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Keywords

climate risk, consumer prices, sectoral inflation, temperature anomalies, local projections

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Temperature Anomalies and Sectoral Inflation in Europe*

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Temperature shocks transmit unevenly across consumer prices, with adjustment extending into services and unfolding over several months. This paper combines gridded ERA5-Land temperature data with 17 Harmonised Indices of Consumer Prices in 34 European countries over 2000–2025. Monthly local projections trace price-level responses to country-specific maximum-temperature anomalies over 24 months. Headline prices and services respond gradually, reaching 0.157% and 0.122% at month 20 for a one-country-standard-deviation shock. Larger late-horizon responses appear in alcoholic beverages, tobacco, and narcotics and in personal care, social protection, and miscellaneous goods and services. Several delayed positive responses persist across seven lag-history specifications. The patterns are consistent with temperature-induced supply pressures transmitted through sectors with heterogeneous price adjustment. These findings connect the supply effects of temperature to the literature on sectoral price rigidity and inform the assessment of climate-related inflation risks.

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1 Introduction

Temperature shocks can disrupt supply in exposed activities and transmit price pressures across the consumption basket. Heat reduces effective labor input and productive efficiency, affects agricultural production, and can impair distribution. The resulting cost changes reach consumers through sectors with different input requirements and pricing practices. The economic question is therefore how far these pressures extend across goods and services and how their effects unfold over time. A modest immediate movement in headline inflation can coexist with a gradual adjustment in the prices of downstream and service-intensive activities.

Sectoral price rigidity provides a framework for understanding this timing. Firms face different costs of changing prices, operate under different contractual arrangements, and purchase inputs from suppliers that adjust at different speeds. As cost pressures propagate, consumer prices respond according to both the exposure of each activity and the timing of repricing. European micro price data document particularly infrequent adjustment in services, and multisector models establish the importance of heterogeneous price rigidity for sectoral inflation dynamics (Dhyne et al., 2006; Bouakez et al., 2014). These findings motivate following the response of a broad consumption basket beyond the month of the temperature disturbance.

Existing research provides evidence on both sides of this transmission. Heat-related productivity losses establish a supply-side mechanism (Somanathan et al., 2021), while studies of temperature and inflation document heterogeneous responses across prices and seasons (Kotz et al., 2024; Ciccarelli et al., 2024; Lucidi et al., 2024). Among the closest studies, Ciccarelli et al. (2024) document country and seasonal asymmetries in sectoral inflation responses in the largest euro area economies. The present analysis connects this evidence to the literature on sectoral price adjustment by examining the price-level response paths of a broad set of consumer-price indices within a common monthly framework.

We analyze monthly data for 34 European countries over 2000–2025, covering all-items HICP, all 13 broad consumption divisions, and three special aggregates. Temperature exposure is constructed from daily ERA5-Land fields and expressed as a country-specific standardized anomaly in the monthly national maximum. Local projections trace price-level responses through month 24. The monthly identification strategy uses differences in country-specific temperature exposure within a dated month, conditional on price and temperature histories and country-specific seasonality.

The estimates reveal delayed price adjustment across a broad range of goods and services. The all-items response is close to zero on impact and reaches 0.157% at month 20 for a one-country-standard-deviation anomaly. Services reach 0.122% at the same horizon. Alcoholic beverages, tobacco, and narcotics reach 0.346% at month 22, and personal care, social protection, and miscellaneous goods and services reach 0.218% at month 24. The pointwise 90% intervals for headline prices and these three categories exclude zero at month 20 in all seven lag-history specifications.

The comparison with mean temperature yields different delayed headline and services responses. This distinction ties the baseline findings to the national maximum-temperature measure. The bootstrap results also support several individual delayed responses, including headline prices at month 20. The analysis therefore documents both the sensitivity to the exposure measure and the stability of several price responses across alternative lag histories.

The central contribution is to show that the price consequences of temperature disturbances extend into services and a broad range of consumption categories, with much of the adjustment emerging over subsequent months. This finding changes the emphasis from immediate movements in directly weather-sensitive prices to the transmission of a disturbance through the wider consumption basket. The service-price response is particularly informative: its gradual increase places the timing of retail-price adjustment at the center of the economic interpretation.

A second contribution is to connect these response paths to heterogeneous sectoral price rigidity. The results bring together two established features of the economy: temperature affects productive capacity and costs, and firms adjust prices at different frequencies across sectors. Their interaction provides a coherent account of the delayed responses. Sectoral exposure determines where cost pressures arise, while input relationships and price-setting decisions influence where and when they reach consumers. The empirical contribution consists of the estimated sectoral price paths. The microeconomic and multisector literatures provide the mechanism through which their timing can be interpreted.

The combination of spatially detailed weather data and harmonized consumer prices supports this economic comparison. A common exposure definition and estimation framework place goods and services on the same analytical footing while retaining the observations available for each index. Following price-level responses over 24 months reveals adjustment that would be missed by a focus on contemporaneous inflation. For the assessment of climate-related price risks, the findings establish the relevance of both the sectoral reach of temperature shocks and the horizon over which consumer prices respond.

The paper proceeds as follows. Section 2 relates the analysis to research on temperature, consumer prices, and sectoral price rigidity. Section 3 describes the data and temperature exposure. Section 4 presents the monthly identification strategy and local projections. Section 5 reports the results and their economic interpretation. Section 6 concludes. The appendix presents the complete response paths and sensitivity results.

2 Related literature

2.1 Temperature shocks and the supply side

The climate-economics literature documents effects of temperature on production, productivity, and labor supply. Cross-country evidence links temperature to economic activity and shows that its effects depend on the economic and climatic setting (Dell et al., 2012; Burke et al., 2015; Kahn et al., 2021). Reviews connect these findings to the physical and economic channels through which climate exposure affects welfare (Heal & Park, 2016; Auffhammer, 2018; Carleton & Hsiang, 2016; Hsiang & Kopp, 2018). This literature provides the supply-side foundation for studying consumer-price transmission.

Microeconomic evidence identifies effective labor input as an important channel. Graff Zivin & Neidell (2014) document changes in the allocation of time to work under high temperatures. Somanathan et al. (2021) find lower worker productivity and greater absenteeism on hot days in manufacturing. Adhvaryu et al. (2020) show that reducing workplace heat improves production efficiency. These findings motivate treating adverse temperature exposure as a supply disturbance: lower productive efficiency increases the resources required to produce a given quantity. Agricultural and intermediate-input exposure provides additional routes through which cost pressures reach consumer-facing sectors, as illustrated in multisector models of agricultural and oil shocks (Bouakez et al., 2014).

2.2 Temperature and consumer prices

An emerging empirical literature examines the connection between temperature and inflation more directly. Faccia et al. (2021) study extreme temperatures in relation to price stability, and Kotz et al. (2024) analyze inflationary pressures associated with global warming and heat extremes. Ciccarelli et al. (2024) document country and seasonal asymmetries in sectoral inflation responses in the largest euro area economies, with prominent roles for food, energy, and services. Lucidi et al. (2024) show that warmer conditions can reduce European energy demand and inflation, reflecting the balance between heating and cooling needs. These findings establish the importance of distinguishing exposures and sectors: supply pressures and weather-sensitive demand jointly shape the observed price response. Our focus on national maximum-temperature anomalies and broad HICP coverage extends the evidence on the sectoral reach and timing of this transmission.

Research on energy shocks and the green transition examines the transmission of disturbances to relative prices (Corsello & Riggi, 2026; Bettarelli et al., 2025). This work emphasizes how differences in sectoral exposure translate into unequal price pressures. Bilal & Känzig (2026) provide complementary evidence on temperature and annual output. Their analysis connects temperature exposure to aggregate activity. The present study follows monthly consumer-price adjustment

across sectors. Together, these perspectives connect the production consequences of temperature to the evolution of consumer prices.

2.3 Heterogeneous sectoral price rigidity

Micro price data establish substantial heterogeneity in the frequency of price adjustment. Bils & Klenow (2004) document wide dispersion across consumer goods and services in the United States. Nakamura & Steinsson (2008) show that the treatment of sales and product substitutions matters for measured price flexibility and confirm pronounced variation across sectors. For Europe, Dhyne et al. (2006) find frequent adjustment in energy and unprocessed food and less frequent adjustment in services. This evidence provides a basis for interpreting differences in the timing of sectoral responses to a common source of cost pressure.

Multisector models connect heterogeneous price rigidity to shock propagation. Bouakez et al. (2014) link differences in sectoral inflation responses to heterogeneous price rigidity and trace agricultural and oil shocks through intermediate inputs. Pastén et al. (2020) show that price rigidity, sectoral size, and input–output linkages jointly determine the sectoral incidence of monetary transmission. Nakamura & Steinsson (2010) show that heterogeneous adjustment frequencies and intermediate inputs strengthen the propagation of nominal disturbances in a multisector menu-cost model. These results establish the importance of pricing heterogeneity and production linkages for aggregate dynamics. Applied to temperature exposure, this framework connects disruptions in exposed activities to downstream costs and allows retail prices to adjust at different speeds across sectors.

2.4 Local projections and lag-augmented inference

Local projections estimate the response at each horizon through a separate regression (Jordà, 2005). This flexibility is useful for sectoral inflation, where the timing, magnitude, and persistence of adjustment can differ across consumption categories. A common monthly temperature measure provides the exposure, while horizon-specific coefficients trace how each price index responds over the following 24 months. The resulting paths accommodate delayed adjustment and subsequent reversals, allowing the timing of the response to emerge from the estimates. Jordà & Taylor (2025) place this approach within the broader literature on dynamic causal effects and discuss its implementation in time-series and panel settings, including the choice of controls and inference procedures.

Persistence is particularly relevant when the outcome is a price level. Montiel Olea & Plagborg-Møller (2021) establish inference results for lag-augmented local projections across stationary, near-unit-root, and unit-root processes. Conditioning on lagged levels allows the current regressor to be represented by a stationary innovation after removing its predictable component. This separation supports asymptotically Gaussian inference for the response coefficient across different degrees

of persistence. Their results also accommodate projection horizons that increase with the time dimension under the conditions stated in Section 4. These findings motivate the augmented lag history used here. Country clustering and the wild bootstrap provide the panel inference procedures described in that section.

3 Data

The analysis links monthly Eurostat consumer prices to ERA5-Land temperature exposure at the country-month level. The estimation window is 2000–2025 and the baseline includes 34 countries.[1] The source weather panel is broader than the price sample, and observations before 2000 are retained only where needed to construct lags.

