

Imported Climate, Domestic Inflation

Trade-Weighted Transmission of Weather Shocks to Food Prices

Diego Ferreira¹ Andreza A. Palma² Ana C. Kreter³ Jefferson A. R. Staduto⁴

¹ Federal University of São Paulo (Unifesp), Brazil

³ Rhine-Waal University of Applied Sciences (HSRW), Germany

² Federal University of São Carlos (UFSCar), Brazil

⁴ Western Paraná State University (Unioeste), Brazil

Nature and the Macroeconomy

Santiago, Chile — August 10, 2026

Preliminary draft — comments welcome

Whose weather moves a country's food prices?

Food inflation rose in importers with no local climatic stress

2010–11	Russian heatwave, wheat export ban
2022	Russia–Ukraine war, compounding Argentine and European drought
2023–24	Super El Niño

Two design choices in the climate–inflation literature attenuate the signal:

- **Own-country weather** — a single noisy draw against a warming trend
Faccia et al. (2021); Peersman (2022); Kotz et al. (2024)
- **Headline CPI** — food is 21% of the basket

We ask **whose** weather moves domestic food prices, **through which agronomic mechanism**, and **at what horizon**.

This paper

1. **Shift-share exposure** — bilateral food-import shares $\times$ exporter weather
49 importers, monthly, 2005–2023
→ *which exporters' weather moves which importers' prices*
2. **Sign-split, horizon-specific decomposition**
→ three agronomic channels, each at a distinct horizon
3. **Small open economy NK model** — CES food aggregator, asymmetric climate channels
→ calibrated by SMM; import-penetration and optimal-rule counterfactuals

Headline: a one-standard-deviation rainfall shortfall in partners raises monthly food inflation by **0.059 pp** at twelve months. Own rainfall: +0.003.

Design: trade-weighted climate exposure

$$\tilde{C}_{v,i,t} = \sum_{j \neq i} \underbrace{\omega_{ij,\tau(t)}}_{\text{share}} \underbrace{C_{v,j,t}}_{\text{shift}}, \quad v \in \{T, P\}, \quad \tau(t) = [y(t) - 9, y(t) - 5]$$

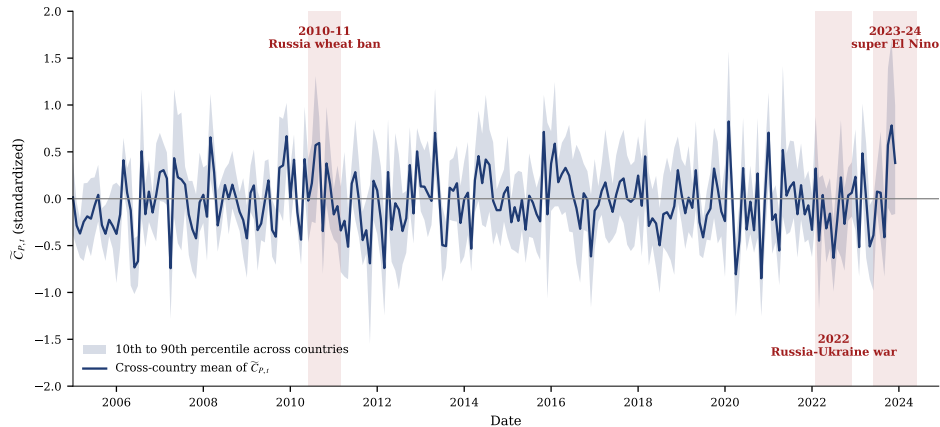
Shifts ERA5 reanalysis, **cropland-weighted** (MapSPAM)
deviations from country $\times$ calendar-month norms 1991–2020, in sd units

Shares FAO bilateral trade matrix, HS 01–24
five-year window, lagged five years

Identification

- (i) weather does not respond to inflation
date FE absorb El Niño, Brent, the FAO price index
- (ii) shares predetermined — cannot adjust to the shock
- (iii) exposure dispersed — **27.7** effective exporter shocks (largest, US: 10.7%)

The identifying variation is the band, not the line



Cross-country mean of $\tilde{C}_{P,t}$ and the 10th–90th percentile band across the 49 importers. Date fixed effects absorb the common component.

