor work (Gray et al., 2023). Rainfall variability, by contrast, produces a sharp initial increase in unemployment followed by a sustained negative response for the remainder of the horizon. The initial spike is consistent with intense rainfall episodes acutely disrupting outdoor activity, while the prolonged negative phase points toward recovery hiring and post-disruption demand.

Fire-risk variables do not enter significantly at the national level; their effects are concentrated in the Algarve subsample, where tourism dependence amplifies the event-driven disruption channel. Overall, the unemployment responses suggest that Portugal's services-dominated economy partially absorbs the productivity losses documented in more agriculture-dependent settings, with the correction phase of the temperature response and the sustained negative rainfall effects pointing toward a demand-stimulus offset operating through tourism and indoor services (Colmer, 2021; Gray et al., 2023).

6.3. Weather and house prices

The house price index serves a dual role: it is an outcome in its own right and also proxies local demand pressure, wealth and collateral effects, and cost-of-living conditions not captured by sub-national CPI. The literature invokes two mechanism sets. Transitory search and transaction frictions arise when weather alters search intensity, curb appeal, and bargaining position, generating short-run effects unrelated to fundamental value (Gourley, 2021; Livy, 2020). Demand fundamentals operate via labour income, employment, and risk perceptions (Chen et al., 2025; Spencer, 2023); Chen et al. (2025) argue the net effect of heat depends on the balance of secondary-sector losses and tertiary-sector gains, connecting house-price dynamics to the unemployment results above.

The temperature-anomaly response is initially negative before turning positive at longer horizons, mirroring the timing of the unemployment correction documented in Section 6.2. The short-run decline is consistent with the search-friction channel, as extreme conditions deter transactions and reduce curb appeal (Gourley, 2021); the subsequent positive phase aligns with the demand-fundamental channel, as tourism-driven employment gains feed through to housing demand (Chen et al., 2025). Temperature variability follows a similar two-phase pattern; a sharp initial contraction gives way to a sustained positive response, consistent with within-day fluctuations initially disrupting search activity before demand fundamentals dominate at longer horizons (Livy, 2020; Badorf and Hoberg, 2020).

The rainfall-anomaly response is positive over the first half of the horizon before turning negative, a pattern distinct from the search-friction prediction that rain depresses prices through reduced foot traffic. In a fire-prone economy, wetter conditions plausibly reduce perceived wildfire risk and support environmental amenity; the positive phase also coincides with the gradual recovery in purchase growth (Section 6.1), suggesting an indirect demand-fundamental channel. Rainfall variability generates the largest house-price movements among the four shocks. The deep initial contraction is consistent with intense downpours signalling flood and damage risk, depressing valuations through the risk-perception channel (Beltrán et al., 2018); the subsequent rebound is consistent with post-event recovery dynamics, in which reconstruction activity and insurance-funded renovation are documented to support prices (Beltrán et al., 2019); we do not test this channel directly.

Read as a proxy for local demand pressure, the house-price results align with the patterns documented above. The differentiated sign patterns across the three outcomes provide indirect support for the identification strategy, since residual seasonality or model misspecification would more likely produce uniform signs.

7. Conclusion

This study investigates the regional impacts of weather shocks on local economic activity in Portugal using a panel vector autoregressive framework and panel local projections. With quarterly data from 2010 to 2021, we compute impulse response functions to analyze the effects of temperature, wildfire risk, and precipitation volatility on point-of-sale purchases, unemployment, and housing prices.

Our central finding is that hourly precipitation volatility ($mm\,hour^{-1}$) yields semi-elasticities for purchases an order of magnitude larger, with opposing signs, than the conventional daily measure ($mm\,day^{-1}$), suggesting that the existing literature systematically understates the economic significance of high-intensity rainfall. For purchases, our primary outcome, variability shocks generate the largest responses; both temperature and rainfall variability are associated with sharp positive impact effects that subsequently reverse, consistent with compensatory purchasing and intertemporal reallocation. Anomaly shocks are smaller but display clear dynamic adjustment; temperature and rainfall anomalies initially depress purchases before a gradual positive rebound over subsequent quarters. For unemployment, the temperature response initially aligns with the broader finding that heat raises unemployment through productivity losses, but a subsequent correction that exceeds the initial increase is consistent with tourism-driven labour demand in a services-dominated economy; rainfall anomalies are associated with predominantly negative unemployment responses over the horizon. House prices display broadly consistent dynamics, with rainfall variability generating the largest movements and temperature responses mirroring the timing of the unemployment correction.

