Quantifying Climate Damages When Regions Trade: A Structural Gravity Approach

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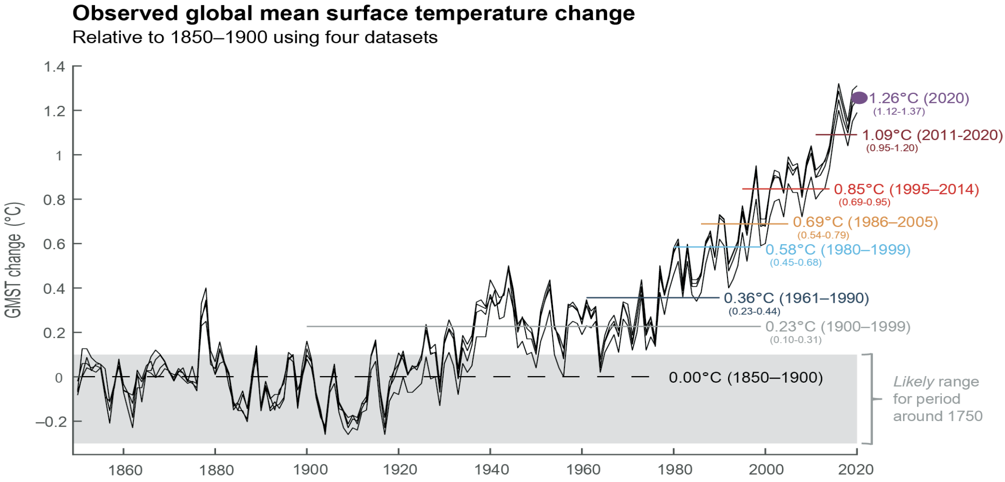
The World Continues to Warm



Source: IPCC (2021)

Quantifying Climate Damages

- Historical correlations between weather shocks and economic outcomes using TWFE

  Deschênes & Greenstone (2007); Dell, Jones & Olken (2012); Deryugina & Hsiang (2014); Burke, Hsiang & Miguel (2015)

- Structural general equilibrium models calibrated with micro-level elasticities

  Costinot et al.,(2016); Nath, (2025).

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$\Longrightarrow$ New method for quantifying the effects of climate change, accounting for general equilibrium effects due to trade

Road Map

- General Framework for Causal Effects with Spillovers
  - Reduced-Form Estimators
    - TWFE
    - Heterogeneous Robust (HR) (de Chaisemartin et al. (2024))
    - Upstream/Downstream (Das et al. (2022); Feng et al. (2023); Zappalà (2024))
    - Global Aggregate (Bilal & Känzig (2024))
  - What do we learn from TWFE?
    - TWFE picks up the slope of the Best Linear Approximation
    - Hence, TWFE identifies *relative* effects, but rarely the *level* of effects
- Structural Approach based on Trade Theory
- Monte Carlo Experiments
- Quantifying the Effect of Warming
  - Observed Warming (1991 - 2019)
  - Future Warming (2019 - 2100)

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Literature

- Environmental Literature on Weather Shocks

  Deschênes & Greenstone (2007); Dell, Jones & Olken (2012); Burke, Hsiang & Miguel (2015); Costinot et al. (2016); Dingle, Meng & Hsiang (2022); Zappalà (2024); Rossi-Hansberg & Cruz (2024); Nath (2025); Rudik et al. (2022); Bilal & Känzig (2024)

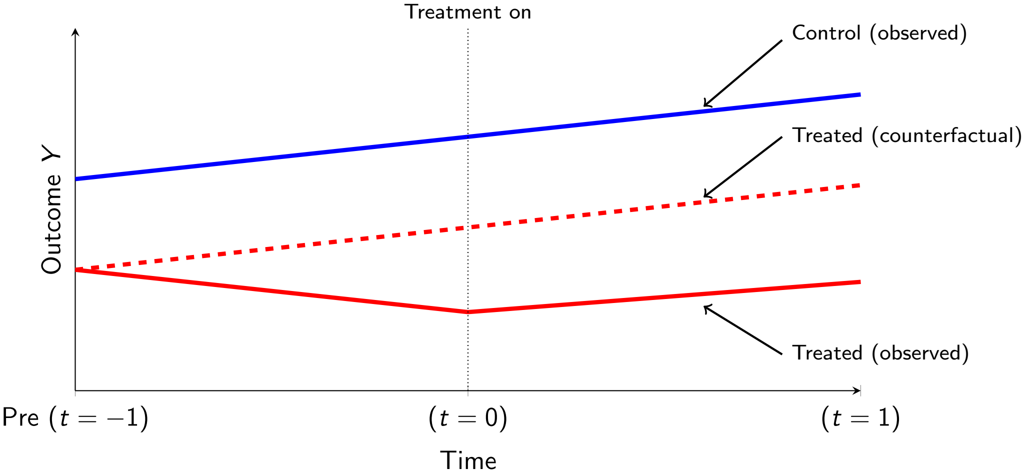
- Quantitative Trade Models to Evaluate Counterfactuals

  Dekkle, Eaton & Kortum (2007); Redding & Venables (2004); Head & Mayer (2014); Bartelme (2018); Fally & Markusen (2020); Hsieh & Ossa (2016); Shapiro & Walker (2018); Anderson Yotov (2020)

- Discussion of output of TWFE in general conditions (SUTVA violation)

  de Chaisemartin and D'Haultfœuille (2020); de Chaisemartin et al (2024); Borusyak, Dix-Carneiro & Kovak (2022); Vazquez-Bare (2023); Barrows, Calel, Jégard & Ollivier (2023); Alves et al (2023); Gouel (2025)

Difference-in-Differences (No Spillovers)



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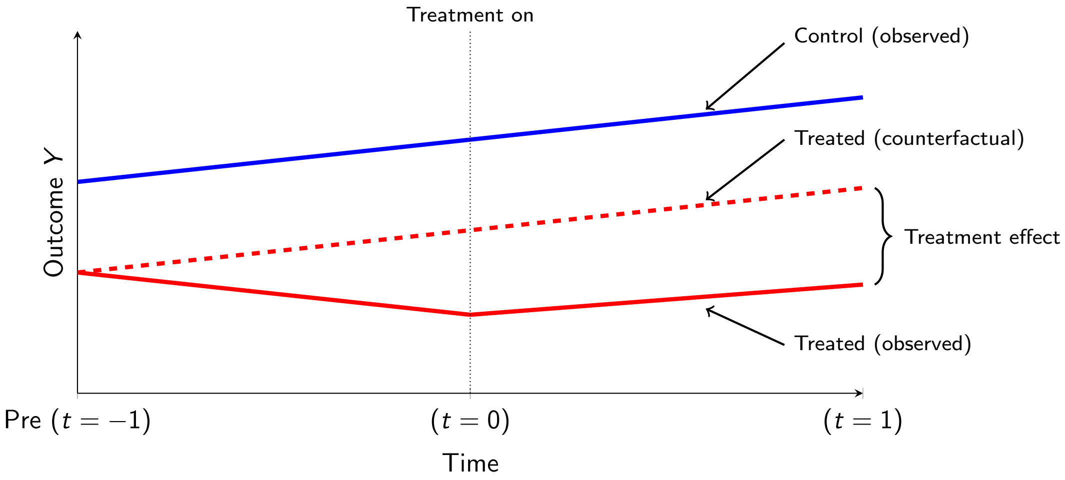
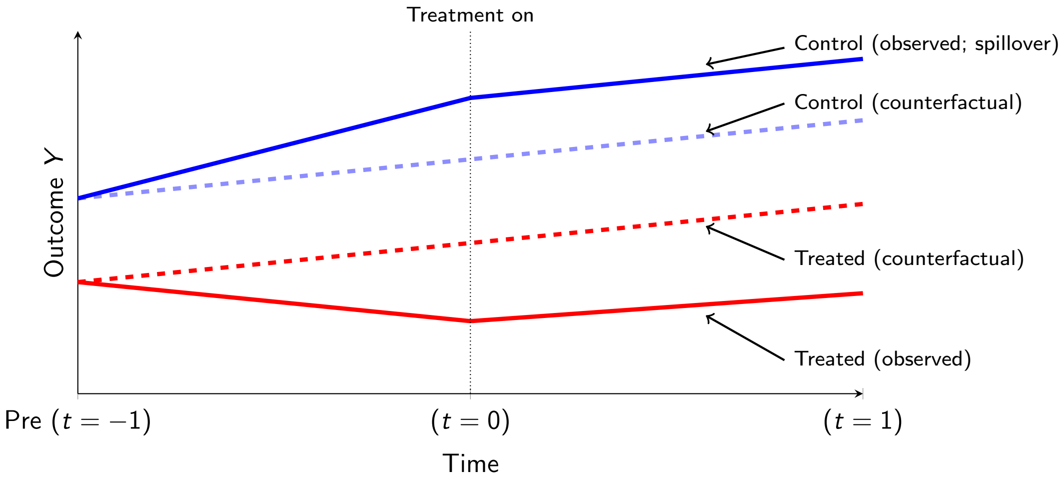
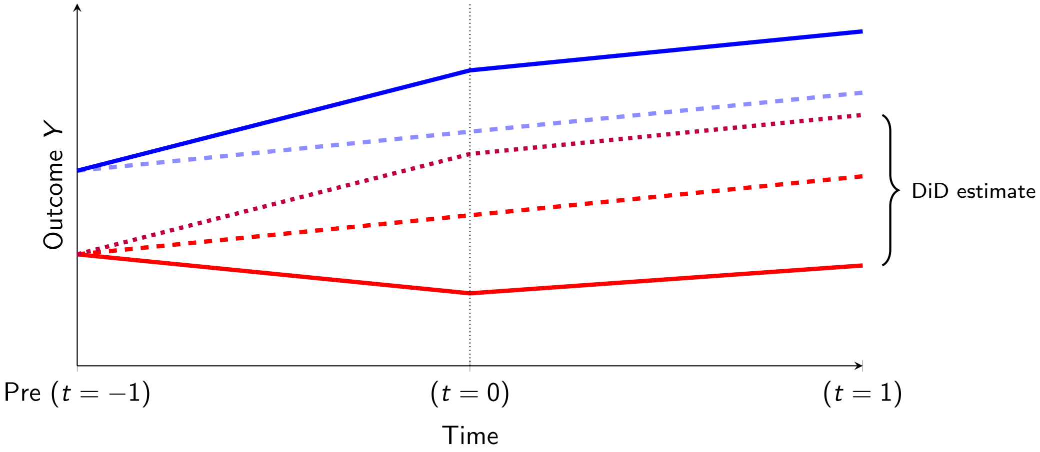