Specification and inference

$$\pi_{i,t+h}^k = \alpha_{i,h}^k + \mu_{t,h}^k + \theta_{T,h}^k \tilde{C}_{T,i,t} + \theta_{P,h}^k \tilde{C}_{P,i,t} + \gamma_{T,h}^k C_{T,i,t}^{\text{own}} + \gamma_{P,h}^k C_{P,i,t}^{\text{own}} + \mathbf{r}_h^{k'} \mathbf{X}_{i,t} + \varepsilon_{i,t+h}^k$$

Panel local projections (Jordà, 2005) — month-on-month log change of the food CPI

- $\mathbf{X}$ 3 lags of the dependent variable and of each of the four climate regressors;
 $\Delta \log \text{NEER}$, contemporaneous and 3 lags

$\tilde{C}$ and C^{own} enter *jointly* — the horse race is within one regression

Inference

- **AKM cluster-shift** (Adão, Kolesár and Morales, 2019)
exporter shifts as the unit of variation; all three aggregation schemes
(*independent cells, exporter-year, exporter*)
- **Share-randomization placebo** (Borusyak and Hull, 2022), $B = 500$
permute importers in the share matrix, rebuild the shift, re-estimate

Dataset: 49 importers, monthly, shocks 2005:04–2023:11

Partner rainfall moves domestic food prices — own rainfall does not

h	Temperature				Precipitation			
	Trade-wtd		Own		Trade-wtd		Own	
	$\hat{\theta}_T$	p	$\hat{\gamma}_T$	p	$\hat{\theta}_P$	p	$\hat{\gamma}_P$	p
0	+0.092	0.10	−0.058	0.006	−0.017	0.57	+0.006	0.52
3	−0.031	0.39	−0.017	0.50	−0.019	0.35	−0.003	0.80
6	−0.063	0.31	+0.000	0.98	+0.018	0.61	−0.007	0.53
12	−0.030	0.26	+0.046	0.071	−0.059	0.007	+0.003	0.67

Rainfall — why the gap

Aggregation averaging dozens of exporters cancels idiosyncratic noise and keeps common supply stress — the index is far less noisy than any single country's weather

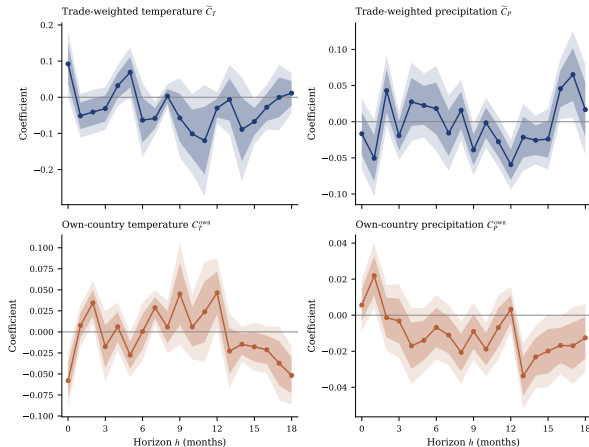
Composition it weights the regions that actually grow the importer's food; own weather matters only for the share of the basket produced at home

Horizon soil moisture → harvest → export contracts → margins $\approx$ one year, hence $h = 12$

Magnitude food is 21% of the basket → headline displacement $\approx$ **0.013 pp/month**

Own heat negative — local perishables oversupply, demand reduction; not a trade channel

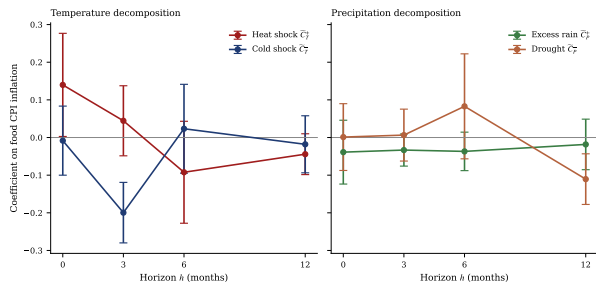
Partner rainfall concentrates at $h = 12$; own heat at impact



Trade-weighted precipitation (top right) is deepest and significant at $h = 12$. Own-country temperature (bottom left) acts at impact, $h = 0$ (-0.058 , $p = 0.006$). Bands 68% and 90%, pointwise.