3.1 HICP outcomes

Consumer prices are measured using Eurostat's monthly Harmonised Indices of Consumer Prices (HICP) (Eurostat, 2026c).[2] The indices are produced under harmonized definitions and classification rules, supporting comparisons across countries and consumption categories. We select indices expressed with 2015=100. The historical series follow the updated ECOICOP version 2 classification, which distinguishes 13 consumption divisions, including separate divisions for insurance and financial services and for personal care, social protection, and miscellaneous goods and services. The estimated set comprises all-items HICP, all 13 broad consumption divisions, and three special aggregates: food including alcohol and tobacco, liquid fuels and fuels for personal transport equipment, and overall services. The broader food aggregate includes food and non-alcoholic beverages together with alcohol and tobacco. The fuel aggregate covers liquid fuels and fuels for personal transport equipment, while electricity, gas, and other household fuels enter the broader housing division. Table 1 gives the names and Eurostat codes of all 17 outcomes.

ECOICOP is the European Classification of Individual Consumption According to Purpose, which groups household consumption by purpose and follows the international COICOP classification (Eurostat, 2026b,a; United Nations Statistics Division, 2018). The historical series in the October 2026 extraction use ECOICOP version 2, aligned with UN COICOP 2018. Eurostat introduced this classification for HICP in February 2026 alongside a change in the index reference period to 2025=100 (Eurostat, 2026b). The classification version and index reference period are distinct: the series used here are expressed with 2015=100, and the estimation sample ends in December 2025.

The divisions and special aggregates overlap, and each response is estimated separately. Official

[1] Albania, Austria, Belgium, Bulgaria, Switzerland, Cyprus, Czechia, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Croatia, Hungary, Ireland, Iceland, Italy, Lithuania, Luxembourg, Latvia, Montenegro, North Macedonia, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovenia, Slovakia, and Türkiye.

[2] Eurostat, HICP monthly indices and rates of change, accessed 14 October 2026.

HICP aggregates incorporate expenditure weights, while the regressions estimate pooled country-month slopes. The comparison therefore concerns the price paths of the specified indices, with each outcome retaining its full available sample.

Table 1: HICP categories and Eurostat codes used in the analysis

Code	Eurostat category
TOTAL	Total HICP
CP01	Food and non-alcoholic beverages
CP02	Alcoholic beverages, tobacco and narcotics
CP03	Clothing and footwear
CP04	Housing, water, electricity, gas and other fuels
CP05	Furnishings, household equipment and routine household maintenance
CP06	Health
CP07	Transport
CP08	Information and communication
CP09	Recreation, sport and culture
CP10	Education services
CP11	Restaurants and accommodation services
CP12	Insurance and financial services
CP13	Personal care, social protection and miscellaneous goods and services
FOOD	Food including alcohol and tobacco
FUEL	Liquid fuels and fuels for personal transport equipment (special aggregate)
SERV	Services (overall index excluding goods)

Notes: The HICP data follow Eurostat's updated COICOP classification. All-items is TOTAL, CP12 is insurance and financial services, and CP13 is personal care, social protection, and miscellaneous goods and services. The estimated basket contains these 17 series. FOOD, FUEL, and SERV are pre-defined Eurostat aggregates. The indices overlap and are not a decomposition of TOTAL HICP. CP045 and its components are not separately estimated.

The estimation window is held fixed at 2000–2025. Each baseline regression includes observations from all 34 countries, but the number of country-month observations ranges from 8,613 to 9,656. Differences across outcomes reflect series availability. Within each outcome, the requirement that the response be observed through month $t + h$ reduces the usable sample as the horizon rises. Albania, Iceland, Montenegro, North Macedonia, and Switzerland enter later than most other countries for at least some outcomes. Each regression retains the full available sample for its outcome and horizon. Exposure dates and response endpoints are restricted to the study period, with no response extending past December 2025. Earlier observations are used only to construct lag histories.

For each positive index $P_{i,k,t}$, let $p_{i,k,t} = \log P_{i,k,t}$. The dependent variable is $100[p_{i,k,t+h} - p_{i,k,t-1}]$, the log price level at horizon h relative to the month immediately before exposure, scaled by 100. At $h = 0$, it compares the index in the exposure month with the prior month. At $h = 24$, it compares the index 24 months after exposure with that same reference month. The local-projection coefficient measures the price-level response to the temperature shock in approximate percentage terms.

3.2 Temperature exposure

Temperature data are derived from ERA5-Land 2-m air-temperature fields, produced by the European Centre for Medium-Range Weather Forecasts within the Copernicus Climate Change Service (Muñoz Sabater, 2019).[3] ERA5-Land provides hourly land-surface fields at a native spatial resolution of approximately 9 km (Muñoz-Sabater et al., 2021). Its land-surface simulation is driven by ERA5 atmospheric forcing. The underlying atmospheric reanalysis assimilates satellite and conventional meteorological observations. Elevation adjustments account for differences between the atmospheric and land grids. This reconstruction combines detailed spatial coverage with a consistent framework for measuring temperature variation over time.

Daily temperature fields are aggregated using fixed 2016 NUTS0 boundaries. Daily spatial means use fractional cell-area weights, whereas daily minima and maxima are unweighted extrema over the included grid cells. Monthly maximum temperature is measured as the highest of the daily country-level maxima within that month. This construction retains the intensity of the national monthly extreme, while the alternative mean-temperature measure captures average conditions. Fixed boundaries and a common aggregation rule maintain the same geographic basis for within-country comparisons throughout the study period.

Each grid cell's fractional area within a country is estimated using a 10×10 subpixel mask. The weights for daily country means are renormalized over nonmissing cells. Temperature values are converted to degrees Celsius, and the monthly mean measure is the average of daily country means.

For country i and month t, the primary exposure is

$$A_{i,t} = \frac{T^{\max}_{i,t} - \overline{T}^{\max}_{i,m(t)}}{sd_i(T^{\max}_{i,t} - \overline{T}^{\max}_{i,m(t)})}, \tag{1}$$

where $m(t)$ is the calendar month and the country-specific calendar-month means and the standard deviation of the resulting anomalies are computed over 2000–2025. Subtracting the calendar-month mean removes the country's recurring seasonal temperature cycle. Dividing by the standard deviation of the demeaned series expresses exposure in country-specific standard-deviation units. A one-unit increase corresponds to a one-standard-deviation departure from the country's usual temperature for that calendar month. The associated Celsius change varies across countries. The underlying measure captures the hottest reconstructed conditions within the national territory, so its physical interpretation also depends on country size and within-country temperature variation.

Figure 1 distinguishes the spatial temperature field from the country-level exposure used in the regressions. The gridded comparison shows mean daily maximum temperature in August 2000 and August 2025, alongside their difference. This two-date contrast provides a descriptive comparison.

[3] Copernicus Climate Change Service, ERA5-Land hourly data from 1950 to present. The Climate Data Store distributes the product on a regular $0.1^\circ \times 0.1^\circ$ grid.

The country map shows the standardized anomaly in the monthly national maximum for August 2025, calculated using the same country-calendar-month normalization as the empirical analysis. Positive values indicate a hotter-than-usual August relative to each country's own 2000–2025 distribution.

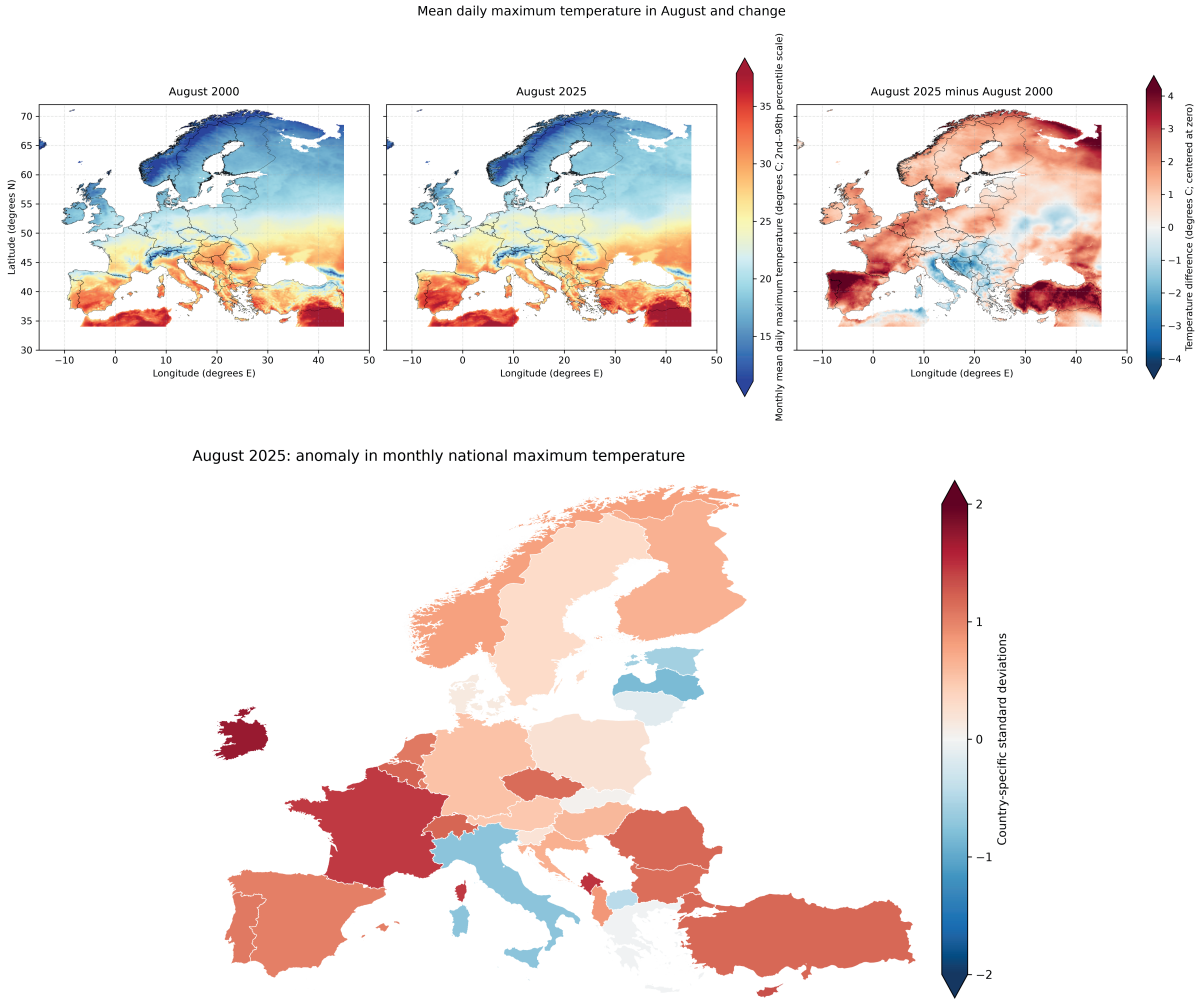


Figure 1: Gridded temperature context and the country-level exposure. The upper map compares mean daily maximum temperature in August 2000 and August 2025 and shows the August 2025 minus August 2000 difference. The absolute-temperature panels share a color scale, while the difference panel is centered at zero. The lower map shows the standardized anomaly in the monthly national maximum for August 2025 for the analysis countries shown. Anomalies use country-specific calendar-month means and the country-specific standard deviation of the demeaned series over 2000–2025. The gridded comparison is descriptive, and the lower map visualizes the exposure used in the regressions. Country boundaries are fixed at the 2016 NUTS0 vintage.