Difference-in-Differences (With Spillovers)



Difference-in-Differences (With Spillovers)



A General Framework For Studying Spillovers

- Model

$$\ln \boldsymbol{y_t} = f(\boldsymbol{z_t}, \boldsymbol{\epsilon_t})$$

  - z_{it} observed shock, ϵ_{it} unobserved shock
  - $f(\cdot)$ allows for arbitrary spillovers from z_{jt}, ϵ_{jt} to $\ln y_{it}$

- Estimands

  - Individual Overall Causal Effect (IOCE)

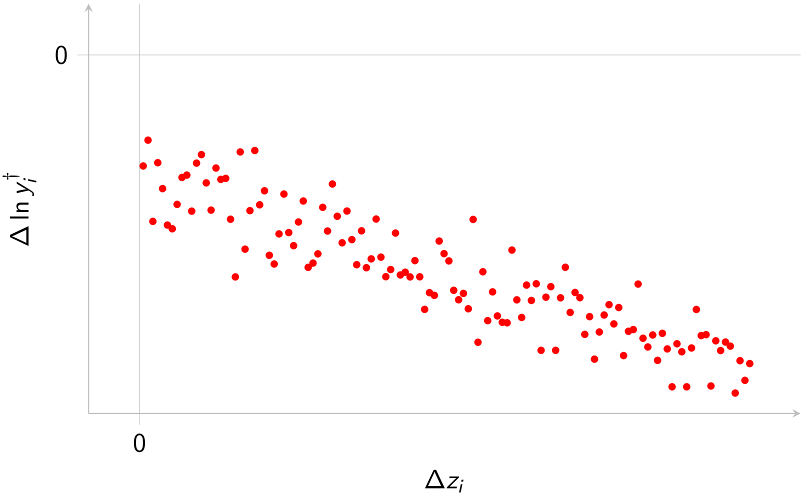
$$\Delta \ln y_i^{\dagger}(\boldsymbol{z_1}, \boldsymbol{z_0}; \boldsymbol{\epsilon_1}) \equiv f_i(\boldsymbol{z_1}, \boldsymbol{\epsilon_1}) - f_i(\boldsymbol{z_0}, \boldsymbol{\epsilon_1})$$

  - Best Linear Approximation (BLA):

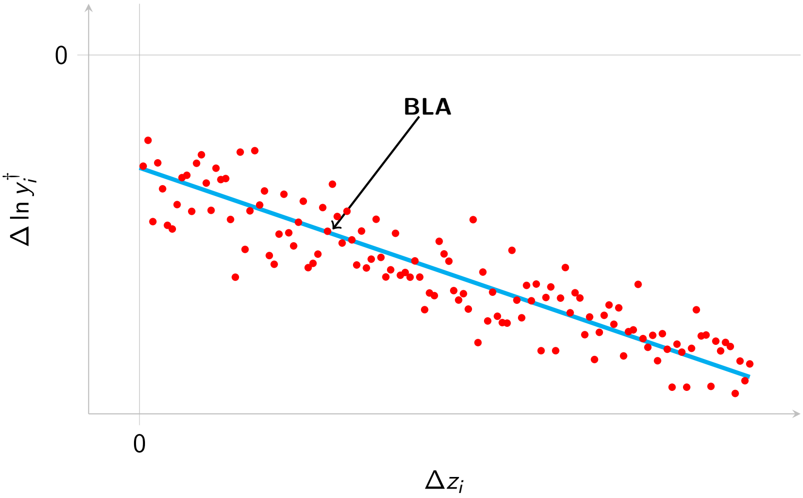
$$(\alpha^{BLA}, \beta^{BLA}) \equiv \arg\min_{a,b} \sum_{i=1}^{N} \left(\Delta \ln y_i^{\dagger} - a - b\Delta z_i\right)^2.$$

BLA vs ASIOCE

Best Linear Approximation (BLA) to the Individual Overall Causal Effect (IOCE)



Best Linear Approximation (BLA) to the Individual Overall Causal Effect (IOCE)



A General Framework For Studying Spillovers

- Taylor expansion around $f(\boldsymbol{z_0}, \boldsymbol{\epsilon_0})$,

$$\Delta \ln y_i = \underbrace{\sum_{a=1}^{N} \frac{\partial f_i}{\partial z_a}\bigg|_{(\boldsymbol{z^0},\boldsymbol{\varepsilon^0})} \Delta z_a + \sum_{b=1}^{N} \frac{\partial f_i}{\partial \varepsilon_b}\bigg|_{(\boldsymbol{z^0},\boldsymbol{\varepsilon^0})} \Delta \varepsilon_b}_{\text{first order terms}}$$

$$+ \underbrace{\sum_{k=2}^{\infty} \sum_{r=0}^{k} \frac{1}{r!\,(k-r)!} \sum_{a_1,\dots,a_r=1}^{N} \sum_{b_1,\dots,b_{k-r}=1}^{N} \frac{\partial^k f_i}{\partial z_{a_1} \cdots \partial z_{a_r} \partial \varepsilon_{b_1} \cdots \partial \varepsilon_{b_{k-r}}}\bigg|_{(\boldsymbol{z^0},\boldsymbol{\varepsilon^0})} \prod_{u=1}^{r} \Delta z_{a_u} \prod_{v=1}^{k-r} \Delta \varepsilon_{b_v}}_{\text{higher order terms}}$$

- In matrix form

$$\begin{pmatrix} \Delta \ln y_1 \\ \Delta \ln y_2 \\ \vdots \\ \Delta \ln y_N \end{pmatrix} = \underbrace{\begin{pmatrix} b^z_{11} & b^z_{12} & \cdots & b^z_{1N} \\ b^z_{21} & b^z_{22} & \cdots & b^z_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ b^z_{N1} & b^z_{N2} & \cdots & b^z_{NN} \end{pmatrix}}_{\equiv B^z} \begin{pmatrix} \Delta z_1 \\ \Delta z_2 \\ \vdots \\ \Delta z_N \end{pmatrix} + \underbrace{\begin{pmatrix} b^\epsilon_{11} & b^\epsilon_{12} & \cdots & b^\epsilon_{1N} \\ b^\epsilon_{21} & b^\epsilon_{22} & \cdots & b^\epsilon_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ b^\epsilon_{N1} & b^\epsilon_{N2} & \cdots & b^\epsilon_{NN} \end{pmatrix}}_{\equiv B^\epsilon} \begin{pmatrix} \Delta \epsilon_1 \\ \Delta \epsilon_2 \\ \vdots \\ \Delta \epsilon_N \end{pmatrix} + \underbrace{\begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_N \end{pmatrix}}_{\text{HO terms}}$$

with $b^z_{ij} = \frac{\partial f_i(z_0,\epsilon_0)}{\partial z_{0j}}$, $b^\epsilon_{ij} = \frac{\partial f_i(z_0,\epsilon_0)}{\partial \epsilon_{0j}}$

Reduced-Form Estimator 1: TWFE

$$\Delta \ln y_i = \alpha^{FE} + \beta^{FE} \Delta z_i + \Delta \xi_i,$$

$$\begin{pmatrix} \Delta \ln y_1 \\ \Delta \ln y_2 \\ \vdots \\ \Delta \ln y_N \end{pmatrix} = \underbrace{\begin{pmatrix} \beta^{FE} & 0 & \cdots & 0 \\ 0 & \beta^{FE} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \beta^{FE} \end{pmatrix}}_{\equiv B^z} \begin{pmatrix} \Delta z_1 \\ \Delta z_2 \\ \vdots \\ \Delta z_N \end{pmatrix} + \underbrace{\begin{pmatrix} b^{\epsilon} & 0 & \cdots & 0 \\ 0 & b^{\epsilon} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & b^{\epsilon} \end{pmatrix}}_{\equiv B^{\epsilon}} \begin{pmatrix} \Delta \epsilon_1 \\ \Delta \epsilon_2 \\ \vdots \\ \Delta \epsilon_N \end{pmatrix} + \underbrace{\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}}_{\text{HO terms}}$$

$$\Delta \ln y_i^{\dagger} \left(\boldsymbol{z_1}, \boldsymbol{z_0}; \boldsymbol{\epsilon_1} \right) \quad = \quad \beta^{FE} \times \Delta z_i = E\left[\check{\beta}^{FE} \right] \times \Delta z_i$$

Reduced-Form Estimator 2: Heterogeneous-Robust Estimator

$$\check{\beta}^{HR} = \frac{1}{N}\sum_i \frac{sign(\Delta z_i) \times \left(\Delta \ln y_i - \check{E}[f(z_0, \epsilon_1) - f(z_0, \epsilon_0)|z_0]\right)}{|\Delta z_i|}. \quad (1)$$

$$\begin{pmatrix} \Delta \ln y_1 \\ \Delta \ln y_2 \\ \vdots \\ \Delta \ln y_N \end{pmatrix} = \underbrace{\begin{pmatrix} b_1^{HR} & 0 & \cdots & 0 \\ 0 & b_2^{HR} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & b_N^{HR} \end{pmatrix}}_{\equiv B^z} \begin{pmatrix} \Delta z_1 \\ \Delta z_2 \\ \vdots \\ \Delta z_N \end{pmatrix} + \underbrace{\begin{pmatrix} b^{\epsilon} & 0 & \cdots & 0 \\ 0 & b^{\epsilon} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & b^{\epsilon} \end{pmatrix}}_{\equiv B^{\epsilon}} \begin{pmatrix} \Delta \epsilon_1 \\ \Delta \epsilon_2 \\ \vdots \\ \Delta \epsilon_N \end{pmatrix} + \underbrace{\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}}_{\text{HO terms}}$$

$$\Delta \ln y_i^{\dagger}(\boldsymbol{z_1}, \boldsymbol{z_0}; \boldsymbol{\epsilon_1}) \quad = \quad b_i^{HR} \Delta z_i$$