The central finding: three channels, three horizons

$\tilde{C}_V^+ = \max(\tilde{C}_V, 0)$ and $\tilde{C}_V^- = \min(\tilde{C}_V, 0)$, entered jointly with own-country analogues



Channel	h	$\hat{\theta}$	p
Heat $\tilde{C}_T^+$	0	+0.140	0.100
Cold $\tilde{C}_T^-$	3	-0.200	<0.001
Drought $\tilde{C}_P^-$	12	-0.111	0.009
Excess rain $\tilde{C}_P^+$	-	no effect at any h	

Reading the signs. $\tilde{C}_T^-, \tilde{C}_P^- \leq 0$ by construction, so a negative coefficient means colder or drier partners *raise* food inflation — **all three channels are inflationary.**

Heat $h = 0$

Cold $h = 3$

Drought $h = 12$

priced by forward and spot markets, before shipments move
frost at planting; damage assessed, replanted, next shipment short
the harvest cycle

Pooling hides this

linear temperature at $h = 3$ is -0.031 against **-0.200** for cold alone
linear rainfall at $h = 12$ is -0.059 against **-0.111** for drought alone

Cold is the anchor — heat and drought are directional

	Heat ($h = 0$)	Cold ($h = 3$)	Drought ($h = 12$)
Cluster p	0.100	0.0002	0.009
AKM p (range over schemes)	0.045–0.126	≤ 0.002	0.024–0.133
Bonferroni over 76 flex-lag cells	fails	clears	fails
Share-randomization placebo	$p < 1/500$	$p < 1/500$	$p = 0.026$

- AKM p** the schemes differ in how much within-exporter serial correlation they allow; none dominates, so we report the worst case with the range
- Flex-lag grid** of the 76 cells, only cold's peak clears the family-wise threshold ($0.05/76 = 0.00066$); five others cross 5% — about what chance predicts
- Bonferroni** assumes 76 independent tests; they share one panel and two underlying series — **clearing it is decisive, failing it is not damning**

The design holds for all three channels (a defensible empirical regularity)

- precision and multiplicity are what leave **cold as the only tightly identified one**

The effect is concentrated in food, and stops there

Non-food & core nothing — headline $+0.004$ ($p = 0.80$); expenditure-weighted core $+0.001$ ($p = 0.94$); core ex-energy -0.018 ($p = 0.15$)

Transport the design check — if partner weather moves world food prices, the date FE must absorb that global channel; any leak would surface in transport, the most commodity-exposed non-food division. -0.073 ($p = 0.080$), **not robust**

Pass-through to the **policy rate** and the **NEER**: null at the panel mean ($p > 0.26$)
One exception before correction: at $h = 6$ the NEER response to heat differs by **inflation-targeting regime** (interaction $\hat{\delta} = +0.59$, $p = 0.021$)

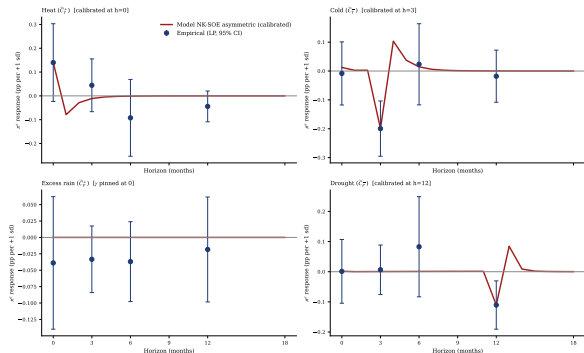
- non-IT (base): **depreciate** ≈ 28 bp — no anchor, the **currency** absorbs it
- IT (base + $\hat{\delta}$): **appreciate** $\approx 0.3\%$ — a credible target holds, so **relative prices** adjust instead of the currency

A shock that displaces food and does not reach core is one a credible targeter should look through. The model puts that intuition on a criterion.

A small open economy NK model with asymmetric climate channels

Galí–Monacelli extended along four dimensions, **three of them forced by the empirics**:

- **CES food aggregator** over domestic and imported supply
- **Three imposed delay horizons** (0, 3, 12), matched to the estimated peaks
- **Flexible food prices** alongside sticky non-food
- External sector — NFA accumulation, debt-elastic premium; *closes the model* (SGU, 2003)