Results are stable to alternate specifications: adding household disposable income leaves contemporaneous weather semi-elasticities essentially unchanged; quadratic and cubic terms reveal thresholds without overturning main effects; including the Mediterranean factor attenuates some domestic precipitation coefficients without altering central conclusions. Defining volatility hourly rather than daily captures the short, intense events that drive the largest spending responses, exposing a methodological gap: $mm\,day^{-1}$ measures understate the economic significance of extreme precipitation. Replacing continuous indices with event counts mainly attenuates magnitudes, not signs.

This paper extends the literature on weather and consumer spending (Starr-McCluer, 2000; Rose and Dolega, 2021; Martínez-de Albéniz and Belkaid, 2021) to a European setting with sub-annual point-of-sale data, complements macro evidence on temperature and GDP (Dell et al., 2012; Burke et al., 2015) by documenting the local-transaction-activity channel, and adds to evidence on weather and unemployment in service-oriented economies (Colmer, 2021; Gray et al., 2023) by showing that the initial productivity-loss channel operates as documented elsewhere but is more than offset at longer horizons by services-sector demand in tourism-intensive Portugal. To our knowledge, the house-price results provide the first sub-national European evidence linking weather shocks to housing valuations, complementing US work (Chen et al., 2025; Spencer, 2023).

Our results echo Kotz et al. (2022) and Waidelich et al. (2024) on adverse effects of rainfall variability, with the additional nuance that temporal resolution matters: hourly volatility yields semi-elasticities an order of magnitude larger than daily, suggesting that the existing literature, which predominantly relies on daily aggregates, systematically understates the importance of high-intensity events that climate projections indicate will become more frequent (Lima et al., 2023).

We acknowledge a few limitations. First, our quarterly frequency may obscure finer dynamics. Second, because our measure of purchases is not disaggregated, we cannot examine which types of sales are affected, limiting our ability to provide a more detailed account of how transaction patterns respond. Third, the 2010–2021 window may miss longer-term trends. Finally, omitting wind data limits identification of cyclone and convective-storm channels relevant for Portugal.

CRediT authorship contribution statement

Dhruv Akshay Pandit: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **Paulo M.M. Rodrigues:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **João Seixo:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors thank Editor Roger H. von Haefen and two anonymous referees for their constructive feedback, and Nuno Alves, António Antunes, Nuno Lourenço, and László Tétényi for useful comments and suggestions on an earlier draft. Pandit acknowledges this work was supported by national funds through FCT (Fundação para a Ciência e a Tecnologia), under the project – UIDB/04152 – Centro de Investigação em Gestão de Informação (MagIC)/NOVA IMS. Rodrigues thanks the Portuguese Science Foundation (FCT) for financial support through projects 2023.15199.PEX and UIDB/00124/2020, UIDP/00124/2020 and Social Sciences DataLab – PINFRA/22209/2016, POR Lisboa and POR Norte (Social Sciences DataLab, PINFRA/22209/2016), through project UID/ECO/00124/2013 and Social Sciences DataLab, Project 22209, POR Lisboa (LISBOA-01-0145-FEDER-007722) and POR Norte (Social Sciences DataLab, Project 22209).

Appendix A. Supplementary data

Supplementary data for this article can be found online at doi:10.1016/j.jeem.2026.103409.

Data availability

Data will be made available on request.