Reduced-Form Estimator 3: Upstream and Downstream Spillovers

$$\Delta \ln y_i = \beta^{Own} \Delta z_i + \beta^{Upstream} \sum_{j \neq i} \pi_{ij,0} \Delta z_j + \beta^{Downstream} \sum_{k \neq i} \gamma_{ki,0} \Delta z_k + \alpha^{UD} + \xi_i,$$

$$\begin{pmatrix} \Delta \ln y_1 \\ \Delta \ln y_2 \\ \vdots \\ \Delta \ln y_N \end{pmatrix} = \underbrace{\begin{pmatrix} \beta^{Own} & \beta^{Up}\pi_{12,0} + \beta^{Down}\gamma_{21,0} & \cdots & \beta^{Up}\pi_{1N,0} + \beta^{Down}\gamma_{N1,0} \\ \beta^{Up}\pi_{21,0} + \beta^{Down}\gamma_{12,0} & \beta^{Own} & \cdots & \beta^{Up}\pi_{2N,0} + \beta^{Down}\gamma_{N2,0} \\ \vdots & \vdots & \ddots & \vdots \\ \beta^{Up}\pi_{N1,0} + \beta^{Down}\gamma_{1N,0} & \beta^{Up}\pi_{N2,0} + \beta^{Down}\gamma_{2N,0} & \cdots & \beta^{Own} \end{pmatrix}}_{\equiv B^z} \begin{pmatrix} \Delta z_1 \\ \Delta z_2 \\ \vdots \\ \Delta z_N \end{pmatrix} + \underbrace{\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}}_{\text{HO terms}}$$

Reduced-Form Estimator 4: Global spillovers

$$y_{t+h} - y_t = \alpha_h + \beta_h z_t^{shock} + \sum_{l=1}^{L} \gamma_{h,l} X_{t-l} + \xi_{t+h}$$

Valid if all columns of B^z sum to β_h / N

$$\begin{pmatrix} \Delta \ln y_1 \\ \Delta \ln y_2 \\ \vdots \\ \Delta \ln y_N \end{pmatrix} = \underbrace{\begin{pmatrix} \beta^h/N - (N-1)a_1 & a_2 & \cdots & a_N \\ a_1 & \beta^h/N - (N-1)a_2 & \cdots & a_N \\ \vdots & \vdots & \ddots & \vdots \\ a_1 & a_2 & \cdots & \beta^h/N - (N-1)a_N \end{pmatrix}}_{\equiv B^z} \begin{pmatrix} \Delta z_1 \\ \Delta z_2 \\ \vdots \\ \Delta z_N \end{pmatrix} + \underbrace{\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}}_{\text{HO terms}}$$

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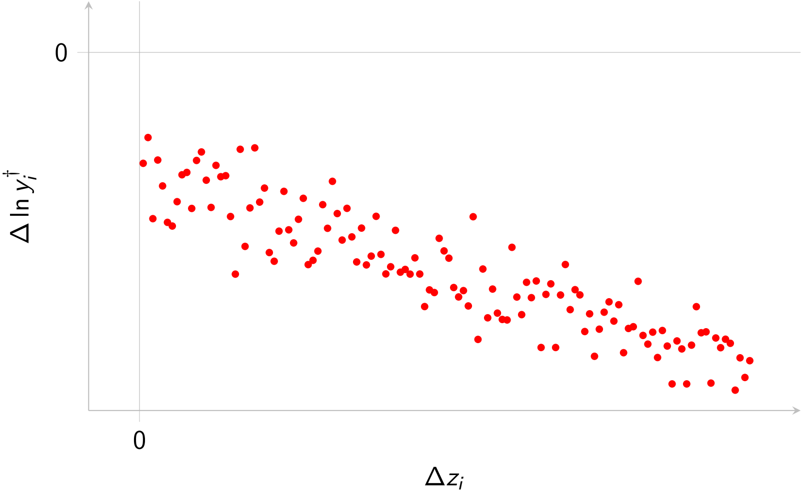

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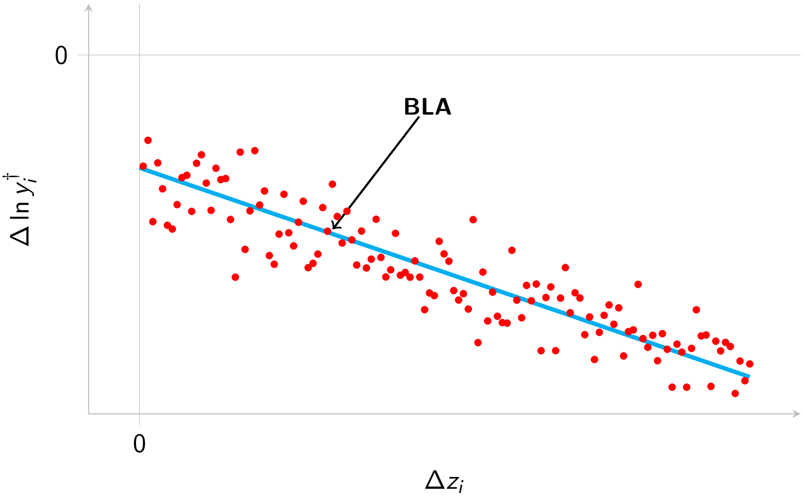

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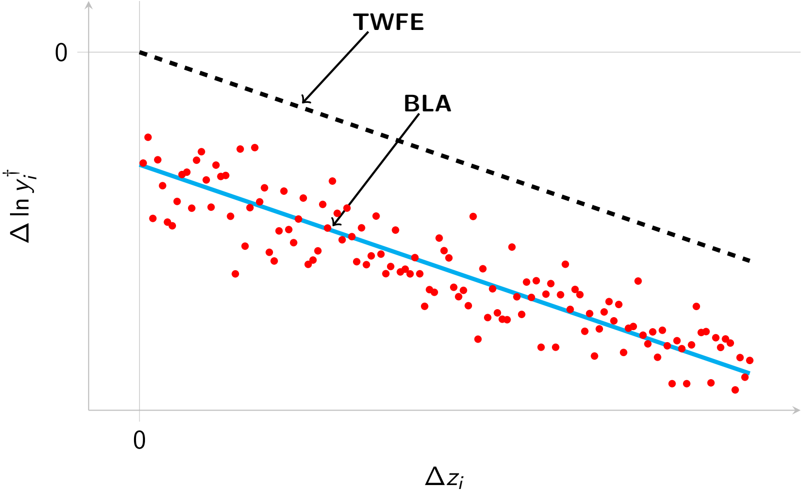
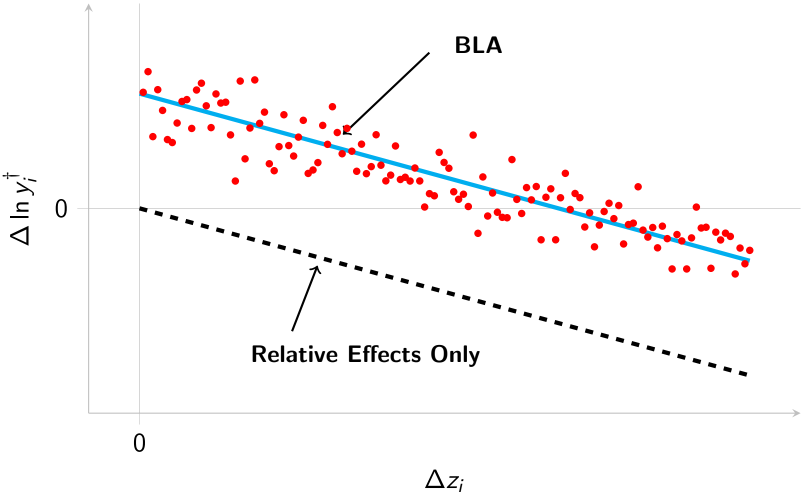


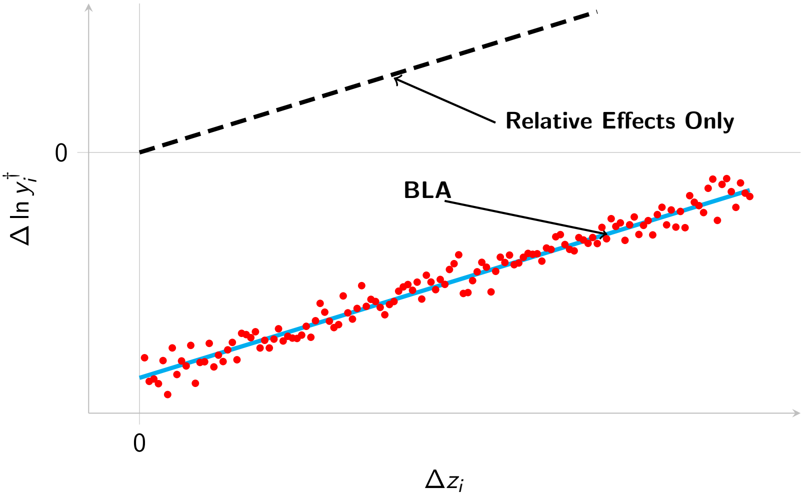
Is It That Bad to Miss the Intercept?

There could be sign reversals. Either Partially



Is It That Bad to Miss the Intercept?