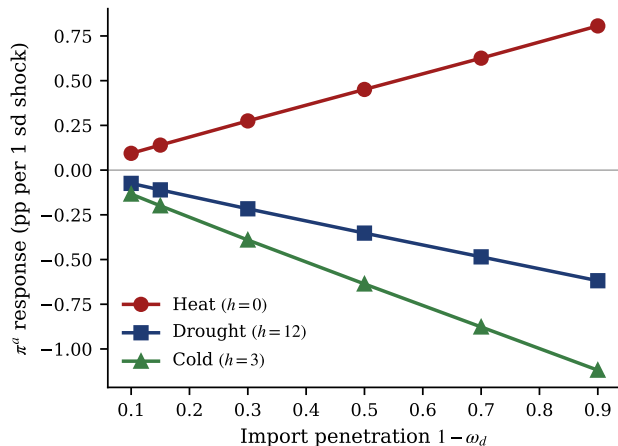
Calibration. Three elasticities, three peak moments — exactly identified, so **the peaks match by construction**.

Off-peak. The model stays inside the empirical bands — a consistency check on amplitudes, **not a test of the dynamics**.

What it adds. With one elasticity per variable, heat and cold would share a horizon. **Separate elasticities and lags** are what generate the three-month cold peak — state dependence without disaster shocks.

Exposure scales with import penetration

π^a at each channel's peak horizon, varying the domestic share ω_d in the food basket



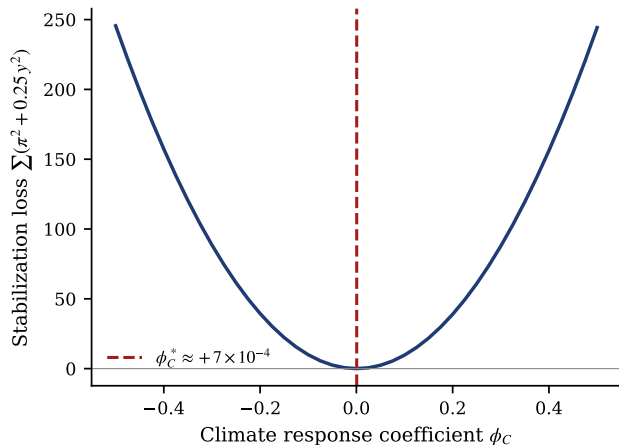
Monotone in all three channels. At **90% penetration** drought is -0.62 , against -0.11 at the 15% baseline. Stylized grid: the panel's most dependent country (Saudi Arabia) sits at 0.77.

Mostly an accounting weight. The slope is the imported share in the CES basket; substitution bends it by **7%** across the grid. A consistency check, not a finding.

What is not mechanical. The same arithmetic on the domestic side fails — own weather is a **null**. Lowering import exposure is real **adaptation**, not a swap of one weather risk for another.

And the rule should look through the channel we identify

Taylor rule augmented with the trade-weighted climate index $\tilde{C}_t$, under quadratic stabilization loss



The optimum is $\phi_C^* \approx 7 \times 10^{-4}$ — three orders below any policy-relevant value.

Why. A material response injects **interest-rate noise**, raising inflation and output variance with nothing stabilized in return.

How wrong would we have to be? ϕ_C^* scales one-for-one with the identified elasticities: they would have to be **75× larger** before ϕ_C^* reached 0.05.

Scope. The claim is about the channel we identify. Own-country rainfall is a **null** in the horse race (+0.003) — nothing there for a climate rule to stabilize.

Whose weather — why bilateral exposure, and not an aggregate index

An aggregate indicator cannot answer this. A world food-price index, an ENSO index, a global temperature anomaly — each is **one time series**. It is collinear with date fixed effects, and without them it cannot be told apart from oil, war, or global demand.

Bilateral shares $\times$ exporter weather instead generate variation across countries within each date. Every importer buys from a different basket, so the identifying comparison is Portugal against Spain in the same month.

That is what buys the two answers: whose weather — and at what horizon. Heat at impact, cold at three months, drought at twelve; excess rain never. No aggregate index can separate these by construction.

And the design holds up:

- Own-country weather is a **null** (-0.059 against $+0.003$) — an internal control no aggregate index has
- **27.7** effective exporter shocks; the largest (US) is 10.7%
- Leave-one-exporter-out: $[-0.066, -0.039]$, significant in 49 of 50
- Share-randomization placebo: $p = 0.026$
- Survives country trends and region $\times$ date

What it means for policy, and what we are still building

Lessons for central banks

- The shock is **forecastable**: partner drought reaches the CPI twelve months out. That is a lead, not news.
- **Looking through** the identified channel is the calibrated benchmark — it would have to be 75× larger to warrant a response.
- But exposure **scales with import dependence**. The panel mean is not a universal prescription.
- Diversification of food import sources, food security reserves, and price-hedging instruments dominate rate policy here — and do not substitute for targeted fiscal support.

