The Missing Intercept of Climate Change

Evidence from Agriculture

Pierre Coster

pcoster@usc.edu · Ph.D. candidate, 4th year, Department of Economics, University of Southern California

Problem & Question: TWFE and the Missing Intercept

Literature estimates **effect of heat on agriculture** with **two-way fixed effects** (TWFE)

$$\log y_{i,t} = \gamma_i + \lambda_t + \beta_L H_{i,t} + \text{controls} + \varepsilon_{i,t}, \quad (1)$$

and combine $\hat{\beta}_L$ with climate projections to compute long-run losses [1–4].

What if local outcome depends on both local (β_L) and aggregate (β_A) weather?

$$\log y_{i,t} = \gamma_i + \beta_L H_{i,t} + \beta_A \bar{H}_t + \gamma'_{\text{macro}} M_t + \text{controls} + \varepsilon_{i,t}, \quad (2)$$

where $\bar{H}_t = \frac{1}{I}\Sigma_i H_{i,t}$ is aggregate average heat.

The **missing intercept problem** [5, 6]:

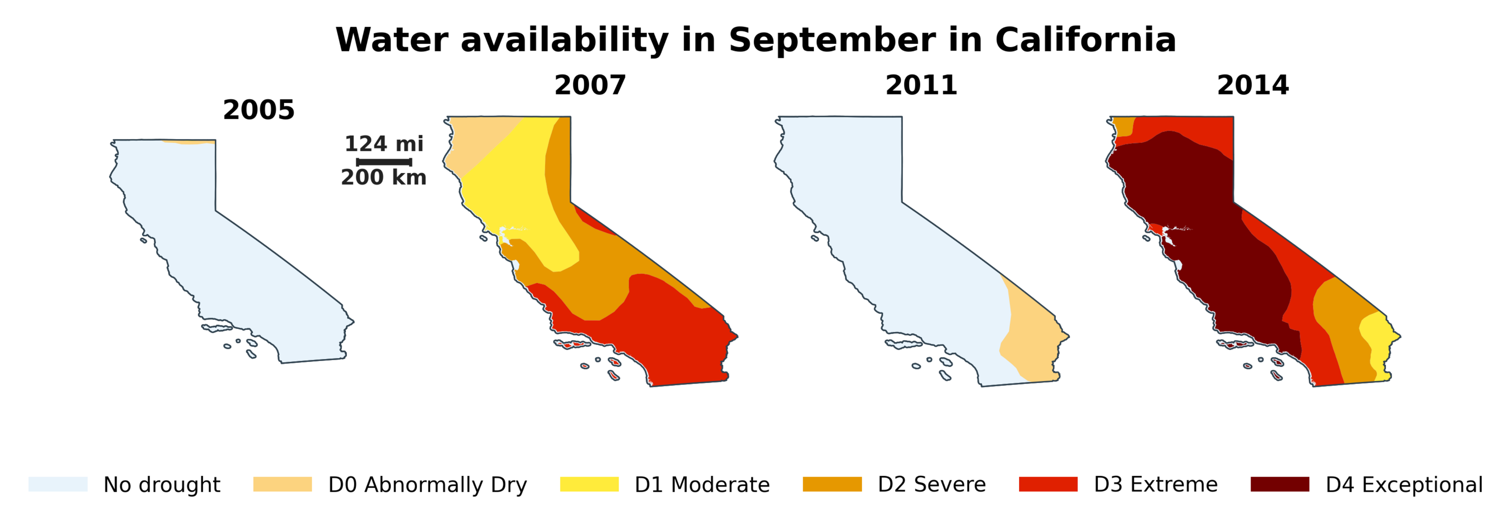
- Common **general equilibrium** forces affect **local outcomes**.
- These effects are captured by λ_t.

Why not estimate (2) directly?

- Spurious correlation between yield and temperatures [7].
- Feedback / reverse causality from land-use on temperature [8].
- Collinearity between $H_{i,t}$ and $\bar{H}_t$ [9].