Table 2 reports summary statistics for both temperature measures, their standardized anomalies, and the 17 HICP indices and monthly inflation series. All rows cover the same 34 countries. Temperature measures and HICP index levels span January 2000–December 2025. Monthly inflation begins in February 2000 because it requires the preceding monthly index. Observation counts vary

with series availability. Temperature levels are in degrees Celsius, and anomalies are demeaned by country and calendar month and divided by the country-specific standard deviation. HICP indices are rebased to 2015=100, and monthly inflation is the exact, non-annualized percentage change, $100(P_t/P_{t-1} - 1)$, calculated only for adjacent monthly observations. Outcome codes are defined in Table 1.

Table 2: Summary statistics for the analysis sample (January 2000–December 2025)

Series	Measure	N	Mean	SD	Min	Max
Climate variables						
TEMP	Monthly maximum (deg C)	10608	24.077	9.196	-0.194	48.066
TEMP	Monthly mean (deg C)	10608	9.799	8.195	-15.153	29.911
TEMP	Maximum-temperature anomaly (SD)	10608	0.000	0.998	-3.357	3.756
TEMP	Mean-temperature anomaly (SD)	10608	0.000	0.998	-4.967	3.363
HICP variables						
TOTAL	HICP index (2015=100)	9929	101.264	55.903	11.450	1348.170
TOTAL	Monthly inflation (percent)	9895	0.277	0.806	-3.968	13.570
CP01	HICP index (2015=100)	9929	103.491	71.225	10.360	1676.670
CP01	Monthly inflation (percent)	9895	0.316	1.117	-8.885	15.970
CP02	HICP index (2015=100)	9929	95.945	56.628	6.260	1246.640
CP02	Monthly inflation (percent)	9895	0.398	1.337	-12.588	44.985
CP03	HICP index (2015=100)	9929	103.122	23.898	16.200	467.140
CP03	Monthly inflation (percent)	9895	0.316	6.791	-30.723	43.905
CP04	HICP index (2015=100)	9929	99.153	57.815	9.400	1466.670
CP04	Monthly inflation (percent)	9895	0.384	1.529	-14.223	28.940
CP05	HICP index (2015=100)	9929	104.006	59.774	15.450	1425.850
CP05	Monthly inflation (percent)	9895	0.166	0.945	-7.544	16.537
CP06	HICP index (2015=100)	9929	99.349	57.269	20.460	1354.710
CP06	Monthly inflation (percent)	9895	0.276	1.012	-10.940	29.594
CP07	HICP index (2015=100)	9929	102.756	63.529	12.210	1470.310
CP07	Monthly inflation (percent)	9895	0.254	1.509	-11.146	28.221
CP08	HICP index (2015=100)	9929	109.996	25.810	26.100	459.730
CP08	Monthly inflation (percent)	9895	-0.071	0.965	-11.109	19.425
CP09	HICP index (2015=100)	9929	101.606	45.805	12.810	1065.860
CP09	Monthly inflation (percent)	9895	0.278	1.508	-12.289	10.385
CP10	HICP index (2015=100)	9929	97.943	55.584	10.980	1572.270
CP10	Monthly inflation (percent)	9895	0.321	1.891	-45.290	82.860
CP11	HICP index (2015=100)	9929	103.057	77.868	8.060	1875.710
CP11	Monthly inflation (percent)	9895	0.378	1.833	-21.221	20.137
CP12	HICP index (2015=100)	9871	100.876	65.951	3.160	1471.340
CP12	Monthly inflation (percent)	9837	0.336	1.777	-17.555	62.911
CP13	HICP index (2015=100)	9929	100.500	64.514	9.220	1533.110
CP13	Monthly inflation (percent)	9895	0.265	0.759	-5.597	13.370
FOOD	HICP index (2015=100)	10098	101.240	68.103	9.620	1601.200
FOOD	Monthly inflation (percent)	10064	0.332	0.985	-7.289	15.306
FUEL	HICP index (2015=100)	10098	103.367	63.226	11.720	1375.930

Continued on next page

Table 2 – continued

Series	Measure	N	Mean	SD	Min	Max
FUEL	Monthly inflation (percent)	10064	0.352	3.410	-17.410	37.500
SERV	HICP index (2015=100)	10065	100.033	58.898	11.230	1535.620
SERV	Monthly inflation (percent)	10031	0.309	1.013	-10.816	12.920

Notes: All series cover 34 countries. Temperature measures and HICP levels span January 2000–December 2025. Monthly inflation begins in February 2000. N is the number of country-month observations, and SD is the standard deviation. Temperature levels are in degrees Celsius, and anomalies use country-calendar-month demeaning and country-specific standardization. HICP indices use 2015=100. Monthly inflation is $100(P_t/P_{t-1} - 1)$ for adjacent monthly observations. Outcome codes are defined in Table 1.

4 Empirical Strategy

We estimate a pooled price-level impulse response for each index using monthly local projections. At every horizon, the dependent variable measures the log price level relative to the month before the temperature shock. The specification combines dated-month fixed effects, country-specific seasonality, and price and temperature histories.

4.1 Local projections

For each price index k, country i, exposure month t, and horizon $h = 0, \ldots, 24$, we define the dependent variable as

$$Y_{i,k,t}(h) = 100 \left[p_{i,k,t+h} - p_{i,k,t-1} \right]. \tag{2}$$

This outcome equals cumulative monthly log inflation from the exposure month to horizon h. Here, $p_{i,k,t}$ is the log of the HICP for country i and index k. Multiplication by 100 expresses log-price differences in approximate percentage terms. The fixed reference month $t-1$ provides a common normalization across horizons. Following Jordà (2005), we estimate a separate regression at each horizon.

For each horizon, our preferred specification is

$$Y_{i,k,t}(h) = \lambda_{t,h} + \mu_{i,m(t),h} + \beta_{k,h} A_{i,t} + \sum_{j=1}^{13} \rho_{k,h,j} p_{i,k,t-j} + \sum_{j=1}^{13} \theta_{k,h,j} A_{i,t-j} + u_{i,k,t,h}. \tag{3}$$

The coefficient $\beta_{k,h}$ is the price-level impulse response at horizon h to a one-country-standard-deviation temperature shock, expressed in approximate percentage terms. Since $p_{i,k,t-1}$ is included

among the regressors, subtracting $100p_{i,k,t-1}$ from the dependent variable leaves the temperature coefficient unchanged relative to a regression with $100p_{i,k,t+h}$ as the outcome.

The preferred specification uses maintained dynamic order 12 plus one augmentation lag: 13 lagged log-price terms and 13 lagged temperature anomalies, in addition to the current anomaly. Including price history conditions on recent outcome dynamics, while including exposure history separates the current anomaly from recent local temperature conditions. The additional lag follows the lag-augmentation approach of Montiel Olea & Plagborg-Møller (2021).

In their finite-order vector-autoregressive framework, the uniform coverage result assumes stationary innovations that are mean independent of innovations at other dates, together with moment, weak-dependence, and nonsingularity conditions. For inference covering near-unit-root and unit-root cases, the maximum horizon grows more slowly than the time dimension, $\bar{h}_T/T \to 0$. Under these conditions, lag augmentation yields serially uncorrelated regression scores, supporting heteroskedasticity-robust covariance estimation in that time-series setting. Our panel implementation uses country-clustered covariance estimates to account for dependence within each country's observations.

The seven sensitivity specifications vary the maintained lag order and the relative lengths of the price and weather histories. Four joint-history variants use maintained orders 2, 6, 12, and 18, each with one augmentation lag for both price and temperature histories. Three additional variants use maintained price orders 6, 12, and 18, again with one augmentation lag, while holding the weather history at three lags. The preferred 12-order joint-history specification is thus compared with both shorter and longer histories and with specifications that change the price history while keeping the weather controls short. Each specification uses its valid observations, so the comparison incorporates the sample changes implied by different lag requirements.

The specification includes full dated-month fixed effects $\lambda_{t,h}$ and country-by-calendar-month effects $\mu_{i,m(t),h}$. The latter absorb time-invariant country differences and recurring within-year country patterns. Dated-month effects absorb shocks common to countries in a particular month, including common seasonal or macroeconomic movements. The coefficient $\beta_{k,h}$ is consequently estimated from differences in country-specific exposure within a month, conditional on the included histories and country-calendar-month patterns. It describes a common pooled slope, with country contributions determined by the available observations and identifying variation. A temperature movement shared by all countries is absorbed by the dated-month effects.

We estimate fixed-effects regressions and cluster standard errors by country, allowing arbitrary dependence within countries. Country-clustered inference requires independence across country clusters after conditioning on the regressors and fixed effects. With 34 country clusters, confidence intervals and tests use a t reference distribution with 33 degrees of freedom. We report pointwise 68% and 90% intervals and complement conventional tests with null-imposed wild-country-cluster-bootstrap p-values. The bootstrap uses 9,999 repetitions, Webb weights, and a fixed seed, as

documented in Appendix C. It provides a finite-cluster assessment of the individual coefficient tests while retaining country-level clustering. Each outcome and horizon uses its own valid observations.

4.2 Monthly identification

Identification rests on short-run conditional exogeneity of the current temperature anomaly given the dated-month effects, country-specific seasonality, and lagged price and temperature histories in equation (3). At each horizon, the residual variation in current temperature must be orthogonal to other determinants of the subsequent price outcome. Meteorological conditions are determined outside the monthly domestic price-setting process, providing the economic basis for this restriction. The price history accounts for pre-existing inflation dynamics, the temperature history accounts for recent weather conditions, and dated-month effects absorb common macroeconomic disturbances. Under this conditional exogeneity assumption, $\beta_{k,h}$ measures the price-level response to the current temperature shock. The supply-side interpretation draws on the mechanisms established in the literature, while the estimates capture the overall price response to temperature, including accompanying weather-sensitive demand effects.