What we are still working on

- **Cold**. A below-norm monthly mean is not frost — rebuilding from ERA5 daily minima and crop calendars.
- **LP-IV**. Instrumenting bilateral import prices with the weather shift — a genuine first stage.
- **Model**. Disciplining the own-country elasticities; distributed lags from the crop cycle.
- **Welfare**. Our loss is **ad hoc** — quadratic, on headline inflation, where the frontier is micro-founded, sector-weighted and distributional (Aoki, 2001).

Thank you.

Backup

Additional results

B1. Descriptive statistics, effective estimation sample

	Mean	SD	Min	Max
<i>Inflation (pp per month, SA)</i>				
π^{food}	0.36	1.11	−17.13	42.94
π^{headline}	0.29	0.81	−14.38	30.74
π^{core}	0.25	0.72	−3.48	26.07
<i>Trade-weighted climate (sd units)</i>				
$\tilde{C}_T$	0.27	0.63	−2.47	2.53
$\tilde{C}_P$	−0.02	0.51	−1.98	2.50
<i>Own-country climate (sd units)</i>				
C_T^{own}	0.27	0.96	−3.58	4.29
C_P^{own}	0.00	1.01	−3.32	5.90
<i>Dependence and controls</i>				
Net food import dep. (FAO IDR)	0.04	0.30	−0.75	0.77
$\Delta \log \text{NEER}$	−0.05	1.69	−60.36	10.59

Computed on the exact regression rows, 49 countries, $N = 10,273$. The right tail of food inflation is Argentina (42.9% in November 2023) and Türkiye, both excluded in the robustness batteries. Dependence is net imports over apparent consumption; the most dependent economy is Saudi Arabia at 0.77.

B2. Is the design driven by a few exporters?

- **Concentration.** 168 exporter-level shocks. Herfindahl of the importance weights 0.036, **effective number of shocks 27.7**. Largest weights: US 10.7%, Germany 7.4%, Netherlands 5.8%, France 5.0%, Brazil 4.8%; top five 33.7%.
- **Leave-one-exporter-out**, dropping each of the fifty largest in turn: $\hat{\theta}_{P,12} \in [-0.066, -0.039]$, significant at 5% in **49 of 50**. The exception is dropping the United States (-0.039 , $p = 0.069$).
- **Dropping Russia leaves the coefficient unchanged** at -0.059 ; Argentina gives -0.056 , Brazil -0.061 .
- **Excluding the 2010–11 Russian export-ban window** (Aug 2010–Jun 2011): -0.058 ($p = 0.009$). The result is not the Russian episode.

Scripts: m2_loeo_concentration.R; tables shock_concentration.csv, loeo_headline.csv.

B3. Share exogeneity: trends, not levels

The trade-weighted temperature exposure has a positive mean (the warming trend), so the concern is that the channels load on import composition interacted with differential inflation trends.

	Cold ($h = 3$)	Heat ($h = 0$)	Drought ($h = 12$)
Baseline	-0.200	+0.140	-0.111
Country-specific linear trends	-0.196	+0.150	-0.119
Region $\times$ date FE	-0.157 ($p = 0.036$)	+0.109	-0.132

Country trends leave all three essentially unchanged. Under region-by-date fixed effects — identifying only from within-region cross-country variation at each date — the cold anchor survives at 5%; heat and drought preserve their point estimates but lose precision under the sharply reduced identifying variation.

Script: `m3_trends_region.R`.

B4. Heavy tails, functional form, and influence

Treatment of the dependent variable	$\hat{\theta}_{P,12}$	p
Baseline	−0.059	0.007
Winsorized at 1/99	−0.045	0.006
Winsorized at 2.5/97.5	−0.040	0.007
Trimmed, $ \pi^{\text{food}} > 3$ dropped	−0.044	0.004

Significant at 1% under every treatment, though the heavy tails inflate the point estimate by roughly a quarter to a third — we say so in the text rather than reporting the baseline alone.

Influence. Leave-one-importer-out keeps the coefficient in $[-0.067, -0.049]$ across all 49. Argentina and Türkiye are the most influential by DFBETA (+0.011, +0.010); removing them gives −0.049 and −0.050, still significant.