There could be sign reversals. ... Or Fully



Quantitative Trade Model Set Up

- N countries endowed with L_{it} worker-consumers, mobile across S sectors
- Nested preferences: Cobb-Douglas over S sectors (α^C_{ns}), and CES over a continuum of varieties $j \in \Lambda_{nst}$ within s ($\sigma_s > 0$)
- Output Q_{ist} obtained with C-D technology (CRS) with labor (η_{is}) and intermediate inputs ($1 - \eta_{is}$), where output from each sector is combined in C-D (α^M_{ish}, with $\sum_h \alpha^M_{ish} = 1$)
- Total expenditure on s in i, X_{ist}, is the sum of final expenditures, purchases from firms, recycled tariff revenue
- Country-sector-time-specific Productivity

$$A_{ist} = \exp\left(\sum_{v=1}^{\mathscr{V}} \mu^v_s z^v_{it}\right) \exp\left(\psi_{is} + \iota_{st} + \omega_{ist}\right)$$

Structural Gravity

- Trade Flows

$$X_{nist} = \frac{Y_{ist}}{\Omega_{ist}} \frac{X_{nst}}{\Phi_{nst}} \phi_{nist} \;\text{ with }\; \Phi_{nst} = \sum_k \frac{Y_{kst}}{\Omega_{kst}} \phi_{nkst}, \quad \Omega_{ist} = \sum_k \frac{X_{kst}}{\Phi_{kst}} \phi_{kist}$$

- Gross Output

$$Y_{ist} = \exp\left(\sum_{v=1}^{\mathcal{V}} \beta_{z,v}^{i,s} z_{it}^{v}\right) L_{ist}^{\beta_L^{i,s}} \Omega_{ist}^{\beta_\Omega^{i,s}} \left(\prod_{h=1}^{S} \Phi_{iht}^{\beta_{\Phi_h}^{i,s}}\right) \exp\left(\delta_{is} + \delta_{st} + \epsilon_{ist}\right)$$

- What we need to compute counterfactuals Details:
  - Trade frictions ϕ_{nist}
  - Multilateral Resistance Ω_{ist}, Φ_{ist}
  - Structural parameters
    - trade elasticity θ_s
    - elasticity of productivity to climate μ_s

Gravity

- Calibrated approach (Similar to Egger & Nigai 2015)
  - Residualize trade flows

$$\ln X_{nist} = \delta_{ist} + \delta_{nst} + \varrho_{nist} \quad , \quad \check{\phi}_{nist} \equiv \frac{\exp(\varrho_{nist})}{\exp(\varrho_{nnst})} = \frac{\phi_{nist}}{\phi_{nnst}} \times \frac{\exp(\overline{\ln \phi^e_{nst}})}{\exp(\overline{\ln \phi^e_{ist}})} \equiv \frac{\phi_{nist}}{\phi_{nnst}} \times \frac{\phi^e_{nst}}{\phi^e_{ist}}$$

  - Solve MR system using $\check{\phi}_{nist}$ and normalize by m_{1st}

$$m_{nst} = \sum_k \frac{Y_{kst}}{e_{kst}} \check{\phi}_{nkst} \quad , \quad e_{ist} = \sum_k \frac{X_{kst}}{m_{kst}} \check{\phi}_{kist}$$

  - Solution implies:

$$\check{\Phi}_{nst} = \frac{\Phi_{nst}}{\Phi_{1st}} \frac{\phi^e_{nst}}{\phi^e_{1st}} \frac{\phi_{11st}}{\phi_{nnst}} \quad , \quad \check{\Omega}_{ist} = \frac{\Omega_{ist}}{\phi^e_{ist} \phi_{11st}} \Phi_{1st} \phi^e_{1st}$$

- Parametric Gravity Details

$$\check{\phi}_{nist} = \delta_{ist} \times \delta_{nst} \times \underbrace{\exp\left(-\theta_s \nu_1 DIST_{ni} - \theta_s \nu_2 COMLANG_{ni} - \ldots - \theta_s \ln\left(1 + tariff_{nist}\right) + u_{nist}\right)}_{=\phi_{nist}}$$

Estimating μ

- Residualize output

$$\underbrace{\left(1+\theta_s\eta_{i,s}\right)\ln Y_{ist}-\theta_s\eta_{i,s}\ln L_{ist}-\theta_s\left(1-\eta_{i,s}\right)\sum_{h=1}^{S}\frac{\alpha^M_{i,s,h}}{\theta_h}\ln\check{\Phi}_{iht}-\ln\check{\Omega}_{ist}}_{observed}$$

$$=\underbrace{\sum_{v=1}^{\mathscr{V}}\mu^v_s z^v_{it}+\psi_{is}+\iota_{st}+\omega_{ist}+\Big(\ln\left(\Phi_{1st}\phi^e_{1st}/\phi_{11st}\right)-\ln\phi^e_{ist}\Big)+\theta_s(1-\eta_{i,s})\sum_h\frac{\alpha^M_{i,s,h}}{\theta_h}\left(\ln\frac{\phi^e_{iht}}{\phi_{iist}}-\ln\left(\frac{\Phi_{1ht}\phi^e_{1ht}}{\phi_{11st}}\right)\right.}_{=\ln\check{A}_{ist}}$$

- Estimate structural damage function:

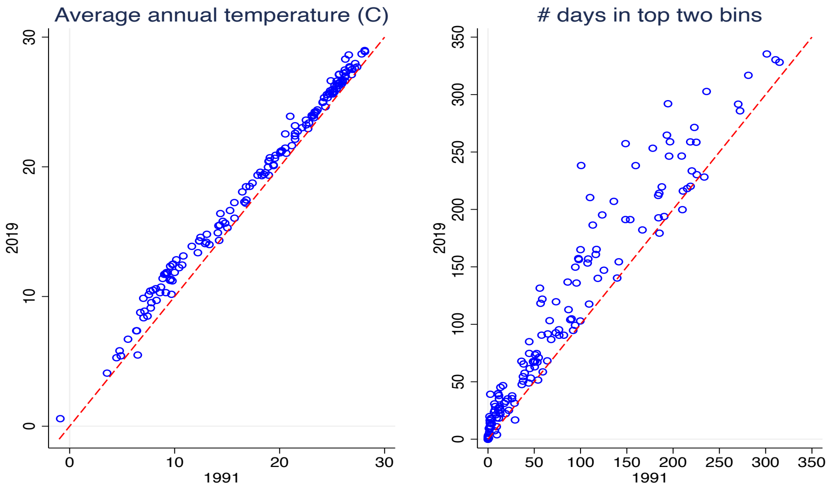
$$\Delta\ln\check{A}_{ist} = \delta_i+\delta_{st}+\sum_{v=1}^{\mathscr{V}}\delta^v_s\Delta z^v_{it}$$

$$+\underbrace{\Delta\omega_{ist}-\Delta\ln\phi^e_{ist}+\sum_h\theta_s(1-\eta_{i,s})\alpha^M_{i,s,h}\left(\Delta\ln\left(\frac{\phi^e_{iht}}{\phi_{iist}}\right)\right)-\sum_h\theta_s(1-\eta_{i,s})\alpha^M_{i,s,h}\left(\Delta\ln\left(\frac{\Phi_{1ht}\phi^e_{1ht}}{\phi_{11ht}}\right)\right)}_{=\text{OLS residual}}$$

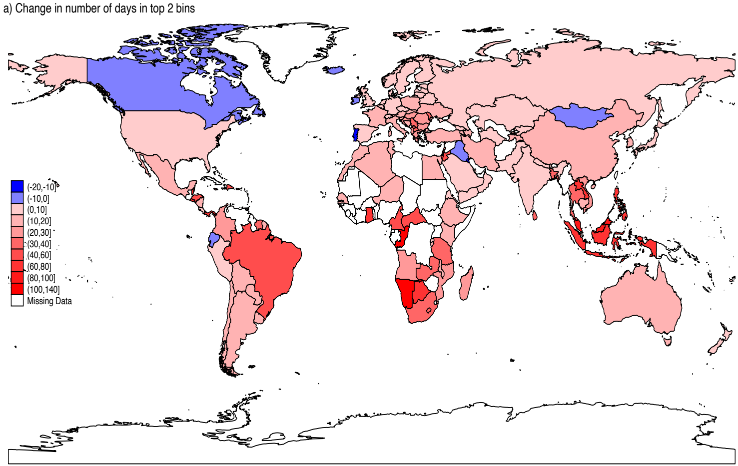
Data

- Sources
  - Trade and Production Datasets:
    - UNIDO INDSTAT2 + UN ComTrade + FAOSTAT for trade flows (incl. self-trade) for agriculture and manufacturing for 162 countries over 1966-2019 (manuf) or 1991-2019 (ag)
    - CEPII gravity dataset for other gravity variables
  - ERA-5 weather data (temperature and precipitation bins)
  - GTAP input-output tables
  - Country-sector-year labor data (ILO)
- After merging, 132 countries from 1991 to 2019, with Ag and Manuf

Warming Experienced between 1991 and 2019



Changes in Weather between 1991 and 2019



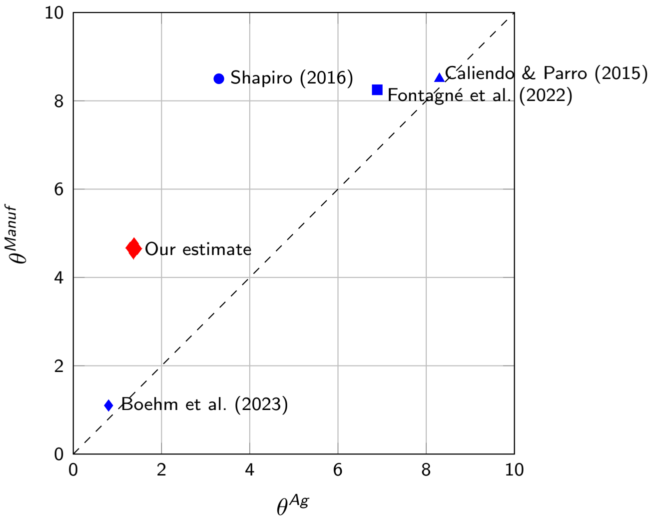
Monte Carlo Simulations

- Data Generating Process
  - 132 countries with their observed characteristics
  - Single treatment variable: number of days in the top two bins (> 30℃)
  - Draw random trade cost term, build trade costs
  - Draw random productivity term, compute exogenous component of A_{ist} based on baseline temperature and random walk process
  - Solve the system of equations year by year from 1991 to 2019
  - Counterfactual imposes treatment from first period: $z'_{i,2019} = z_{i,1991}$
- Estimators
  - TWFE
  - Heterogeneous-Robust
  - Upstream-Downstream
  - Global Aggregate
  - Structural Approach