5 Results

5.1 Baseline responses

The baseline paths display gradual increases in headline and services prices, delayed positive responses in several goods and service divisions, and substantial variation in the magnitude and precision of adjustment across categories.

Table 3 summarizes the preferred price-level response paths at six selected horizons. For headline prices, the point estimate rises from approximately zero on impact to 0.051% at month 6, 0.080% at month 12, 0.136% at month 18, and 0.157% at month 20. Its largest point estimate over the 25 estimated horizons is 0.173% at month 23. The month-20 and month-24 pointwise 90% intervals are 0.037 to 0.277 and 0.027 to 0.307, respectively. The path indicates a gradual increase in the price-level response between months 12 and 24.

Services also show a gradual positive path. The estimate is 0.025% at month 6, 0.072% at month 12, and 0.122% at month 20 (90% interval: 0.038 to 0.206). It is 0.136% at month 24, with an interval that includes zero.

Responses differ across the product indices. Alcoholic beverages, tobacco, and narcotics rise from 0.040% on impact to 0.212% at month 18 and reach their largest point estimate, 0.346%, at month 22 (90% interval: 0.116 to 0.576). Personal care, social protection, and miscellaneous goods and services reach 0.195% at month 20 and 0.218% at month 24 (90% interval at month 24: 0.062

to 0.375). Other divisions also have positive month-20 estimates whose pointwise 90% intervals exclude zero. These include the housing division, health, transport, recreation and culture, and restaurants and accommodation services. For example, transport reaches 0.215% at month 20 (0.043 to 0.387), while the housing division reaches 0.159% (0.029 to 0.289). The sectoral breadth of these responses is consistent with cost transmission through production and distribution links.

Table 3: Pooled price-level responses: selected horizons

Outcome	Month 0	Month 6	Month 12	Month 18	Month 20	Month 24
TOTAL	0.001	0.051**	0.080*	0.136**	0.157**	0.167*
	(0.007)	(0.024)	(0.046)	(0.061)	(0.071)	(0.083)
SERV	0.002	0.025	0.072**	0.096**	0.122**	0.136
	(0.005)	(0.016)	(0.035)	(0.046)	(0.050)	(0.082)
FOOD	−0.016*	0.077**	0.101	0.122	0.160	0.184*
	(0.008)	(0.036)	(0.065)	(0.083)	(0.096)	(0.105)
FUEL	0.010	0.115	0.087	0.274*	0.290*	0.250
	(0.026)	(0.068)	(0.126)	(0.150)	(0.163)	(0.154)
CP01	−0.024***	0.086**	0.119*	0.111	0.138	0.150
	(0.007)	(0.038)	(0.067)	(0.079)	(0.092)	(0.097)
CP02	0.040*	0.063*	0.108***	0.212**	0.284***	0.322**
	(0.023)	(0.035)	(0.032)	(0.081)	(0.103)	(0.134)
CP03	−0.000	0.036	0.030	0.039	0.024	0.058
	(0.022)	(0.032)	(0.045)	(0.064)	(0.073)	(0.074)
CP04	−0.007	−0.009	−0.005	0.132*	0.159**	0.148*
	(0.018)	(0.053)	(0.065)	(0.070)	(0.077)	(0.082)
CP05	0.009	0.031	0.070	0.103	0.106	0.095
	(0.008)	(0.022)	(0.051)	(0.067)	(0.075)	(0.078)
CP06	−0.003	0.028	0.082**	0.096*	0.132**	0.183**
	(0.009)	(0.018)	(0.037)	(0.048)	(0.061)	(0.084)
CP07	0.002	0.081**	0.129*	0.200**	0.215**	0.229**
	(0.013)	(0.038)	(0.071)	(0.092)	(0.102)	(0.108)
CP08	0.014	0.006	0.035	0.027	0.017	0.025
	(0.013)	(0.026)	(0.042)	(0.065)	(0.074)	(0.093)
CP09	−0.010	0.006	0.050	0.100	0.139*	0.131
	(0.009)	(0.026)	(0.033)	(0.063)	(0.070)	(0.081)
CP10	0.045**	0.063	0.105	0.088	0.070	0.092
	(0.022)	(0.064)	(0.074)	(0.088)	(0.092)	(0.099)
CP11	0.004	0.022	0.050	0.064	0.098*	0.080
	(0.011)	(0.021)	(0.036)	(0.052)	(0.055)	(0.072)
CP12	0.037	0.054	0.028	0.044	0.120	0.162
	(0.022)	(0.054)	(0.090)	(0.128)	(0.141)	(0.157)
CP13	0.010	0.038	0.111**	0.170**	0.195**	0.218**
	(0.009)	(0.023)	(0.052)	(0.073)	(0.081)	(0.093)

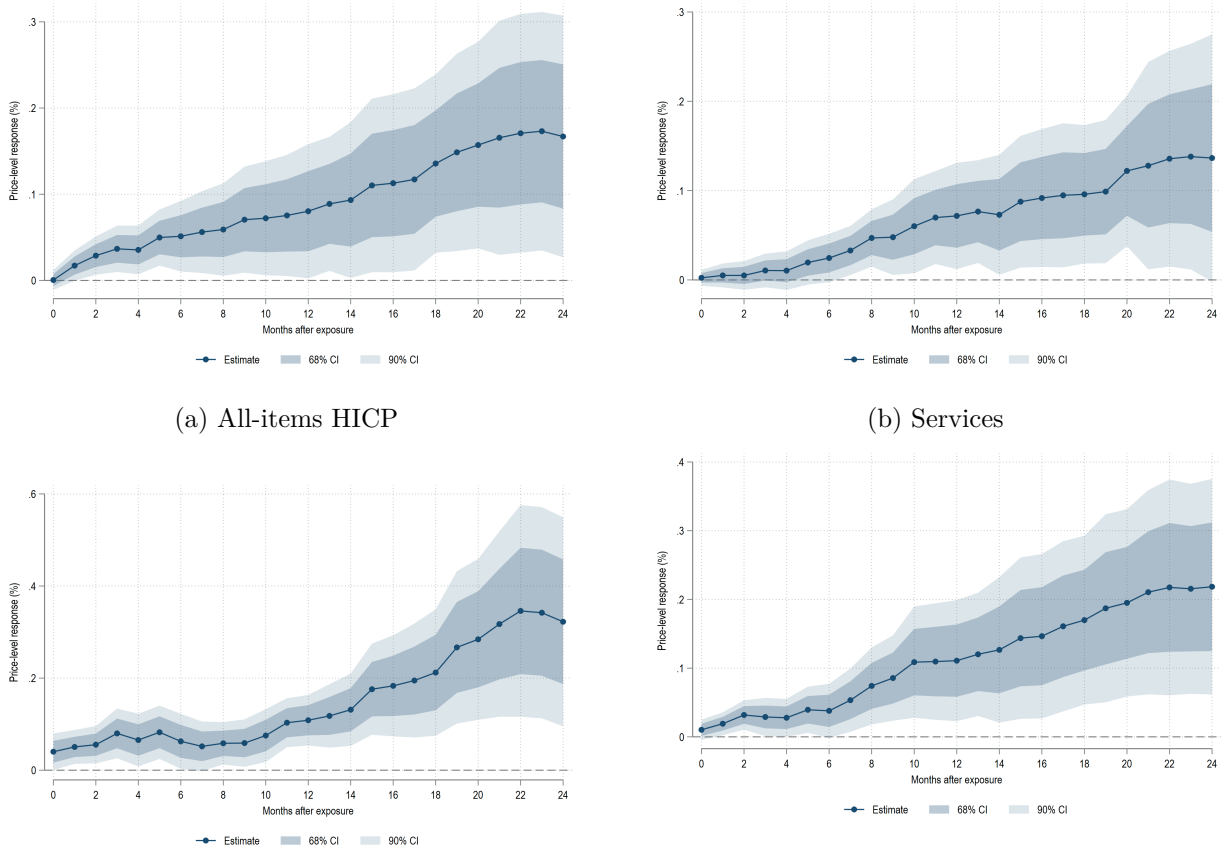
Notes: Entries are price-level responses in approximate percentage terms to a one-country-standard-deviation maximum-temperature anomaly. The specification includes 13 log-price lags and 13 temperature-anomaly lags, dated-month and country-by-calendar-month fixed effects, and country-clustered standard errors. Standard errors are in parentheses below estimates. Stars use two-sided t tests with 33 degrees of freedom: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Samples vary by outcome and horizon, with 8,613–9,656 country-month observations. Outcome codes are defined in Table 1.

The food measures follow a different path. Food and non-alcoholic beverages and the broader food aggregate including alcohol and tobacco both have negative impact estimates: -0.024% (90% interval: -0.036 to -0.011) for the former and -0.016% (-0.029 to -0.002) for the latter. Their estimates become positive at later horizons, but month-20 intervals include zero. The broader food

aggregate's month-24 estimate is 0.184% (0.007 to 0.362), while food and non-alcoholic beverages remain imprecisely estimated at month 24. The initial decline and subsequent reversal highlight the diversity of short-run adjustment across the basket.

Insurance and financial services are much less precisely estimated across the path. The month-20 estimate is 0.120% (90% interval: -0.117 to 0.358), and no baseline horizon has a pointwise 90% interval excluding zero. Liquid fuels and fuels for personal transport equipment have a positive month-20 estimate of 0.290% (0.014 to 0.566). This result applies to the specified fuel aggregate, while household electricity and gas enter the housing division.

Table entries are scaled to a one-standard-deviation country-specific anomaly. Standard errors appear below estimates, and stars use two-sided t tests with 33 degrees of freedom. The table selects six horizons for readability, while the complete paths are shown in Figure 2 and Appendix A. The reported intervals describe individual coefficients. Differences between categories and the locations of the largest point estimates are descriptive features of the estimated paths.



(a) All-items HICP

(b) Services

(c) Alcoholic beverages, tobacco, and narcotics

(d) Personal care, social protection, and miscellaneous goods and services

Figure 2: Selected price-level impulse responses

Notes: Responses are expressed in percent following a one-country-standard-deviation maximum-temperature shock. Shaded areas show pointwise 68% and 90% confidence intervals based on country-clustered standard errors. The horizontal axis measures months after the shock.