Script: m10_heavy_tails.R.

B5. The NEER is a mediator, not a confounder

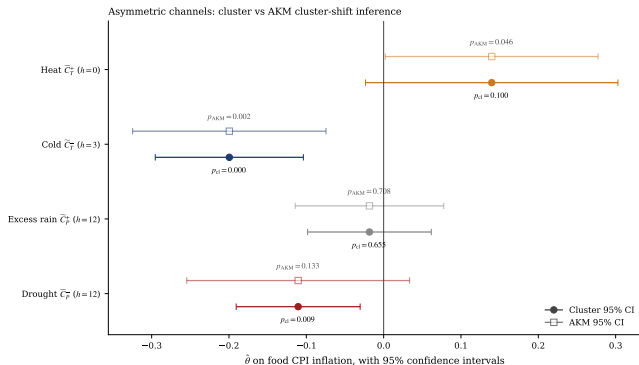
The baseline controls for contemporaneous and lagged NEER changes. If the exchange rate is on the causal path from the climate shock to domestic prices, that control is a bad one and the baseline recovers a partial rather than a total effect.

Specification	$\hat{\theta}_{P,12}$	p
Baseline, NEER controls included	-0.059	0.007
Total effect , NEER dropped, same sample	-0.062	0.009
Total effect, NEER-unrestricted 59-country sample	-0.050	0.024

Because pass-through to the exchange rate is null on average, the mediator bias is negligible: the total effect coincides with the partial to within five percent, and if anything is slightly larger. We report it as a labeled robustness row rather than switching the headline.

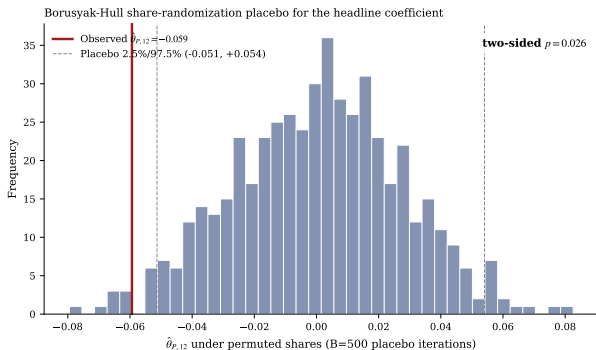
Script: m5_neer_bad_control.R.

B6. AKM inference across shock-aggregation schemes



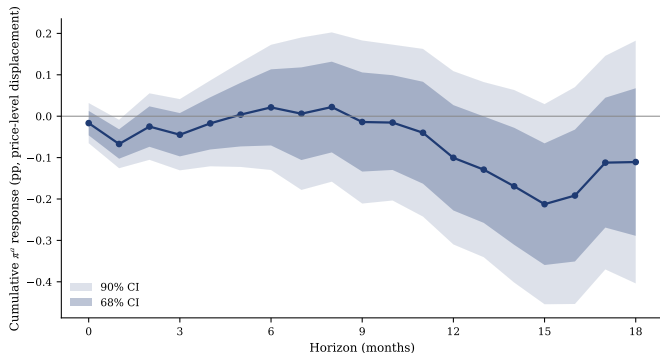
Residuals are aggregated to exporter-month cells, treated as independent. Because climate shocks are serially correlated within exporter, this can understate or overstate the shock-level variance, so we report all three schemes (independent cells, exporter-year clusters, exporter clusters) rather than privileging one. They disagree in channel-specific directions and none dominates. Cold is significant under all three; heat runs 0.045–0.126, drought 0.024–0.133.

B7. Share-randomization placebo



Borusyak–Hull placebo, $B = 500$: the importer dimension of the share matrix is permuted, the shift rebuilt, the projection re-estimated. The null centers at $+0.001$ (sd 0.027); the observed -0.059 falls in the bottom 1.6 percent (two-sided $p = 0.026$). For cold at $h = 3$ the null centers at $+0.003$ (sd 0.043) and *no* permutation reaches the observed magnitude ($p < 1/500$). This holds the weather shifts fixed and asks whether arbitrary share patterns could produce the coefficient.