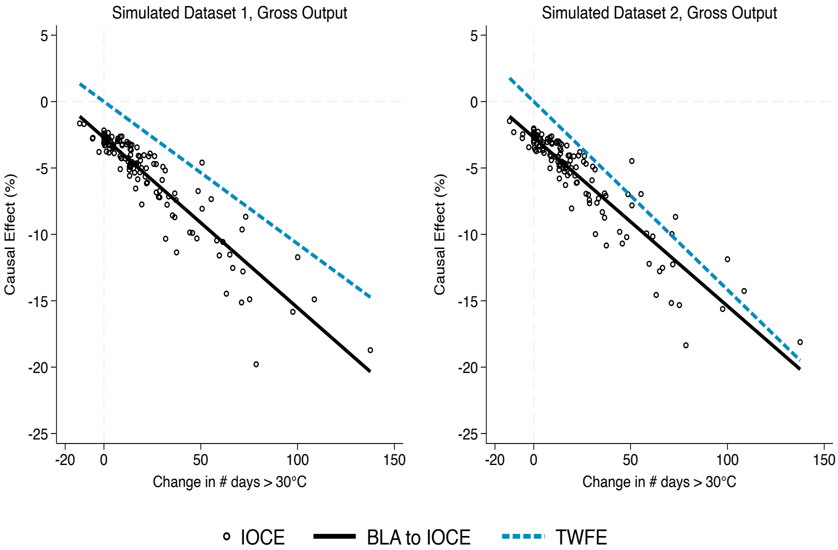
Gravity Regressions

	Agriculture		Manufacturing	
	OLS	IV	OLS	IV
$\ln(1 + \text{tariff}_{nist})$	-1.004	-1.473	-2.358	-4.591
	(0.590)	(0.778)	(0.452)	(0.955)
$\ln(distance_{ni})$	-1.448	-1.501	-1.353	-1.331
	(0.104)	(0.106)	(0.070)	(0.072)
$Border_{ni}$	-3.742	-3.635	-1.233	-1.104
	(0.397)	(0.411)	(0.241)	(0.240)
$Contiguous_{ni}$	0.880	0.795	0.698	0.680
	(0.162)	(0.167)	(0.173)	(0.170)
$CommonLanguage_{ni}$	0.514	0.564	0.776	0.758
	(0.145)	(0.148)	(0.104)	(0.103)
$ColonialLink_{ni}$	0.259	0.204	0.845	0.849
	(0.198)	(0.201)	(0.201)	(0.202)
# Obs	39,843	27,447	88,098	59,967
# Importers	122	122	122	122
# Exporters	130	129	130	130
# Importers × Exporters	8,682	7,623	14,373	13,399

Trade Elasticities

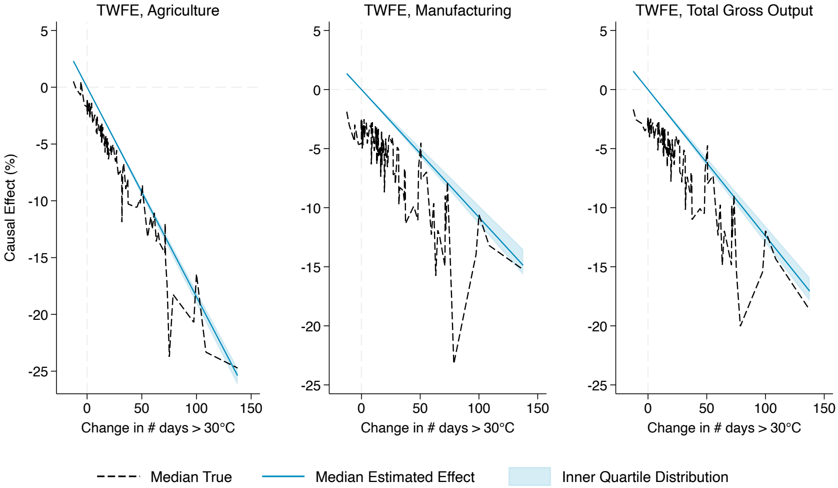


Simulation Results, Two Replications



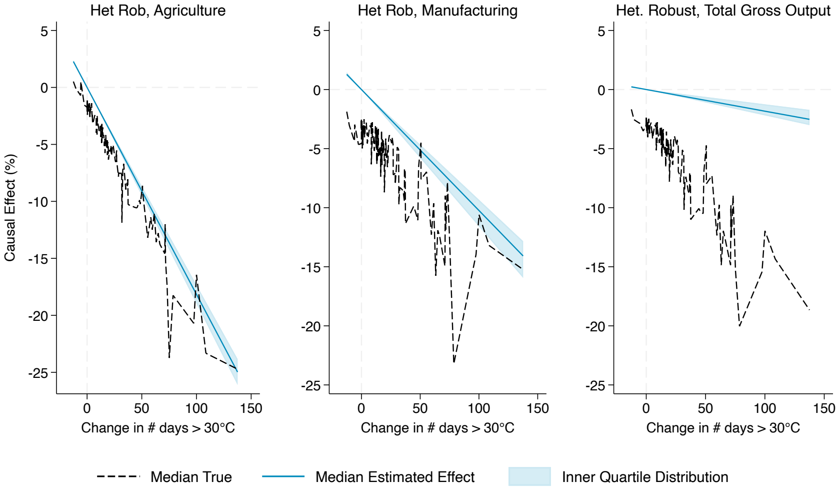
Simulations, TWFE

errors



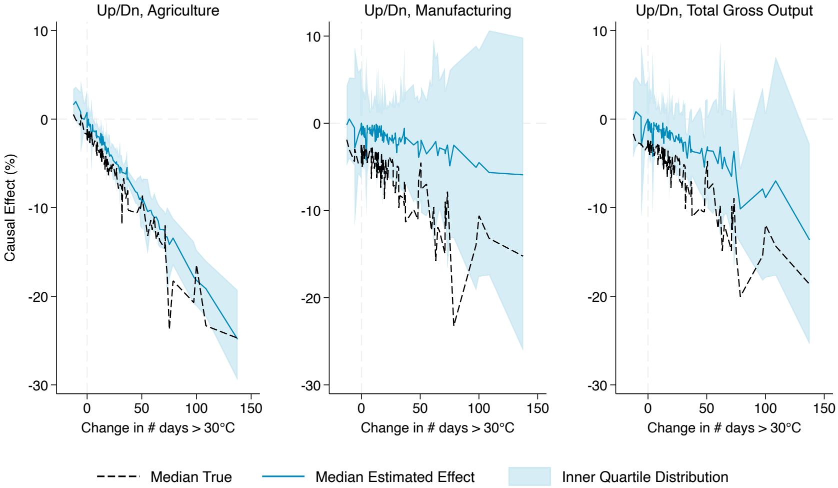
Simulations, Heterogeneous-Robust Estimator