Why would $\beta_A \neq 0$? General Equilibrium Channels

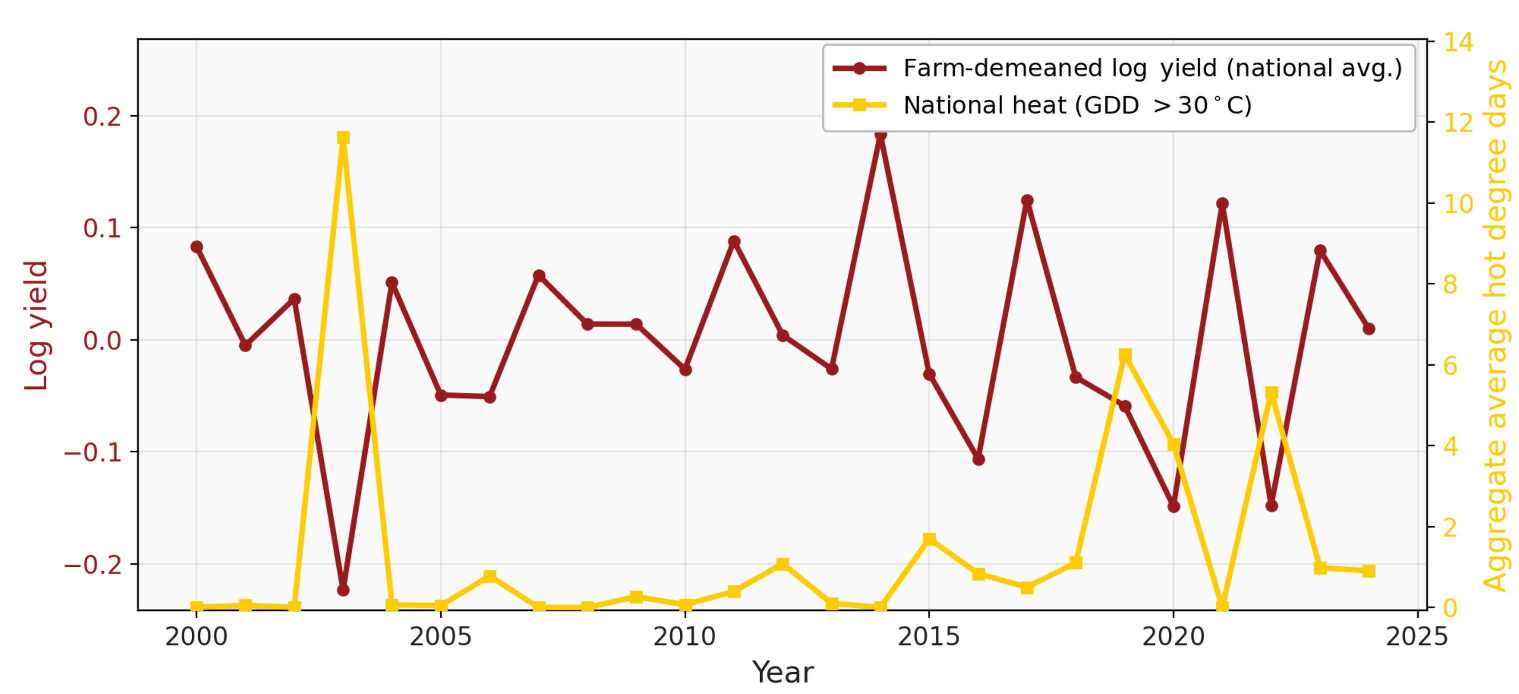
Shared water basins → Weather miles away affects local water availability.



Source: Weekly U.S. Drought Monitor.

Aggregate supply and prices → Weather miles away affects local prices.

French corn → **Correlation of** -0.71 between national heat and cross-sectional average of yields (after removing local means). λ_t would absorb that channel.



Data

Farm-level data for France (RICA):

- ~90% of agricultural output and surface; ~65% of all farms, 2000-2024.
- Output & input quantity + prices. Balance sheet. Farm head information.

Weather data (Copernicus):

- Hourly gridded data on temperature, rain, sun. Aggregated at yearly level.
- Main variable: Hot Degree Days for farm i and year t $H_{i,t}$ [10].

[1] Marshall Burke and Kyle Emerick. Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy*, 8(3):106–140, August 2016. ISSN 1945-7731.

[2] Elodie Blanc and Wolfram Schlenker. The Use of Panel Models in Assessments of Climate Impacts on Agriculture. *Review of Environmental Economics and Policy*, 11(2):258–279, July 2017. ISSN 1750-6816.

[3] Maximilian Auffhammer. Quantifying Economic Damages from Climate Change. *Journal of Economic Perspectives*, 32(4):33–52, November 2018. ISSN 0895-3309.

[4] Andrew Hultgren, Tamma Carleton, Michael Delgado, Diana R. Gergel, Michael Greenstone, Trevor Houser, Solomon Hsiang, Amir Jina, Robert E. Kopp, Steven B. Malevich, Kelly E. McCusker, Terin Mayer, Ishan Nath, James Rising, Ashwin Rode, and Jiacan Yuan. Impacts of climate change on global agriculture accounting for adaptation. *Nature*, 642(8068):644–652, June 2025. ISSN 1476-4687.

[5] Benjamin Moll. The Missing Intercept Problem when going from Micro to Macro, 2021.