B8. Cumulative response, and what it is worth



Cumulating the monthly responses, a one-standard-deviation partner drought raises the food price *level* by about 0.10 pp by twelve months, peaking near -0.21 pp at $h = 15$ before partial mean reversion. The object is imprecisely estimated — its bands widen with horizon as it accumulates variance, and it does not attain significance. The identified result therefore remains the monthly-rate response, and we say so.

B9. Heterogeneity by net food import dependence

Interacting each channel with the FAO import-dependency ratio, $IDR = (M - X)/(P + M - X)$ — net imports over apparent consumption, the empirical counterpart of $1 - \omega_d$:

Interaction	Median split	Continuous
δ_P at $h = 3$ (drought)	-0.131 ($p = 0.0004$)	-0.049 ($p = 0.007$)
δ_T at $h = 6$ (heat)	+0.163 ($p = 0.034$)	+0.094 ($p = 0.055$)

Drought amplification by import dependence at three months, significant under both methods, with the economically correct sign. The gross-imports measure we used earlier exceeded one for entrepôt economies and produced neither result; the net measure is the one the model's ω_d corresponds to.

This is the empirical counterpart of the structural gradient in panel (a) of the counterfactual figure.

B10. Calibration and solution diagnostics

Parameter	Value
γ_m^{T+} (heat)	0.01664
γ_m^{T-} (cold)	0.02211
γ_m^{P-} (drought)	0.01419
γ_m^{P+}	0 (fixed)
γ_d^T, γ_d^P	0.20 / 0.10

γ_d are **plug-in priors, not identified** by the impulse-response matching: the design disciplines the imported channel only.

Solution. $eu = (1, 1)$ under a faithful port of the Sims uniqueness test, one unit root (the price level), semisimple. The external closure — exports, NFA accumulation, debt-elastic premium — supplies the fourth explosive direction; without it the model is indeterminate and consumption has no unconditional variance.

Solver. div must sit in $(1, 1/\beta)$. The Sims default of 1.01 classifies the no-Ponzi root $1/\beta = 1.0033$ as stable and returns explosive solutions as if determined.

Imposed, not estimated. The horizons 0, 3, 12 are the argmax of $|\hat{\beta}|$ over the local-projection grid, a calibration choice informed by the reduced form. The projections do not validate the *selection* of horizon.

B11. Why we report stabilization loss and not consumption equivalents

In a variance decomposition of the calibrated model at the baseline import share, the trade-weighted climate channel — the object the empirical design identifies — accounts for about **0.03 percent** of the unconditional consumption variance, against roughly 89 percent for the own-country channel, 9 for the foreign interest rate, 2 for monetary policy.

The own-country channel dominates because γ_d^T and γ_d^P enter at plug-in priors. Any cross-country welfare gradient computed from these variances would be carried by unidentified parameters, and measured against the deterministic rather than the efficient steady state. We therefore dropped the consumption-equivalent layer.

The optimal-coefficient result does not inherit that limitation. ϕ_C^* scales one for one with the *identified* elasticities — they would have to be **75× larger** before it reached 0.05 — while the unidentified γ_d does not shift it at all: own-country shocks do not enter the index the rule responds to, so their loss is additive in ϕ_C . The empirical own-country coefficient is a null in any case (+0.003 at $h = 12$).

Scripts: `m17_gammam_sensitivity.py`, `m8_gammad_sensitivity.py`. Sensitivity to $\eta \in \{0.5, 1\}$: channels within 0.1%, ϕ_C^* within 2%.

B12. Limitations we are not papering over

- **A below-norm monthly mean is not frost.** The linear-in-splits specification imposes damage in every exporter-month, which is not agronomically warranted, and the cold response concentrates in northern-hemisphere winter months of the major exporter calendars. We are rebuilding it from ERA5 daily minima and FAO/SAGE crop calendars. If the anchor does not survive, the framing changes.
- **The tail-risk exercise is not identified.** Quantile local projections point to upper-tail displacement, but rank-score intervals cross zero in the focal cells. It sits in an appendix and carries no weight.
- **The structural model adds little independent identification.** The off-peak fit is a consistency check on amplitudes given a locked dynamic structure; the over-identification test has almost no power.
- **$\phi_C^* = 0$ is a representative-agent result.** A first-order TANK approximation without equilibrium feedback preserves it up to 40% hand-to-mouth, but cannot speak to the integrated case.
- **No first stage.** Instrumenting bilateral food import prices with the weather shift would convert the design into LP-IV and recover the structural pass-through elasticity.