errors

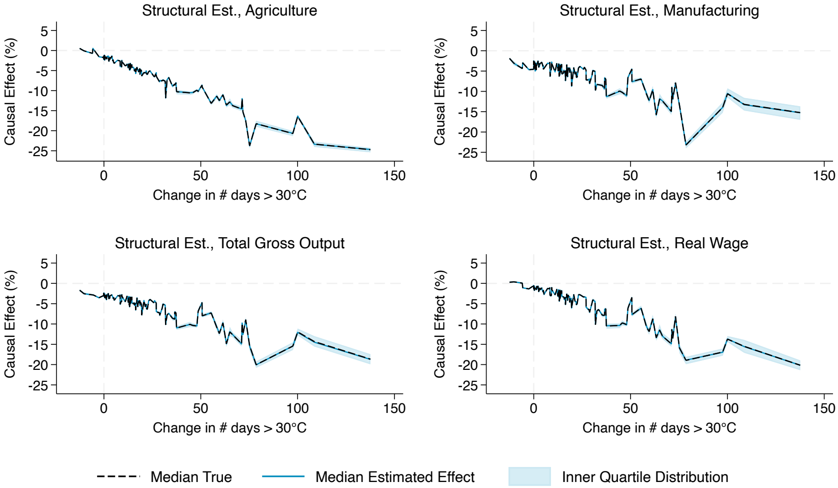


Simulations, Upstream-Downstream Estimator

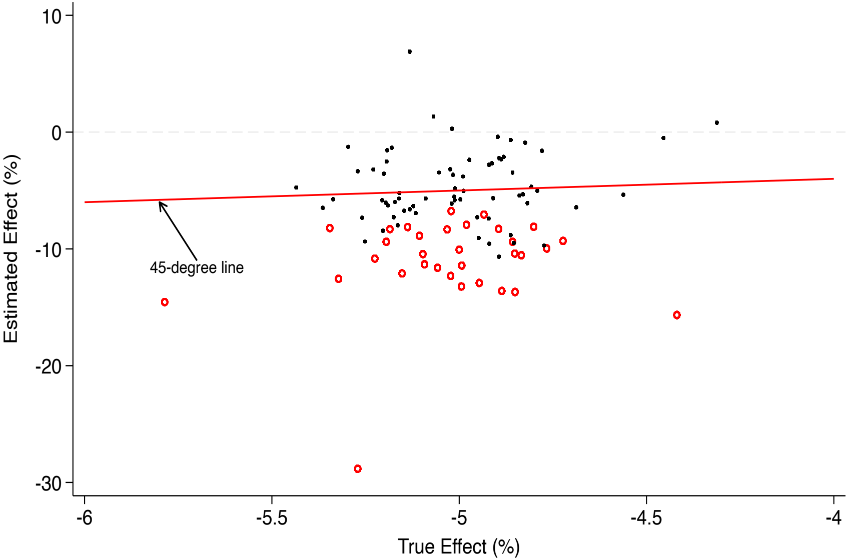
errors



Simulations, Structural Estimator, θ from Gravity errors



Simulations, Global Output



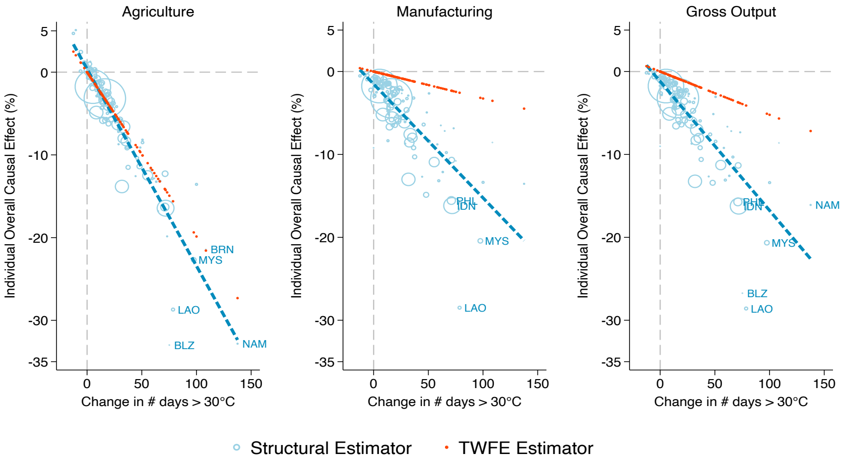
Specifications

- Environmental variables
  - # days over 30 °C
  - annual average °C
  - # days over 30 °C and # days under 0 °C
- Interaction - yes or no
- Include Manufacturing productivity effects - yes or no
- Trade elasticity
  - Preferred Specification ($\theta^{AG} = 1.4$, $\theta^{Manuf} = 4.6$)
  - Shapiro (2016) ($\theta^{AG} = 3.3$, $\theta^{Manuf} = 8.5$)
  - Boehm et al. (2023) ($\theta^{AG} = 0.8$, $\theta^{Manuf} = 1.1$)
  - Fontagné et al. (2022): ($\theta^{AG} = 6.9$,$\theta^{Manuf} = 8.3$)

Point Estimates, # days over 30°C

	Agriculture (1)	Manufacturing (2)	Gross Output (3)
Reduced-Form Models			
TWFE	-0.00198	-0.00033	-0.00052
	(0.00045)	(0.00041)	(0.00047)
Heterogeneous-Robust	-0.00099	-0.00042	-0.00012
	(0.00048)	(0.00049)	(0.00024)
Upstream/Downstream	-0.00633	0.00133	
	(0.00226)	(0.00077)	
Structural Model			
Preferred Specification ($\theta^{ag} = 1.5$, $\theta^{manuf} = 4.6$)	-0.00273	-0.00044	
	(0.00052)	(0.00065)	
Boehm et al (2023) ($\theta^{ag} = 0.8$, $\theta^{manuf} = 1.1$)	-0.00306	-0.00065	
	(0.00059)	(0.00057)	
Shapiro (2016) ($\theta^{ag} = 3.3$, $\theta^{manuf} = 8.5$)	-0.00335	-0.00095	
	(0.00070)	(0.00075)	
Fontagné (2022) ($\theta^{ag} = 6.9$, $\theta^{manuf} = 8.3$)	-0.00485	-0.00129	
	(0.00117)	(0.00076)	

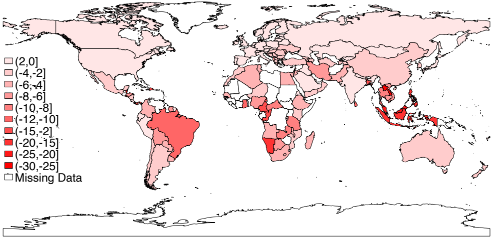
Comparing Structural vs TWFE Estimates



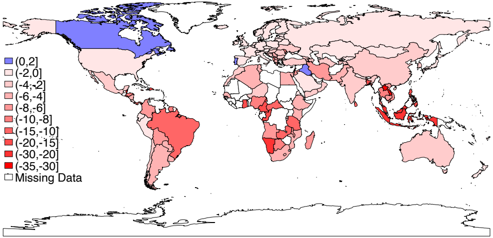
Other estimators

Structural Estimates of Effects by Sector and in Aggregate

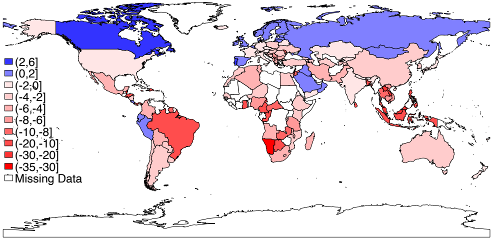
weather shocks



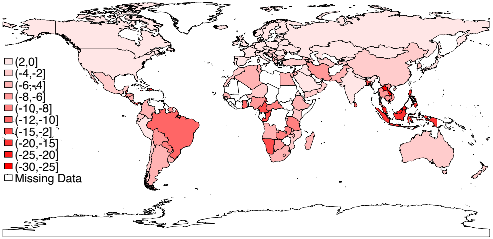
(a) Gross Output



(b) Real Wage

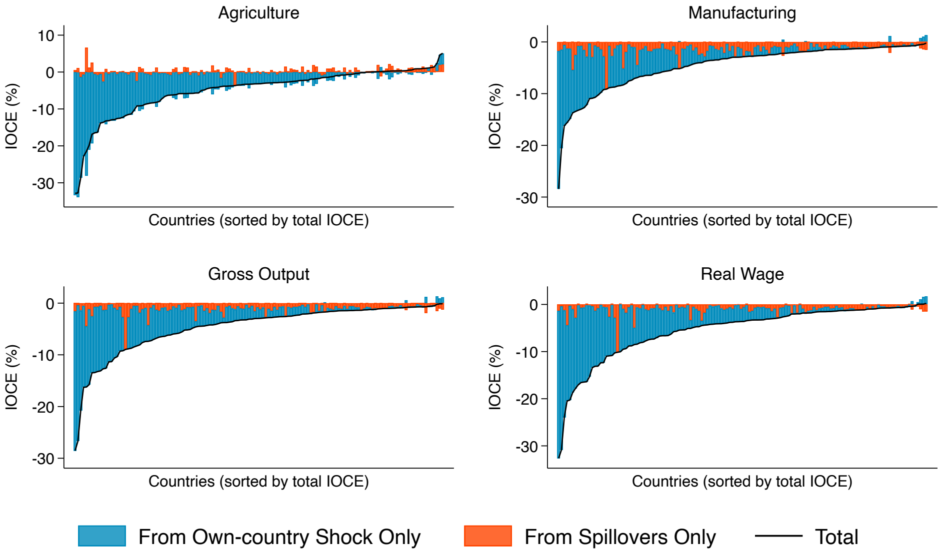


(c) Agriculture

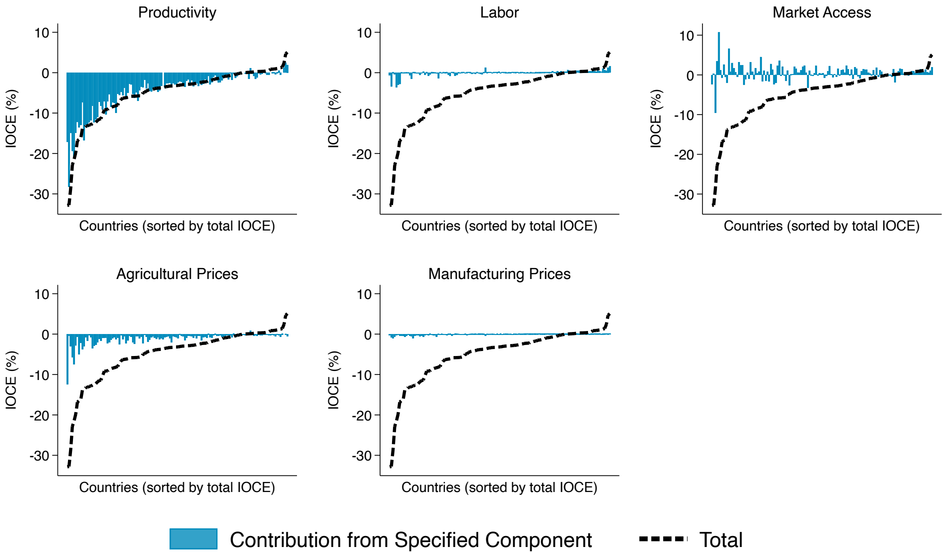


(d) Manufacturing

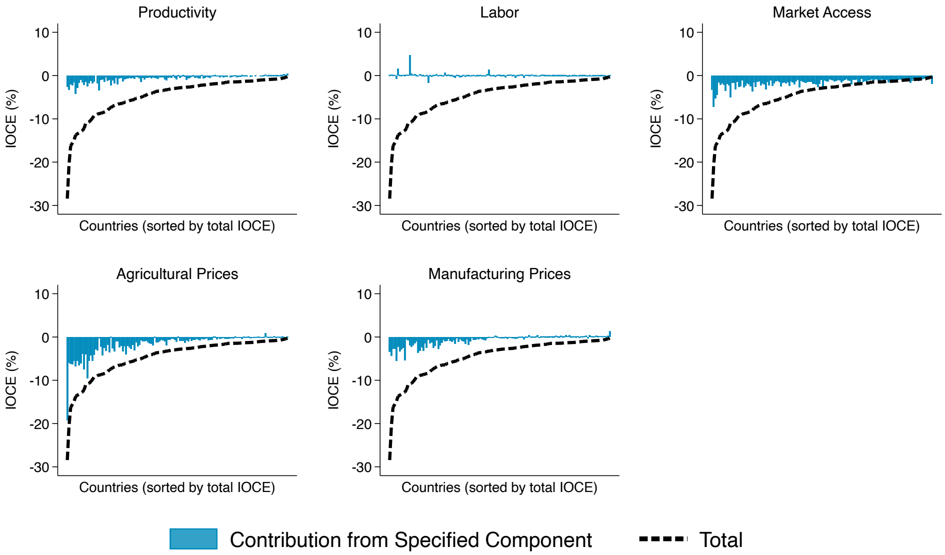
Own-country Shock vs Other-Country Shocks