[6] Christian K. Wolf. The Missing Intercept: A Demand Equivalence Approach. *American Economic Review*, 113(8):2232–2269, 2023.

[7] C. W. J. Granger and P. Newbold. Spurious regressions in econometrics. *Journal of Econometrics*, 2 (2):111–120, July 1974. ISSN 0304-4076.

[8] Wim Thiery, Auke J. Visser, Erich M. Fischer, Mathias Hauser, Annette L. Hirsch, David M. Lawrence, Quentin Lejeune, Edouard L. Davin, and Sonia I. Seneviratne. Warming of hot extremes alleviated by expanding irrigation. *Nature Communications*, 11(1):290, January 2020. ISSN 2041-1723.

[9] Jeffrey M. Wooldridge. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA, USA, 2 edition, October 2010. ISBN 978-0-262-23258-6.

[10] Wolfram Schlenker and Michael J. Roberts. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, 2009.

[11] Christian Matthes, Ryoji Nagasaka, and Felipe Schwartzman. Estimating the Missing Intercept. *Econometrica (Revise and Resubmit)*, 2025.

[12] Adrien Bilal and Diego R Känzig. The Macroeconomic Impact of Climate Change: Global Versus Local Temperature*. *The Quarterly Journal of Economics*, page qjag011, February 2026. ISSN 0033-5533.

[13] Timothy D. Mitchell. Pattern Scaling: An Examination of the Accuracy of the Technique for Describing Future Climates. *Climatic Change*, 60(3):217–242, October 2003. ISSN 1573-1480.

[14] José-Luis Cruz and Esteban Rossi-Hansberg. The Economic Geography of Global Warming. *The Review of Economic Studies*, 91(2):899–939, March 2024. ISSN 0034-6527.

[15] Arnaud Costinot, Dave Donaldson, and Cory Smith. Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World. *Journal of Political Economy*, 124(1):205–248, February 2016. ISSN 0022-3808.

Solution: Factor Model

Adapted from paper "Estimating the Missing Intercept" by Matthes, Nagasaka, and Schwartzman (2025), applied to agricultural climate shocks.

Estimating GE effects via minimal shock assumptions rather than model [11].

1. Assumptions

Two unobserved aggregate shocks, heat (η_t^H) and macro (η_t^M), drive first-differenced deviations from trend in local heat and macro variables [13, 14]:

$$\Delta H_{i,t} = \tau_i^H + B_{\Delta H_{i,t},\eta^H}\, \eta_t^H + e_{\Delta H_{i,t}} \quad (3)$$

$$\Delta M_t = \tau^M + B_{\Delta M_t,\eta^H}\, \eta_t^H + B_{\Delta M_t,\eta^M}\, \eta_t^M + e_{\Delta M_t} \quad (4)$$

$\mathbb{E}[\eta_t] = 0$, $\mathbb{E}[\eta_t \eta_t'] = I_P$, *and* η_t *is independent of idiosyncratic errors.*

2. The Stacked System

Vector $\mathcal{X}_t$ stacks 3 aggregate first-differences ($\Delta \log \bar{y}_t$, $\Delta \bar{H}_t$, ΔM_t) and $2I$ local variables (detrended FD as deviation from aggregate FD $\tilde{\Delta} \log y_{i,t}$ and $\tilde{\Delta} H_{i,t}$):

$$\overbrace{\underset{(2I+3)\times 1}{\mathcal{X}_t}}^{\text{Data}} = \overbrace{\underset{(2I+3)\times 2}{B} \; \underset{2\times 1}{\eta_t}}^{\text{Unknowns}} + \varepsilon_t, \qquad \eta_t = \begin{pmatrix} \eta_t^H \\ \eta_t^M \end{pmatrix} \quad (5)$$

3. Object of Interest: Total Effect of Heat on Yield

$$\beta_{\text{total}} = \frac{B_{\Delta \log \bar{y}_t,\eta^H}}{B_{\Delta \bar{H}_t,\eta^H}} = (\beta_L + \beta_A) + \gamma_{\text{macro}} \frac{B_{\Delta M_t,\eta^H}}{B_{\Delta \bar{H}_t,\eta^H}}$$

4. Identification Restrictions

The system is unidentified ($2I+3$ equations, $(2I+3)\times 2 + 2$ unknowns). We impose:

- *TWFE Coefficient (I constraints):* $B_{\tilde{\Delta} y_{i,t},\eta^H} = \hat{\beta}_L B_{\tilde{\Delta} H_{i,t},\eta^H}$
- *Structural Zeros ($2I+3$ constraints):* Macro shocks do not affect heat, and affect local yields homogeneously: $B_{\tilde{\Delta} H_{i,t},\eta^M} = B_{\Delta \bar{H}_t,\eta^M} = B_{\tilde{\Delta} y_{i,t},\eta^M} = 0$.