5.2 Lag-history sensitivity

Table 4 compares all 17 outcomes under seven lag histories at months 20 and 22, horizons selected to summarize the delayed part of the baseline paths. Four joint-history specifications vary the maintained order from 2 to 18 and add one augmentation lag to both the price and temperature histories. Three further specifications vary the price history while keeping the temperature history at three lags. The comparison assesses the sensitivity of delayed responses to the length of the included dynamics.

At month 20, pointwise 90% intervals exclude zero for headline prices and services, for alcoholic beverages, tobacco, and narcotics, for personal care, social protection, and miscellaneous goods and services, and for the fuel aggregate in all seven specifications. The month-20 estimates for alcoholic beverages, tobacco, and narcotics range from 0.234% to 0.304% across specifications, while those for personal care, social protection, and miscellaneous goods and services range from 0.165% to 0.205%. For headline prices and services, the estimates also remain positive across all seven variants. Insurance and financial services remain imprecisely estimated in every variant at month 20. These comparisons show that the delayed positive responses persist across the reported lag histories.

Each outcome, horizon, and lag structure uses its own valid observations. Changes in coefficients therefore reflect both the included histories and the resulting sample. The complete table reports standard errors and significance markers at both horizons.

Appendix C reports the comparison with mean temperature, bootstrap inference, and regional estimates. Mean temperature yields different delayed headline and services responses on matched samples. For maximum temperature, the wild-cluster-bootstrap p-value for headline prices at month 20 is 0.003. The fuel aggregate has a bootstrap p-value of 0.106 at that horizon, alongside a country-clustered pointwise 90% interval excluding zero. These results distinguish sensitivity to the exposure measure from sensitivity to the inference procedure.

5.3 Supply transmission and sectoral inflation

The delayed headline and services responses are consistent with the propagation of temperature-induced supply pressures through sectors that adjust prices at different speeds. The productivity evidence provides the initial link: heat can reduce effective labor input and productive efficiency, increasing unit costs in exposed activities (Somanathan et al., 2021). Firms purchasing their output then face changes in intermediate-input costs. Retail prices reflect this sequence of cost changes together with the pricing decisions of producers and distributors. As pressures move through production and distribution, consumer prices can adjust gradually over subsequent months.

The services response gives this interpretation a concrete empirical focus. The point estimate rises

from 0.025% at month 6 to 0.072% at month 12 and 0.122% at month 20. European micro data document relatively infrequent repricing in services (Dhyne et al., 2006). In a sector facing both changing input costs and infrequent price adjustment, successive price revisions can translate a disturbance into a gradual movement in the aggregate index. The relevant timing depends jointly on the persistence of costs reaching firms and the frequency at which they revise prices. This interaction connects the estimated service-price path to the sectoral price-setting literature.

Production linkages also give economic meaning to the breadth of the responses. In multisector models, an activity's role as an input supplier and its degree of price rigidity shape the propagation of shocks (Bouakez et al., 2014; Pastén et al., 2020). A disturbance originating in exposed production can therefore affect consumer-facing activities with different direct weather exposure. The positive delayed estimates for housing, transport, health, recreation, and restaurants and accommodation services fit this broader transmission perspective. The estimated indices capture different combinations of direct exposure, purchased inputs, and pricing practices, which provide a basis for their varied adjustment paths.

The larger late-horizon estimates for alcoholic beverages, tobacco, and narcotics and for personal care, social protection, and miscellaneous goods and services further establish that the response extends across diverse categories. Their different production and service content makes the distinction between exposure and repricing especially relevant. The price-rigidity literature supplies an interpretation of the timing, while the estimates document the magnitude and trajectory of each category's response.

The food and energy responses show how sector-specific conditions shape the net effect of a temperature disturbance. The two food measures decline initially and become positive at later horizons, with different degrees of precision. Inventories, sourcing decisions, substitution, and weather-sensitive demand can modify the immediate effect of production costs. The European evidence on temperature and energy demand identifies one such demand channel (Lucidi et al., 2024). The heterogeneous paths are thus consistent with a supply disturbance whose transmission interacts with the economic characteristics of each sector.

The comparison of maximum and mean temperature on matched samples ties the baseline pattern to an unusually high national monthly maximum relative to local seasonal conditions. This exposure definition focuses the analysis on temperature extremes and the subsequent adjustment of sectoral prices.

6 Conclusion

This paper examines how temperature exposure relates to sectoral inflation across 17 HICP indices in 34 European countries. Using monthly local projections, it traces price-level responses over 24 months to country-specific anomalies in monthly maximum temperature. The broad coverage

makes it possible to compare the timing and size of responses across goods and services within a common framework.

The headline and services responses build gradually, reaching 0.157% and 0.122%, respectively, at month 20 for a one-standard-deviation maximum-temperature anomaly. Positive delayed estimates also appear across several consumption divisions. Alcoholic beverages, tobacco, and narcotics, and personal care, social protection, and miscellaneous goods and services have larger late-horizon point estimates. The pattern is not uniform: food measures decline initially before becoming positive at later horizons, insurance and financial services are imprecisely estimated, and the fuel estimate at month 20 is less robust to the bootstrap procedure ($p_W = 0.106$).

The delayed headline and sectoral estimates are broadly persistent across the seven lag-history specifications, although those estimates use different valid samples. Results also differ when mean rather than maximum temperature is used on matched samples. This comparison suggests that the exposure measure matters, but it does not directly test whether the maximum- and mean-temperature coefficients differ.

These patterns are consistent with temperature-related cost pressures being transmitted through sectors with different input relationships and repricing frequencies. They do not, however, identify those channels separately. The estimates are conditional on the monthly identification assumptions. The temperature measure is a country-level maximum derived from grid-cell extrema, not a population-weighted measure of household exposure. Inference allows for within-country dependence but assumes independence across country clusters. Moreover, reported intervals and bootstrap p-values are pointwise or unadjusted across the many outcome–horizon comparisons, so individual rejections should not be read as multiplicity-adjusted evidence of broad sectoral effects.

For assessing climate-related price risks, the results motivate looking beyond contemporaneous headline inflation to the sectors and horizons over which prices adjust. Further work could link local temperature exposure to firm-level costs and prices, examine transmission through production networks, directly test differences across exposure measures, and assess sectoral patterns using inference that accounts for multiple comparisons.

References

Adhvaryu, A., Kala, N., & Nyshadham, A. (2020). The light and the heat: Productivity co-benefits of energy-saving technology. *Review of Economics and Statistics*, *102*(4), 779–792.

Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives*, *32*(4), 33–52.

Bettarelli, L., Furceri, D., Pisano, L., & Pizzuto, P. (2025). Greenflation: Empirical evidence using macro, regional and sectoral data. *European Economic Review*, *174*, 104983.

Bilal, A., & Känzig, D. R. (2026). The macroeconomic impact of climate change: Global versus local temperature. *Quarterly Journal of Economics*, *141*(2), 889–944.
URL https://github.com/dkaenzig/micc_replication

Bils, M., & Klenow, P. J. (2004). Some evidence on the importance of sticky prices. *Journal of Political Economy*, *112*(5), 947–985.

Bouakez, H., Cardia, E., & Ruge-Murcia, F. (2014). Sectoral price rigidity and aggregate dynamics. *European Economic Review*, *65*, 1–22.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*, 235–239.

Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, *353*(6304), aad9837.

Ciccarelli, M., Kuik, F., & Martínez Hernández, C. (2024). The asymmetric effects of temperature shocks on inflation in the largest euro area countries. *European Economic Review*, *168*, 104805.

Corsello, F., & Riggi, M. (2026). Inflation is not equal for all: The heterogeneous effects of energy shocks. *European Economic Review*, *187*, 105298.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95.

Dhyne, E., Álvarez, L. J., Le Bihan, H., Veronese, G., Dias, D., Hoffmann, J., Jonker, N., Lünnemann, P., Rumler, F., & Vilmunen, J. (2006). Price changes in the euro area and the United States: Some facts from individual consumer price data. *Journal of Economic Perspectives*, *20*(2), 171–192.

Eurostat (2026a). European classification of individual consumption according to purpose, version 2. Eurostat classification metadata. Accessed 2 November 2026.
URL https://showvoc.op.europa.eu/#/datasets/ESTAT_European_Classification_of_Individual_Consumption_according_to_Purpose_version_2_%28ECOICOP_2%29/data

Eurostat (2026b). Harmonised index of consumer prices: Information on data. Eurostat. Accessed 2 November 2026.
URL https://ec.europa.eu/eurostat/web/hicp/information-data

Eurostat (2026c). Harmonised index of consumer prices: Monthly indices and rates of change. Dataset prc_hicp_minr. Updated 2 October 2026; accessed 14 October 2026.
URL https://ec.europa.eu/eurostat/databrowser/view/prc_hicp_minr/default/table?lang=en

Faccia, D., Parker, M., & Stracca, L. (2021). Feeling the heat: Extreme temperatures and price stability. Working paper.
URL https://doi.org/10.2139/ssrn.3981219

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, *32*(1), 1–26.

Heal, G., & Park, J. (2016). Reflections—temperature stress and the direct impact of climate change: A review of an emerging literature. *Review of Environmental Economics and Policy*, *10*(2), 347–362.

Hsiang, S. M., & Kopp, R. E. (2018). An economist's guide to climate change. *Journal of Economic Perspectives*, *32*(4), 3–32.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, *95*(1), 161–182.

Jordà, Ò., & Taylor, A. M. (2025). Local projections. *Journal of Economic Literature*, *63*(1), 59–110.

Kahn, M. E., Mohaddes, K., Ng, R. N. C., Pesaran, M. H., Raissi, M., & Yang, J.-C. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics*, *104*, 105624.

Kotz, M., Kuik, F., Lis, E., & Nickel, C. (2024). Global warming and heat extremes to enhance inflationary pressures. *Communications Earth & Environment*, *5*, 116.

Lucidi, F. S., Pisa, M. M., & Tancioni, M. (2024). The effects of temperature shocks on energy prices and inflation in the euro area. *European Economic Review*, *166*, 104771.

Montiel Olea, J. L., & Plagborg-Møller, M. (2021). Local projection inference is simpler and more robust than you think. *Econometrica*, *89*(4), 1789–1823.

Muñoz Sabater, J. (2019). ERA5-Land hourly data from 1950 to present. Copernicus Climate Change Service Climate Data Store.
URL https://doi.org/10.24381/cds.e2161bac

Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., & Thépaut, J.-N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, *13*, 4349–4383.