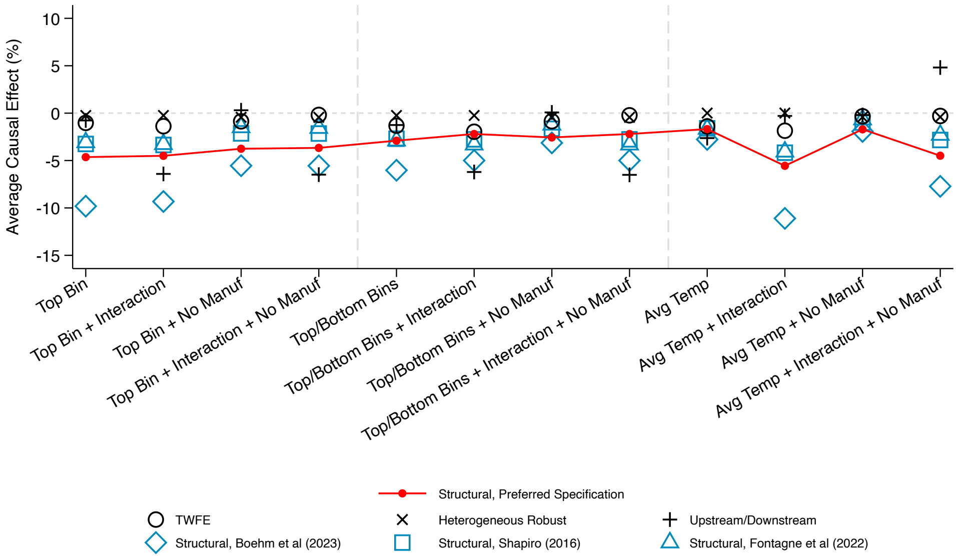
Decomposition, Agriculture



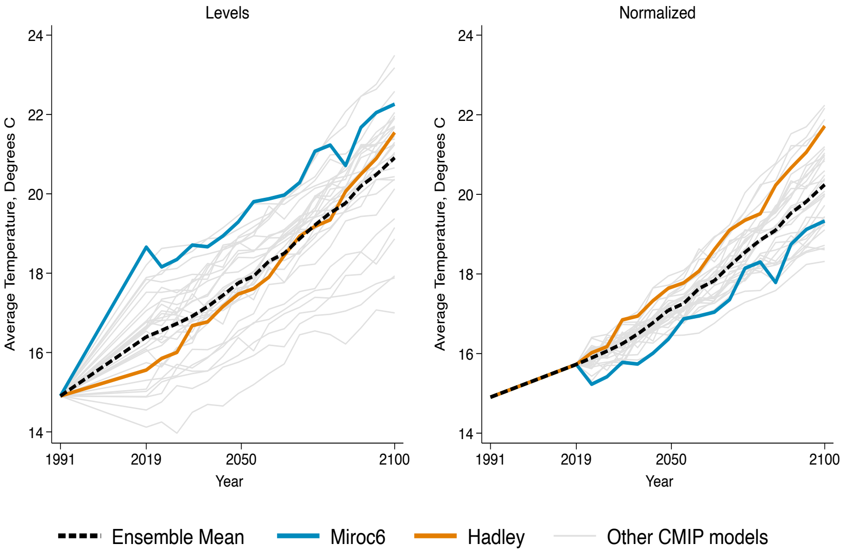
Decomposition, Manufacturing



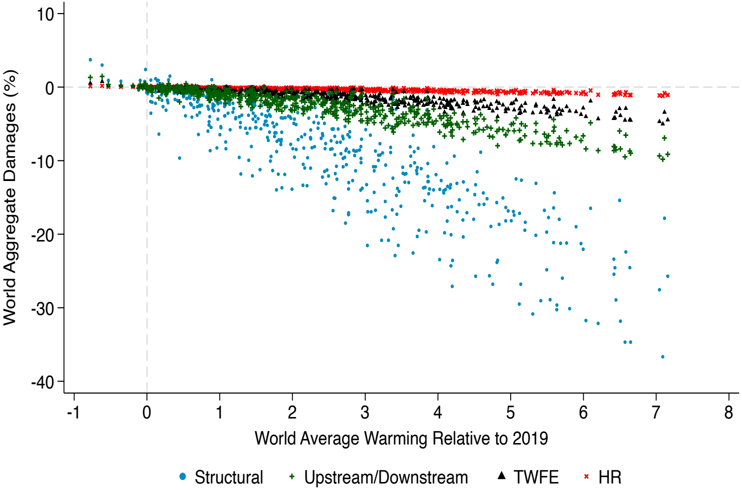
Average Climate Effects (Gross Output) from Warming 1991-2019



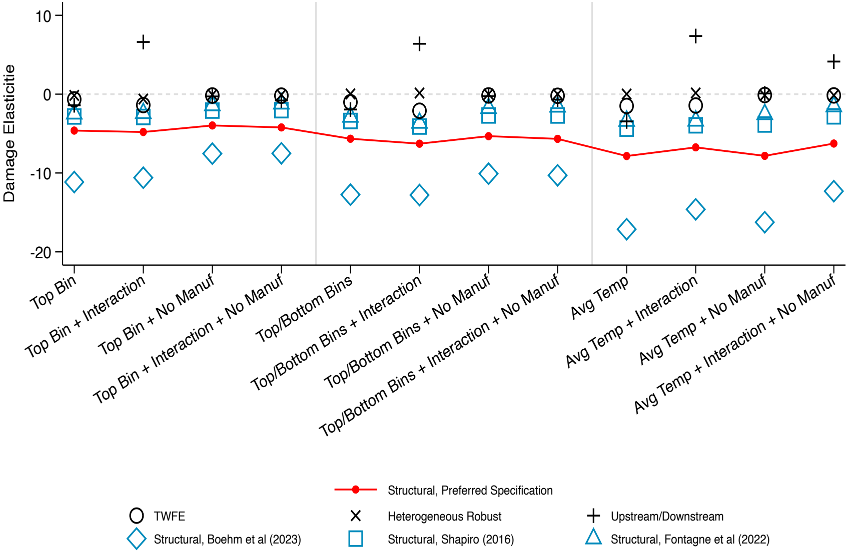
Variation from Climate Models



World Aggregate Damages For Different Counterfactuals



Elasticities of Global Damage to Global Average Temperature °C



Conclusion

- In General
  - When regions trade with each other, the SUTVA likely fails
  - We propose a quantitative trade approach to solving the identification problem
  - TWFE recovers relative effects under some conditions
- In the application
  - Aggregate gross output fell in all countries as a result of climate change between 1991 - 2019: mean loss was 4.5%, with the largest losses up to 30%.
  - World Aggregate Damage Function Elasticities wrt $^{\circ}C$ warming:
    - Structural: 2 - 12 %
    - Reduced Form: 0 - 1 %

Counterfactuals, $\widehat{v} = \frac{v'}{v}$, using exact hat algebra

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- Multilateral Resistance Terms

$$\widehat{\Phi}_{nst} = \frac{\sum_k \frac{\widehat{Y}_{kst} Y_{kst}}{\widehat{\Omega}_{kst} \check{\Omega}_{kst}} \check{\phi}_{knst}}{\sum_k \frac{Y_{kst}}{\check{\Omega}_{kst}} \check{\phi}_{nkst}} \quad , \quad \widehat{\Omega}_{nst} = \frac{\sum_k \frac{\widehat{X}_{kst} X_{kst}}{\widehat{\Phi}_{kst} \check{\Phi}_{kst}} \check{\phi}_{knst}}{\sum_k \frac{X_{kst}}{\check{\Phi}_{kst}} \check{\phi}_{knst}}$$

- Income, Expenditures, and Labor

$$\widehat{Y}_{ist} \quad = \quad \exp\left(\sum_{v=1}^{\mathscr{V}} \frac{\mu_{is}^{v}}{1 + \theta_s \eta_{is}} \left((z_{it}^{v})' - z_{it}^{v} \right) \right) \widehat{L}_{ist}^{\frac{\theta_s \eta_{is}}{1+\theta_s \eta_{is}}} \widehat{\Omega}_{ist}^{\frac{1}{1+\theta_s \eta_{is}}} \left(\prod_{h=1}^{S} \widehat{\Phi}_{iht}^{\alpha_{ish}^{M} \frac{\theta_s}{\theta_h} \frac{(1-\eta_{is})}{1+\theta_s \eta_{is}}} \right)$$

$$\widehat{X}_{ist} X_{ist} \quad = \quad \sum_{h} (\alpha_{is}^{C} \eta_{ih} + (1 - \eta_{ih})\, \alpha_{ihs}^{M}) \widehat{Y}_{iht} Y_{iht} + \alpha_{is}^{C} \sum_{h=1}^{S} \sum_{k=1}^{N} \text{tariff}_{nkht} \widehat{X}_{nkht} X_{nkht}$$

$$\widehat{L}_{ist} = \widehat{Y}_{ist} \frac{\sum_h \eta_{i,h} Y_{iht}}{\sum_h \eta_{i,h} \widehat{Y}_{iht} Y_{iht}}$$

Rudik et al (2022)

- Divide bilateral trade flows by self-trade flows:

$$\ln\left(\frac{X_{nist}}{X_{nnst}}\right) = \sum_{v=1}^{\mathscr{V}} \mu_s^v \left(z_{it}^v - z_{nt}^v\right) + \left(\psi_{is} - \psi_{ns}\right) + \left(\omega_{ist} - \omega_{nst}\right) - \theta_s \ln\left(\frac{w_{it}^{\eta_{is}}}{w_{nt}^{\eta_{ns}}}\right) - \theta_s \ln\left(\frac{\sum_{h=1}^{S} p_{iht}^{\alpha_{ish}^M(1-\eta_{is})}}{\sum_{h=1}^{S} p_{nht}^{\alpha_{nsh}^M(1-\eta_{ns})}}\right) + \phi_{nist}.$$

- parameterize ϕ_{nist} in the usual way and then estimate μ_s^vs directly from the equation above via PPML

- Lacking data on material input prices, these variables are included in the error term.