References

Almeida, M., Coelho, P., 2023. A first assessment of ERA5 and ERA5-land reanalysis air temperature in Portugal. Int. J. Climatol. 43, 6643–6663.
Badorf, F., Hoberg, K., 2020. The impact of daily weather on retail sales: an empirical study in brick-and-mortar stores. J. Retail. Consum. Serv. 52, 101921.
Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models. Econometrica 70, 191–221.
Barnichon, R., Brownlees, C., 2019. Impulse response estimation by smooth local projections. Rev. Econ. Stat. 101, 522–530.
Beck, H.E., Zimmermann, N.E., McVicar, T.R., Vergopolan, N., Berg, A., Wood, E.F., 2018. Present and future köppen-geiger climate classification maps at 1-KM resolution. Sci. Data 5, 180214.
Bednar-Friedl, B., Biesbroek, R., Schmidt, D., Alexander, P., Børsheim, K., Carnicer, J., Georgopoulou, E., Haasnoot, M., Cozannet, G.L., Lionello, P., Lipka, O., Möllmann, C., Muccione, V., Mustonen, T., Piepenburg, D., Whitmarsh, L., 2022. Europe. In: Pörtner, H.O., Roberts, D.C., Tignor, M., Poloczanska, E.S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., Rama, B. (Eds.), Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, USA, pp. 1817–1927.
Beltrán, A., Maddison, D., Elliott, R., 2018. Is flood risk capitalised into property values. Ecol. Econ. 146, 668–685.
Beltrán, A., Maddison, D., Elliott, R., 2019. The impact of flooding on property prices: a repeat-sales approach. J. Environ. Econ. Manag. 95, 62–86.
Bertrand, J.L., Brusset, X., Fortin, M., 2015. Assessing and hedging the cost of unseasonal weather: case of the apparel sector. Eur. J. Oper. Res. 244, 261–276.
Buchheim, L., Kolaska, T., 2017. Weather and the psychology of purchasing outdoor movie tickets. Manag. Sci. 63, 3718–3738.
Burke, M., Hsiang, S.M., Miguel, E., 2015. Global non-linear effect of temperature on economic production. Nature 527, 235–239.
Chen, F., Zhang, J., Chen, Z., 2025. Heat waves and housing markets: assessing the effects on real estate prices in China. Environ. Resour. Econ. 88, 1541–1579.
Colmer, J., 2021. Temperature, labor reallocation, and industrial production: evidence from India. Am. Econ. J. Appl. Econ. 13, 101–124.
Conley, T.G., 1999. GMM estimation with cross sectional dependence. J. Econom. 92, 1–45.
Costantini, M., Lupi, C., 2013. A simple Panel-CADF test for unit roots. Oxf. Bull. Econ. Stat. 75, 276–296.
Dasgupta, S., van Maanen, N., Gosling, S.N., Piontek, F., Otto, C., Schleussner, C.F., 2021. Effects of climate change on combined labour productivity and supply: an empirical, multi-model study. Lancet Planet. Health 5, e455–e465.
Dell, M., Jones, B.F., Olken, B.A., 2012. Temperature shocks and economic growth: evidence from the last half century. Am. Econ. J. Macroecon. 4, 66–95.
Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52, 740–798.
Demetrescu, M., Hassler, U., Tarcolea, A.I., 2006. Combining significance of correlated statistics with application to panel data. Oxf. Bull. Econ. Stat. 68.
Diffenbaugh, N.S., Burke, M., 2019. Global warming has increased global economic inequality. Proc. Natl. Acad. Sci. 116, 9808–9813.
Espinosa, L.A., Portela, M.M., Moreira Freitas, L.M., Gharbia, S., 2023. Addressing the spatiotemporal patterns of heatwaves in Portugal with a validated ERA5-land dataset (1980–2021). Water 15, 3102.
Espinosa, L.A., Portela, M.M., Gharbia, S., 2024. Assessing changes in exceptional rainfall in Portugal using ERA5-land reanalysis data (1981/1982–2022/2023). Water 16, 628.
European Environment Agency, 2024. European Climate Risk Assessment: Executive Summary. Number 2024, 01 in EEA Report. Publications Office of the European Union, Luxembourg.
Gourley, P., 2021. Curb appeal: how temporary weather patterns affect house prices. Ann. Reg. Sci. 67, 107–129.
Gray, H.B., Taraz, V., Halliday, S.D., 2023. The impact of weather shocks on employment outcomes: evidence from South Africa. Environ. Dev. Econ. 28, 285–305.
Habib, H., 2022. Climate change, macroeconomic sensitivity and the response of remittances to the North african countries: a panel VAR analyse. Int. J. Sustain. Dev. World Ecol. 29, 401–414.
Hanck, C., 2013. An intersection test for panel unit roots. Econom. Rev. 32, 183–203.
Heinen, A., Khadan, J., Strobl, E., 2019. The price impact of extreme weather in developing countries. Econ. J. 129, 1327–1342.
Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., others, 2018. ERA5 hourly data on single levels from 1979 to present. Copernic. Clim. Change Serv. (c3s) Clim. Data Store (cds) 10.
Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., others, 2020. The ERA5 global reanalysis. Q. J. R. Meteorol. Soc. 146, 1999–2049.
Higa, M., 2025. Is it too hot to work? Evidence from Peru. Environ. Dev. Econ. 1–20.
Jordá, O., 2005. Estimation and inference of impulse responses by local projections. Am. Econ. Rev. 95, 161–182.
Jordá, O., Schularick, M., Taylor, A.M., 2015. Betting the house. J. Int. Econ. 96, S2–S18.
Kalkuhl, M., Wenz, L., 2020. The impact of climate conditions on economic production. Evidence from a global panel of regions. J. Environ. Econ. Manag. 103, S0095069620300838.
Kotz, M., Wenz, L., Stechemesser, A., Kalkuhl, M., Levermann, A., 2021. Day-to-day temperature variability reduces economic growth. Nat. Clim. Change 11, 319–325.
Kotz, M., Levermann, A., Wenz, L., 2022. The effect of rainfall changes on economic production. Nature 601, 223–227.
Lima, D.C.A., Bento, V.A., Lemos, G., Nogueira, M., Soares, P.M.M., 2023. A multi-variable constrained ensemble of regional climate projections under multi-scenarios for Portugal – Part II: Sectoral climate indices. Clim. Serv. 30, 100377.
Linsenmeier, M., 2023. Temperature variability and long-run economic development. J. Environ. Econ. Manag. 121, 102840.
Livy, M.R., 2020. Determining the effect of abnormal temperatures on the housing market. Appl. Econ. Lett. 27, 233–236.
Martínez-de Albéniz, V., Belkaid, A., 2021. Here comes the sun: fashion goods retailing under weather fluctuations. Eur. J. Oper. Res. 294, 820–830.