Nakamura, E., & Steinsson, J. (2008). Five facts about prices: A reevaluation of menu cost models. *The Quarterly Journal of Economics*, *123*(4), 1415–1464.

Nakamura, E., & Steinsson, J. (2010). Monetary non-neutrality in a multisector menu cost model. *The Quarterly Journal of Economics*, *125*(3), 961–1013.

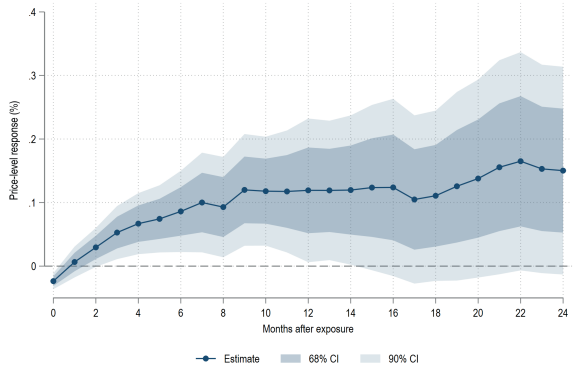
Pastén, E., Schoenle, R., & Weber, M. (2020). The propagation of monetary policy shocks in a heterogeneous production economy. *Journal of Monetary Economics*, *116*, 1–22.

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy*, *129*(6), 1797–1827.

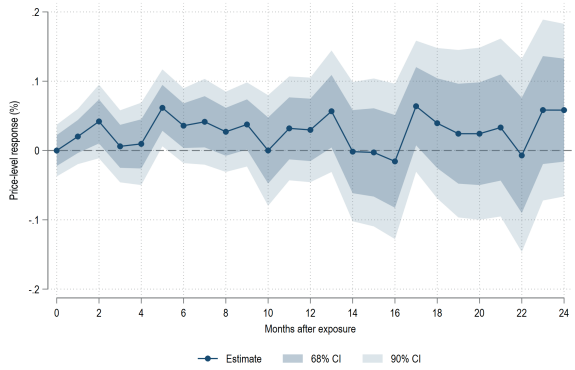
United Nations Statistics Division (2018). Classification of individual consumption according to purpose (coicop) 2018. United Nations Statistics Division.
URL https://unstats.un.org/unsd/classifications/coicop

A Complete set of results

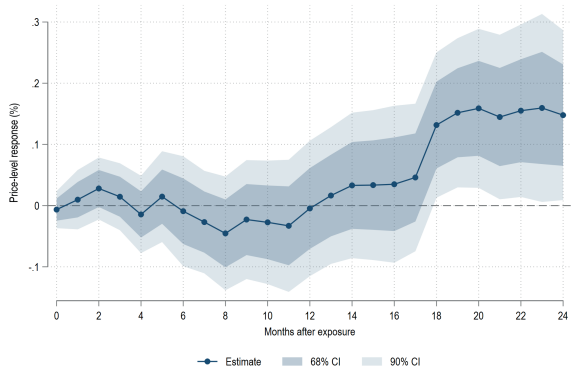
This appendix displays the 13 baseline response paths not selected for the main-text figure, completing the set of 17 outcomes. Each panel reports the price-level response, expressed in percent, to a one-country-standard-deviation maximum-temperature shock at horizons 0–24 months. Shaded areas show pointwise 68% and 90% confidence intervals based on country-clustered standard errors.



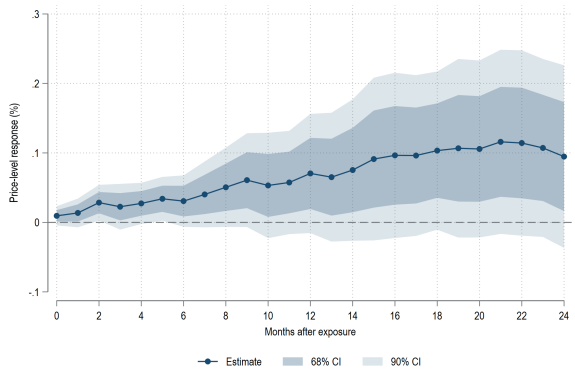
(a) Food and non-alcoholic beverages



(b) Clothing and footwear

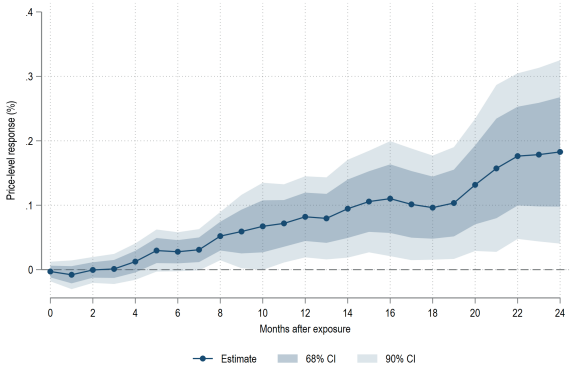


(c) Housing, water, electricity, gas, and other fuels

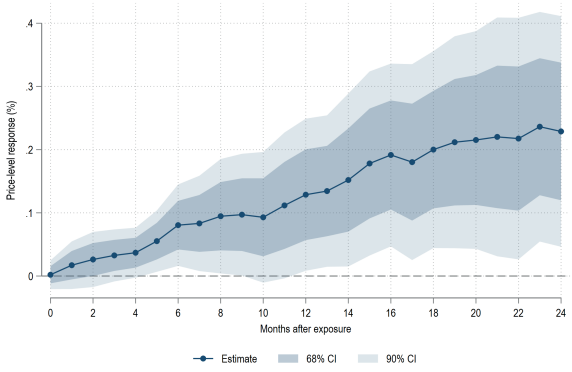


(d) Furnishings and household maintenance

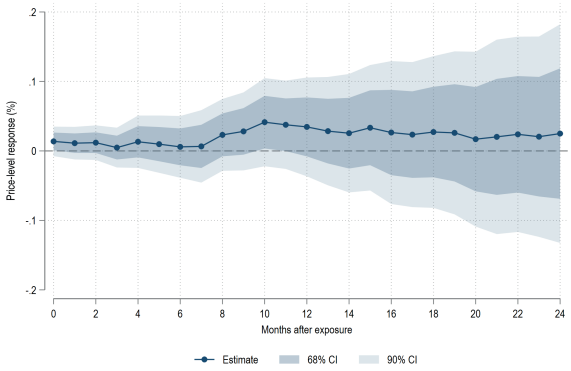
Figure 3: Price-level responses, continued.



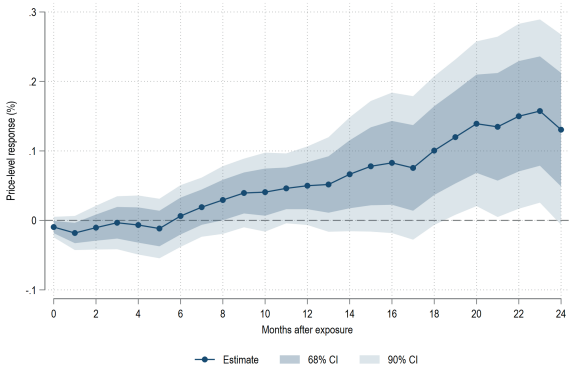
(a) Health



(b) Transport

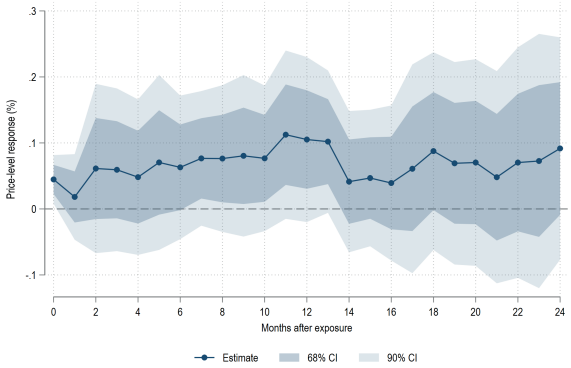


(c) Information and communication

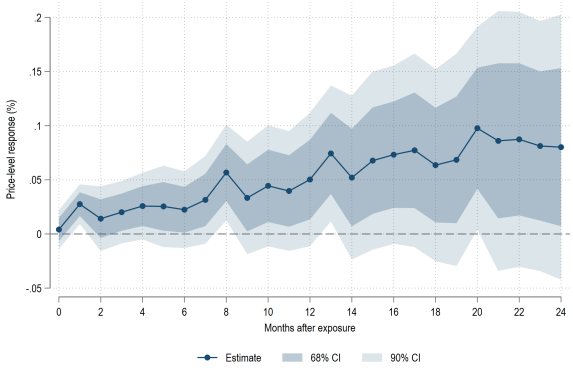


(d) Recreation, sport, and culture

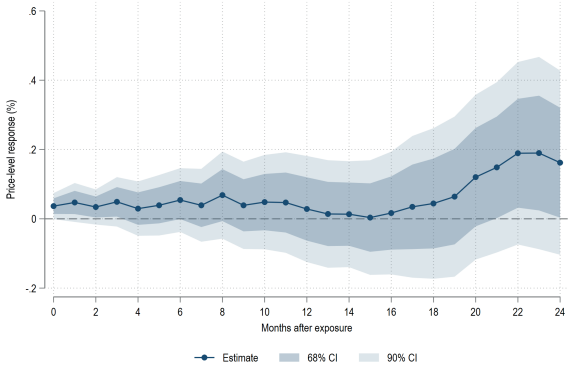
Figure 4: Price-level responses, continued.



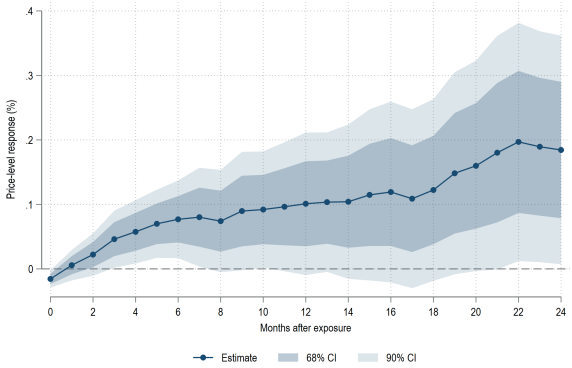
(a) Education services



(b) Restaurants and accommodation services

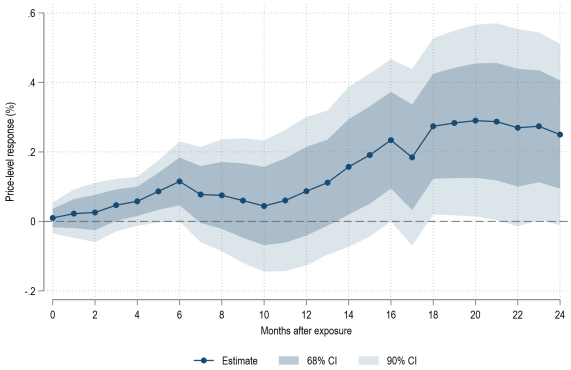


(c) Insurance and financial services



(d) Food including alcohol and tobacco

Figure 5: Price-level responses, continued.