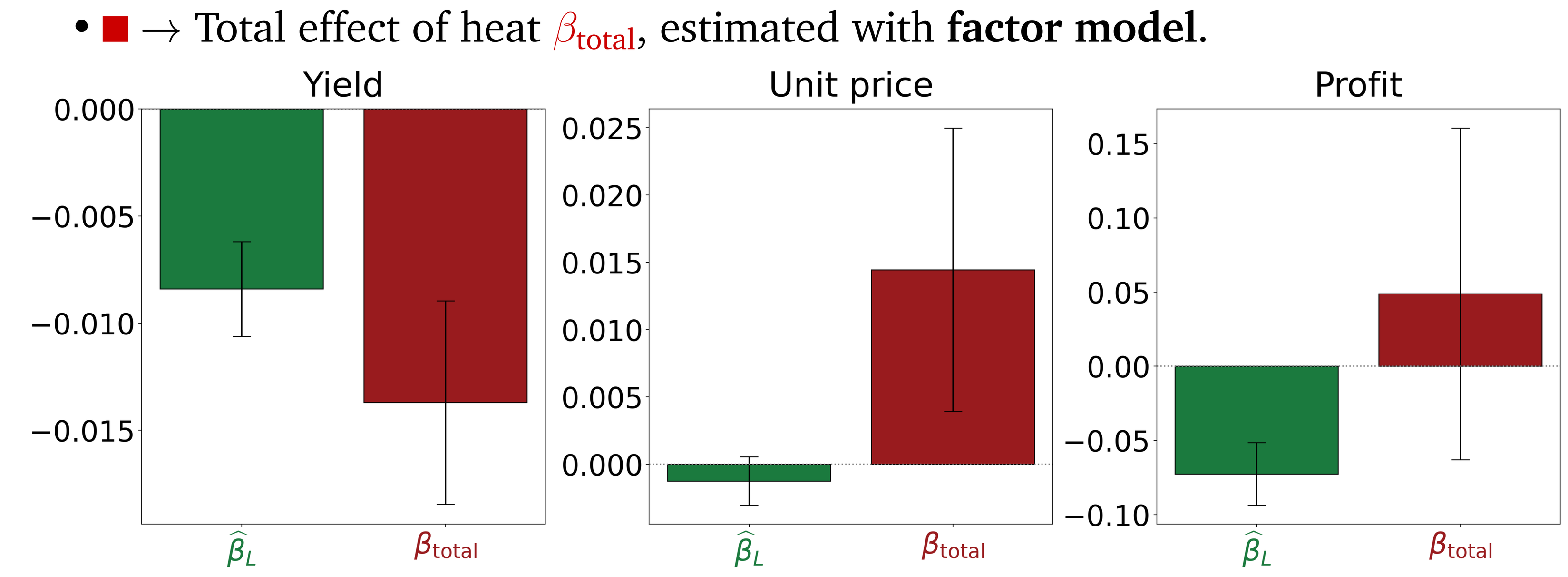
5. Estimation

Use *Frequentist* rather than the *Bayesian* approach of [11].

Results (Corn)

I jointly estimate heat impacts on yield, price, and profit using (5).

- ■ → Local effect $\hat{\beta}_L$, estimated with **TWFE**.
- ■ → Total effect of heat β_{total}, estimated with **factor model**.



- **Yield:** Total effect of heat on yield is *slightly more negative* than TWFE.
- **Price:** TWFE shows *no effect* of heat on prices; total effect is *positive*.
- **Profit:** TWFE suggests *negative effect* of heat on profits; total effect is *null*.

→ ***Lack of profit loss could explain lack of adaptation found in literature*** [1, 4].

Recent Literature: Global vs. local temperatures [12]

1. Mechanism: Weather Extremes vs. General Equilibrium

- Bilal & Känzig (2026): Global temperature shocks harm local GDP more than local ones because they are a better proxy for severe **local extreme events**.
- *This Paper:* **General Equilibrium (GE) channel**. *Local* heat causes direct biological farm damage, while *aggregate* heat drives indirect GE spillovers (prices, water).

2. Methodology: Time Series vs. Factor Model

- Bilal & Känzig (2026): Aggregate time-series methods.
- *This Paper:* **Factor model** to estimate **local biological** and **aggregate GE effects**.

Next steps

- **Factor Model:** Incorporate irrigation/water basin data, understand GE channels, and estimate the factor model using a Bayesian approach.
- **Theory:** Write a structural model [14, 15] and calibrate it via GE results (β_{total}). Estimate policy counterfactuals (e.g., integration, subsidies).