Moberg, A., Jones, P.D., Barriendos, M., Bergström, H., Camuffo, D., Cocheo, C., Davies, T.D., Demarée, G., Martin-Vide, J., Maugeri, M., Rodriguez, R., Verhoeve, T., 2000. Day-to-day temperature variability trends in 160- to 275-year-long European instrumental records. J. Geophys. Res. Atmos. 105, 22849–22868.
Montiel Olea, J.L., Plagborg-Møller, M., 2019. Simultaneous confidence bands: theory, implementation, and an application to SVARs. J. Appl. Econom. 34, 1–17.
Murray, K.B., Di Muro, F., Finn, A., Popkowski Leszczyc, P., 2010. The effect of weather on consumer spending. J. Retail. Consum. Serv. 17, 512–520.
Natoli, F., 2024. The macroeconomic effects of unexpected temperature shocks. SSRN working paper. Social Science Research Network (SSRN).
Parker, M., 2018. The impact of disasters on inflation. Econ. Disasters Clim. Change 2, 21–48.
Plagborg-Møller, M., Wolf, C.K., 2021. Local projections and VARs estimate the same impulse responses. Econometrica 89, 955–980.
Rombeek, N., Hrachowitz, M., Uijlenhoet, R., 2025. Torrential rainfall in Valencia, Spain, recorded by personal weather stations preceding and during the 29 October 2024 floods. Hydrol. Earth Syst. Sci. 29, 6715–6733.
Rose, N., Dolega, L., 2021. 's the weather: quantifying the impact of weather on retail Sales. Appl. Spat. Anal. Policy 15, 189–214.
Schwarzwald, K., Geil, K., 2024. xagg: a Python package to aggregate gridded data onto polygons. J. Open Source Softw. 9, 7239.
Simes, R.J., 1986. An improved Bonferroni procedure for multiple tests of significance. Biometrika 73, 751–754.
Spencer, N., 2023. Wind and water: how extreme weather conditions impact residential real estate in developing countries. Int. J. Disaster Risk Sci. 14, 813–821.
Starr-McCluer, M., 2000. The Effects of Weather on Retail Sales. Finance and Economics Discussion Series 2000-08, Board of Governors of the Federal Reserve System (U.S.).
Stock, J.H., Watson, M.W., 2002. Forecasting using principal components from a large number of predictors. J. Am. Stat. Assoc. 97, 1167–1179.
Stock, J.H., Watson, M.W., 2005. Implications of Dynamic Factor Models for VAR Analysis. Working Paper 11467, National Bureau of Economic Research.
Waidelich, P., Batibeniz, F., Rising, J., Kikstra, J.S., Seneviratne, S.I., 2024. Climate damage projections beyond annual temperature. Nat. Clim. Change 14, 592–599.
World Meteorological Organization, 2017. WMO Guidelines on the Calculation of Climate Normals. World Meteorological Organization, Geneva.
Xie, V.W., 2024. Labor market adjustment to extreme heat shocks: evidence from Brazil. J. Econ. Behav. Organ. 222, 266–283.
Yoo, J., Eom, J., Zhou, Y., 2024. Thermal comfort and retail sales: a big data analysis of extreme temperature's impact on brick-and-mortar stores. J. Retail. Consum. Serv. 77, 103699.