(a) Liquid fuels and fuels for personal transport equipment

Figure 6: Price-level responses, continued.

B Lag-history sensitivity

This appendix reports the seven lag-history specifications for all 17 outcomes at months 20 and 22. The four joint-history variants change the maintained order for both price and temperature histories. The three price-history variants change the maintained price order while keeping the temperature history at three lags. Each specification adds one augmentation lag to its maintained price order. The joint-history variants also augment the temperature history. Table 4 reports point estimates, standard errors, and significance markers. Every model and horizon uses its own valid observations, so coefficient differences combine dynamic specification changes with possible sample-composition changes.

Table 4: Lag-history sensitivity at horizons 20 and 22

Outcome	Lag specification	Month 20	Month 22
TOTAL	Joint, $p = 2$	0.169** (0.064)	0.182** (0.074)
TOTAL	Joint, $p = 6$	0.152** (0.064)	0.160** (0.073)
TOTAL	Joint, $p = 12$	0.157** (0.071)	0.171** (0.082)
TOTAL	Joint, $p = 18$	0.119** (0.048)	0.135** (0.058)
TOTAL	Price-only, $p = 6$	0.182** (0.077)	0.192** (0.088)
TOTAL	Price-only, $p = 12$	0.162** (0.076)	0.177* (0.088)
TOTAL	Price-only, $p = 18$	0.121** (0.053)	0.138** (0.064)
SERV	Joint, $p = 2$	0.165*** (0.052)	0.169** (0.064)
SERV	Joint, $p = 6$	0.124** (0.048)	0.130** (0.064)
SERV	Joint, $p = 12$	0.122** (0.050)	0.136* (0.071)
SERV	Joint, $p = 18$	0.114*** (0.036)	0.131** (0.058)
SERV	Price-only, $p = 6$	0.146** (0.056)	0.153** (0.073)
SERV	Price-only, $p = 12$	0.130** (0.054)	0.142* (0.077)
SERV	Price-only, $p = 18$	0.119*** (0.040)	0.137** (0.064)
FOOD	Joint, $p = 2$	0.126 (0.077)	0.159* (0.089)
FOOD	Joint, $p = 6$	0.147 (0.094)	0.180* (0.106)
FOOD	Joint, $p = 12$	0.160 (0.096)	0.197* (0.109)
FOOD	Joint, $p = 18$	0.103 (0.066)	0.138* (0.075)
FOOD	Price-only, $p = 6$	0.171 (0.109)	0.202 (0.121)
FOOD	Price-only, $p = 12$	0.165 (0.101)	0.203* (0.116)
FOOD	Price-only, $p = 18$	0.105 (0.072)	0.139 (0.084)
FUEL	Joint, $p = 2$	0.283* (0.152)	0.270* (0.156)
FUEL	Joint, $p = 6$	0.265* (0.144)	0.240 (0.148)
FUEL	Joint, $p = 12$	0.290* (0.163)	0.270 (0.168)
FUEL	Joint, $p = 18$	0.251* (0.139)	0.227 (0.141)
FUEL	Price-only, $p = 6$	0.308* (0.161)	0.287* (0.165)
FUEL	Price-only, $p = 12$	0.290* (0.168)	0.272 (0.174)
FUEL	Price-only, $p = 18$	0.248* (0.145)	0.226 (0.149)

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Table 4: Lag-history sensitivity at horizons 20 and 22 (continued)

Outcome	Lag specification	Month 20	Month 22
CP01	Joint, $p = 2$	0.133 (0.088)	0.162 (0.099)
CP01	Joint, $p = 6$	0.137 (0.091)	0.162 (0.101)
CP01	Joint, $p = 12$	0.138 (0.092)	0.165 (0.101)
CP01	Joint, $p = 18$	0.084 (0.066)	0.110 (0.073)
CP01	Price-only, $p = 6$	0.169 (0.105)	0.194 (0.116)
CP01	Price-only, $p = 12$	0.145 (0.097)	0.174 (0.107)
CP01	Price-only, $p = 18$	0.090 (0.074)	0.115 (0.082)
CP02	Joint, $p = 2$	0.262*** (0.088)	0.315** (0.115)
CP02	Joint, $p = 6$	0.265*** (0.092)	0.324** (0.122)
CP02	Joint, $p = 12$	0.284*** (0.103)	0.346** (0.136)
CP02	Joint, $p = 18$	0.238*** (0.082)	0.300*** (0.109)
CP02	Price-only, $p = 6$	0.304** (0.112)	0.361** (0.142)
CP02	Price-only, $p = 12$	0.291*** (0.106)	0.353** (0.141)
CP02	Price-only, $p = 18$	0.234*** (0.081)	0.296** (0.110)
CP03	Joint, $p = 2$	0.004 (0.066)	−0.041 (0.072)
CP03	Joint, $p = 6$	−0.004 (0.064)	−0.036 (0.070)
CP03	Joint, $p = 12$	0.024 (0.073)	−0.007 (0.082)
CP03	Joint, $p = 18$	−0.019 (0.056)	−0.046 (0.064)
CP03	Price-only, $p = 6$	0.011 (0.076)	−0.018 (0.082)
CP03	Price-only, $p = 12$	0.026 (0.077)	−0.002 (0.086)
CP03	Price-only, $p = 18$	−0.023 (0.059)	−0.046 (0.066)
CP04	Joint, $p = 2$	0.187** (0.082)	0.183** (0.088)
CP04	Joint, $p = 6$	0.153** (0.071)	0.151* (0.077)
CP04	Joint, $p = 12$	0.159** (0.077)	0.155* (0.083)
CP04	Joint, $p = 18$	0.118* (0.068)	0.131* (0.073)
CP04	Price-only, $p = 6$	0.193** (0.085)	0.191** (0.091)
CP04	Price-only, $p = 12$	0.158* (0.081)	0.159* (0.088)
CP04	Price-only, $p = 18$	0.114 (0.072)	0.128* (0.075)
CP05	Joint, $p = 2$	0.110 (0.073)	0.120 (0.080)
CP05	Joint, $p = 6$	0.086 (0.064)	0.094 (0.069)
CP05	Joint, $p = 12$	0.106 (0.075)	0.114 (0.079)
CP05	Joint, $p = 18$	0.090 (0.059)	0.099 (0.065)
CP05	Price-only, $p = 6$	0.108 (0.080)	0.117 (0.086)
CP05	Price-only, $p = 12$	0.115 (0.083)	0.125 (0.088)
CP05	Price-only, $p = 18$	0.090 (0.061)	0.099 (0.068)
CP06	Joint, $p = 2$	0.195** (0.074)	0.232*** (0.082)
CP06	Joint, $p = 6$	0.144** (0.057)	0.182** (0.069)
CP06	Joint, $p = 12$	0.132** (0.061)	0.176** (0.076)
CP06	Joint, $p = 18$	0.100* (0.057)	0.142* (0.073)

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Table 4: Lag-history sensitivity at horizons 20 and 22 (continued)

Outcome	Lag specification	Month 20	Month 22
CP06	Price-only, $p = 6$	0.190^{***} (0.068)	0.231^{***} (0.081)
CP06	Price-only, $p = 12$	0.139^{**} (0.065)	0.182^{**} (0.081)
CP06	Price-only, $p = 18$	0.114^{*} (0.062)	0.153^{*} (0.079)
CP07	Joint, $p = 2$	0.241^{*} (0.120)	0.247^{*} (0.131)
CP07	Joint, $p = 6$	0.205^{**} (0.100)	0.203^{*} (0.110)
CP07	Joint, $p = 12$	0.215^{**} (0.102)	0.218^{*} (0.113)
CP07	Joint, $p = 18$	0.201^{**} (0.082)	0.204^{**} (0.093)
CP07	Price-only, $p = 6$	0.253^{**} (0.120)	0.255^{*} (0.131)
CP07	Price-only, $p = 12$	0.226^{**} (0.110)	0.232^{*} (0.123)
CP07	Price-only, $p = 18$	0.205^{**} (0.088)	0.211^{**} (0.099)
CP08	Joint, $p = 2$	0.036 (0.065)	0.045 (0.073)
CP08	Joint, $p = 6$	−0.005 (0.064)	0.002 (0.070)
CP08	Joint, $p = 12$	0.017 (0.074)	0.024 (0.083)
CP08	Joint, $p = 18$	0.043 (0.068)	0.053 (0.079)
CP08	Price-only, $p = 6$	0.018 (0.075)	0.025 (0.081)
CP08	Price-only, $p = 12$	0.025 (0.078)	0.033 (0.088)
CP08	Price-only, $p = 18$	0.052 (0.069)	0.060 (0.081)
CP09	Joint, $p = 2$	0.145^{**} (0.057)	0.154^{**} (0.061)
CP09	Joint, $p = 6$	0.122^{**} (0.056)	0.137^{**} (0.061)
CP09	Joint, $p = 12$	0.139^{*} (0.070)	0.150^{*} (0.079)
CP09	Joint, $p = 18$	0.122^{**} (0.059)	0.134^{*} (0.067)
CP09	Price-only, $p = 6$	0.149^{**} (0.064)	0.164^{**} (0.071)
CP09	Price-only, $p = 12$	0.144^{*} (0.072)	0.154^{*} (0.082)
CP09	Price-only, $p = 18$	0.125^{**} (0.061)	0.139^{*} (0.071)
CP10	Joint, $p = 2$	0.098 (0.094)	0.075 (0.096)
CP10	Joint, $p = 6$	0.096 (0.092)	0.085 (0.096)
CP10	Joint, $p = 12$	0.070 (0.092)	0.070 (0.103)
CP10	Joint, $p = 18$	0.038 (0.079)	0.036 (0.085)
CP10	Price-only, $p = 6$	0.140 (0.112)	0.128 (0.116)
CP10	Price-only, $p = 12$	0.088 (0.097)	0.083 (0.108)
CP10	Price-only, $p = 18$	0.033 (0.081)	0.028 (0.087)
CP11	Joint, $p = 2$	0.211^{**} (0.097)	0.195^{*} (0.105)
CP11	Joint, $p = 6$	0.160^{**} (0.066)	0.143^{*} (0.076)
CP11	Joint, $p = 12$	0.098^{*} (0.055)	0.087 (0.070)
CP11	Joint, $p = 18$	0.083 (0.049)	0.068 (0.060)
CP11	Price-only, $p = 6$	0.195^{**} (0.080)	0.178^{*} (0.090)
CP11	Price-only, $p = 12$	0.105^{*} (0.058)	0.093 (0.074)
CP11	Price-only, $p = 18$	0.083 (0.053)	0.068 (0.066)
CP12	Joint, $p = 2$	0.141 (0.154)	0.196 (0.168)

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Table 4: Lag-history sensitivity at horizons 20 and 22 (continued)

Outcome	Lag specification	Month 20	Month 22
CP12	Joint, $p = 6$	0.135 (0.139)	0.196 (0.155)
CP12	Joint, $p = 12$	0.120 (0.141)	0.189 (0.156)
CP12	Joint, $p = 18$	0.079 (0.127)	0.157 (0.145)
CP12	Price-only, $p = 6$	0.152 (0.146)	0.212 (0.163)
CP12	Price-only, $p = 12$	0.113 (0.137)	0.181 (0.152)
CP12	Price-only, $p = 18$	0.068 (0.124)	0.142 (0.140)
CP13	Joint, $p = 2$	0.186^{**} (0.070)	0.201^{**} (0.078)
CP13	Joint, $p = 6$	0.176^{**} (0.071)	0.194^{**} (0.082)
CP13	Joint, $p = 12$	0.195^{**} (0.081)	0.217^{**} (0.093)
CP13	Joint, $p = 18$	0.165^{***} (0.060)	0.184^{**} (0.070)
CP13	Price-only, $p = 6$	0.193^{**} (0.081)	0.213^{**} (0.093)
CP13	Price-only, $p = 12$	0.205^{**} (0.089)	0.228^{**} (0.102)
CP13	Price-only, $p = 18$	0.174^{**} (0.068)	0.194^{**} (0.078)

Notes: Entries are price-level responses to a one-country-standard-deviation maximum-temperature anomaly, with standard errors in parentheses. The maintained order p is augmented by one lag, giving $p+1$ lags. Joint specifications use $p + 1$ lags of both log prices and temperature, while price-only specifications use $p + 1$ log-price lags and three temperature lags. Stars denote two-sided t tests with 33 degrees of freedom: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Samples can differ across models. Outcome codes are defined in Table 1.

C Exposure, inference, and regional sensitivity

This appendix reports sensitivity results for all 17 outcomes and horizons 0–24. Wild-cluster-bootstrap inference uses 9,999 null-imposed repetitions with Webb weights, clustering by country, and a fixed seed. The maximum-temperature specification reproduces the baseline coefficients, standard errors, observation counts, and country counts across all 425 outcome–horizon pairs.

C.1 Alternative exposure and matched samples

We compare the monthly national maximum with the available monthly mean temperature. Each exposure is demeaned by country and calendar month and divided by its own country-specific anomaly standard deviation over 2000–2025, before sample restrictions. Both models include 13 lags of their respective exposure, 13 log-price lags, and the baseline fixed effects. Each coefficient therefore refers to a one-standard-deviation change in its corresponding temperature measure.

For each alternative, we estimate its own-sample model, a model restricted to the intersection of valid alternative and baseline observations, and the baseline model on that same intersection. Own-sample and matched-sample estimates coincide, and the baseline matched-sample regressions reproduce the baseline throughout. Observation counts, country counts, and date bounds agree for the two exposures at every outcome and horizon. The differences therefore reflect the exposure definition and its included history.

Table 5 displays estimates and country-clustered standard errors at horizons 0, 20, and 24, together with unadjusted wild-bootstrap p-values (p_W). At month 20, the mean-temperature estimates are -0.023% for headline prices and -0.049% for services, with bootstrap p-values of 0.670 and 0.218. The corresponding maximum-temperature estimates are 0.157% and 0.122%. Alcoholic beverages, tobacco, and narcotics remain positive under mean temperature (0.200%, $p_W = 0.005$), whereas personal care, social protection, and miscellaneous goods and services fall to 0.070% ($p_W = 0.539$). These differences establish the importance of distinguishing national temperature extremes from average warmth when interpreting the delayed price responses.

Table 5: Maximum versus mean temperature: selected price-level responses

Outcome	h	Maximum	Mean	Max. p_W	Mean p_W
TOTAL	0	0.001 (0.007)	−0.023 (0.008)	0.950	0.006
TOTAL	20	0.157 (0.071)	−0.023 (0.050)	0.003	0.670
TOTAL	24	0.167 (0.083)	−0.033 (0.052)	0.010	0.526
SERV	0	0.002 (0.005)	0.001 (0.006)	0.669	0.828
SERV	20	0.122 (0.050)	−0.049 (0.040)	0.006	0.218
SERV	24	0.136 (0.082)	−0.047 (0.051)	0.059	0.377

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Table 5 – continued

Outcome	h	Maximum	Mean	Max. p_W	Mean p_W
FOOD	0	−0.016 (0.008)	−0.057 (0.010)	0.057	< 0.001
FOOD	20	0.160 (0.096)	−0.014 (0.062)	0.100	0.835
FOOD	24	0.184 (0.105)	−0.008 (0.065)	0.057	0.910
FUEL	0	0.010 (0.026)	0.033 (0.027)	0.721	0.243
FUEL	20	0.290 (0.163)	0.235 (0.134)	0.106	0.135
FUEL	24	0.250 (0.154)	0.208 (0.111)	0.165	0.070
CP01	0	−0.024 (0.007)	−0.070 (0.015)	0.004	< 0.001
CP01	20	0.138 (0.092)	−0.089 (0.058)	0.156	0.103
CP01	24	0.150 (0.097)	−0.084 (0.056)	0.146	0.125
CP02	0	0.040 (0.023)	0.022 (0.017)	0.039	0.263
CP02	20	0.284 (0.103)	0.200 (0.065)	0.004	0.005
CP02	24	0.322 (0.134)	0.210 (0.073)	0.006	0.009
CP03	0	−0.000 (0.022)	−0.080 (0.024)	0.998	< 0.001
CP03	20	0.024 (0.073)	−0.142 (0.070)	0.790	0.048
CP03	24	0.058 (0.074)	−0.169 (0.058)	0.500	0.003
CP04	0	−0.007 (0.018)	−0.014 (0.032)	0.732	0.726
CP04	20	0.159 (0.077)	0.030 (0.077)	0.048	0.678
CP04	24	0.148 (0.082)	−0.024 (0.095)	0.075	0.807
CP05	0	0.009 (0.008)	−0.004 (0.008)	0.279	0.649
CP05	20	0.106 (0.075)	0.017 (0.071)	0.186	0.871
CP05	24	0.095 (0.078)	−0.021 (0.069)	0.287	0.776
CP06	0	−0.003 (0.009)	0.004 (0.014)	0.775	0.779
CP06	20	0.132 (0.061)	0.026 (0.078)	0.026	0.745
CP06	24	0.183 (0.084)	0.023 (0.093)	0.022	0.820
CP07	0	0.002 (0.013)	0.013 (0.015)	0.881	0.395
CP07	20	0.215 (0.102)	0.067 (0.072)	0.020	0.406
CP07	24	0.229 (0.108)	0.093 (0.060)	0.024	0.117
CP08	0	0.014 (0.013)	0.013 (0.014)	0.279	0.386
CP08	20	0.017 (0.074)	−0.029 (0.047)	0.846	0.514
CP08	24	0.025 (0.093)	−0.048 (0.056)	0.826	0.389
CP09	0	−0.010 (0.009)	0.000 (0.009)	0.256	0.976
CP09	20	0.139 (0.070)	0.036 (0.046)	0.028	0.439
CP09	24	0.131 (0.081)	−0.009 (0.047)	0.086	0.844
CP10	0	0.045 (0.022)	−0.012 (0.030)	0.024	0.768
CP10	20	0.070 (0.092)	−0.030 (0.086)	0.469	0.717
CP10	24	0.092 (0.099)	−0.056 (0.087)	0.366	0.504
CP11	0	0.004 (0.011)	0.007 (0.017)	0.713	0.680
CP11	20	0.098 (0.055)	−0.093 (0.044)	0.066	0.043
CP11	24	0.080 (0.072)	−0.129 (0.054)	0.274	0.019
CP12	0	0.037 (0.022)	0.003 (0.019)	0.072	0.867
CP12	20	0.120 (0.141)	−0.089 (0.100)	0.442	0.387

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Table 5 – continued

Outcome	h	Maximum	Mean	Max. p_W	Mean p_W
CP12	24	0.162 (0.157)	−0.112 (0.114)	0.378	0.341
CP13	0	0.010 (0.009)	−0.002 (0.007)	0.265	0.778
CP13	20	0.195 (0.081)	0.070 (0.078)	< 0.001	0.539
CP13	24	0.218 (0.093)	0.043 (0.075)	0.002	0.765

Notes: Price-level responses to a one-country-standard-deviation anomaly, with country-clustered standard errors in parentheses. Each exposure is standardized using its own anomaly distribution. The columns headed p_W report unadjusted, null-imposed wild-country-cluster-bootstrap p-values based on 9,999 repetitions with Webb weights. Recorded zero bootstrap values are reported as $p_W < 0.001$.

C.2 Finite-cluster inference

Conventional two-sided country-clustered t tests use 33 degrees of freedom. The wild-bootstrap tests provide an additional finite-cluster sensitivity check using the same clustering level. Across the 425 maximum-temperature outcome–horizon pairs, 90 conventional tests and 134 bootstrap tests reject at 5%. These counts summarize individual coefficient tests. The confidence intervals reported in the figures remain pointwise.

For headline prices at month 20, the wild-bootstrap p-value is 0.003. The fuel aggregate has a bootstrap p-value of 0.106 at the same horizon, while its conventional pointwise 90% interval excludes zero. Table 5 reports the individual bootstrap p-values alongside the exposure-specific coefficients and standard errors.

For both food measures under mean temperature on impact, no simulated statistic exceeded the observed statistic in the finite bootstrap sample. We therefore report these bootstrap values as $p_W < 0.001$ in Table 5.