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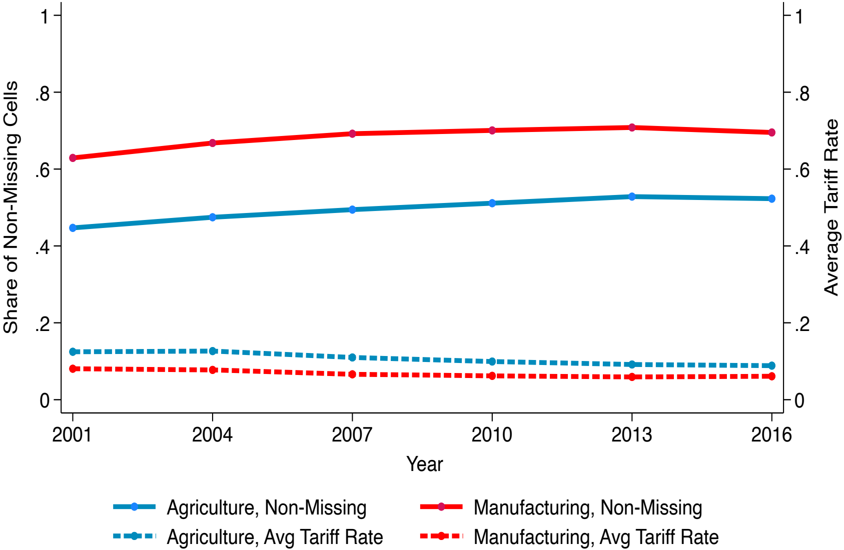
Missing Tariff Data



Weather Variables

Table 1: Observed variation in annual temperature and precipitation measured with daily bins (1991-2019)

	Proportion of country-year observations with number of days in each weather bin [...]% above/below country mean				
	1%	10%	25%	50%	75%
Temperature bins					
$-\infty$-0°C	0.98	0.89	0.76	0.66	0.61
0-20°C	0.93	9.49	0.31	0.22	0.18
20-25°C	0.94	0.49	0.19	0.08	0.05
25-30°C	0.91	0.41	0.13	0.04	0.03
30-35°C	0.95	0.57	0.31	0.18	0.12
¿ 35°C	0.98	0.80	0.63	0.46	0.35
Precipitation bins					
0-1 mm	0.84	0.14	0.02	0.00	0.00
1-10 mm	0.90	0.28	0.04	0.01	0.00
10-20 mm	0.95	0.56	0.20	0.04	0.02
¿ 20 mm	0.97	0.71	0.39	0.15	0.07

Reading: for the (25℃, 30℃] variable, 91% of observations deviate more than 1% from the country mean while only 3% of observations deviate more than 75% from the country mean.

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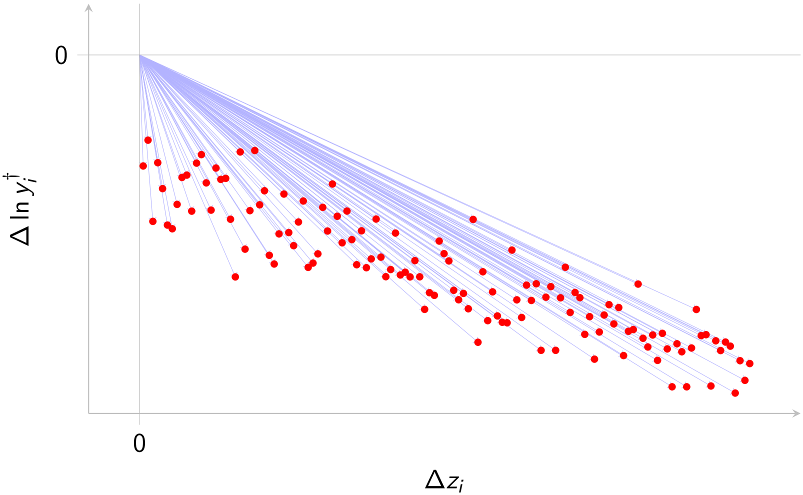
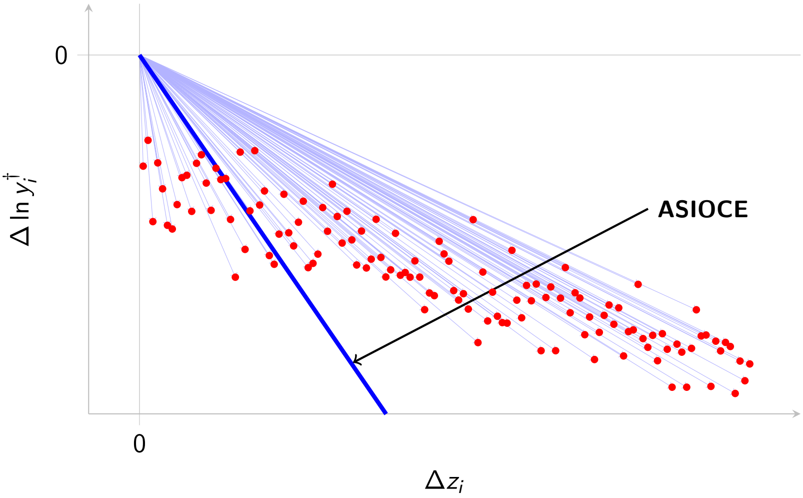
Best Linear Approximation vs ASIOCE

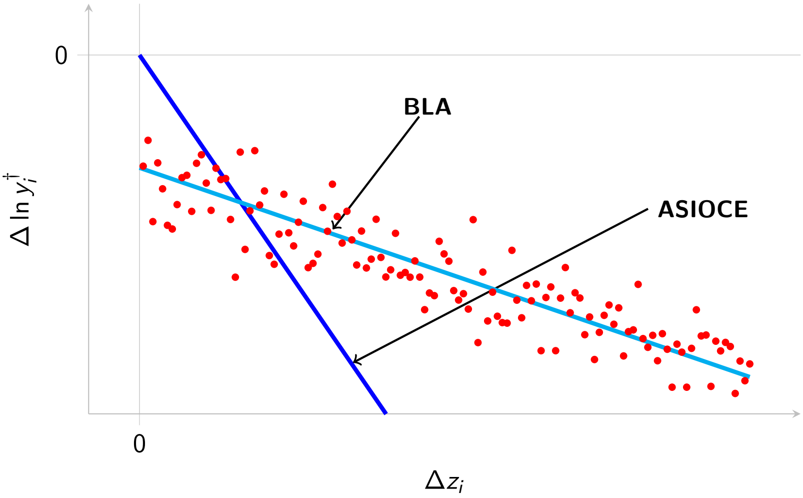
Best Linear Approximation vs ASIOCE



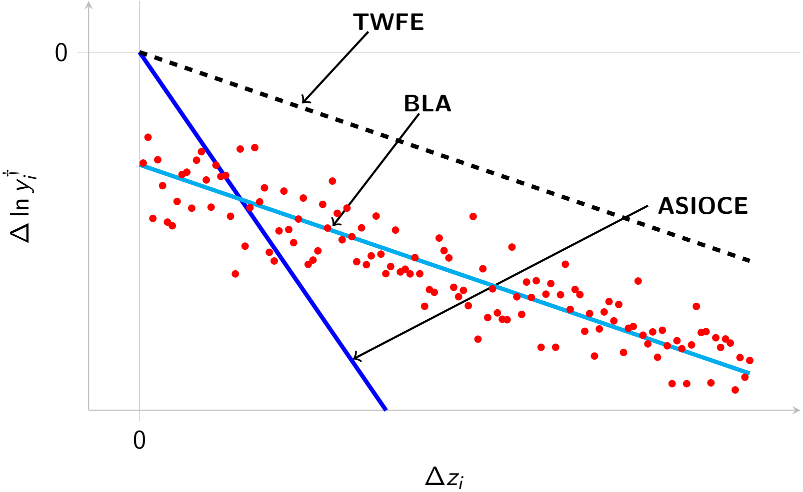
Best Linear Approximation vs ASIOCE



Best Linear Approximation vs ASIOCE



Best Linear Approximation vs ASIOCE



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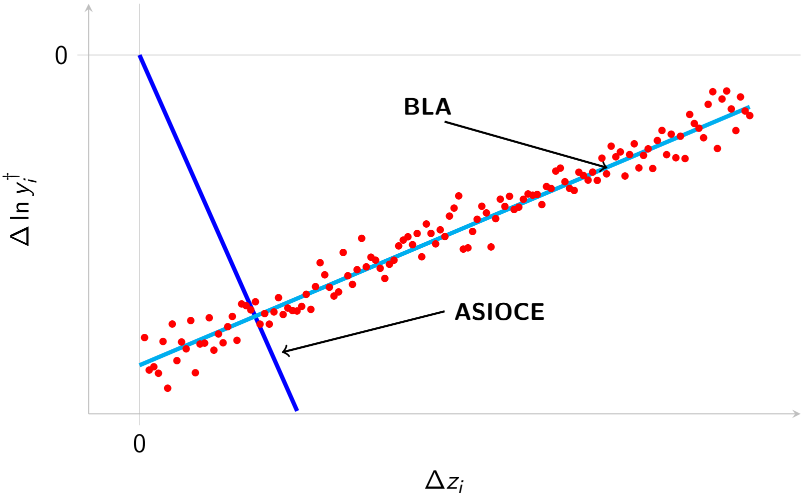
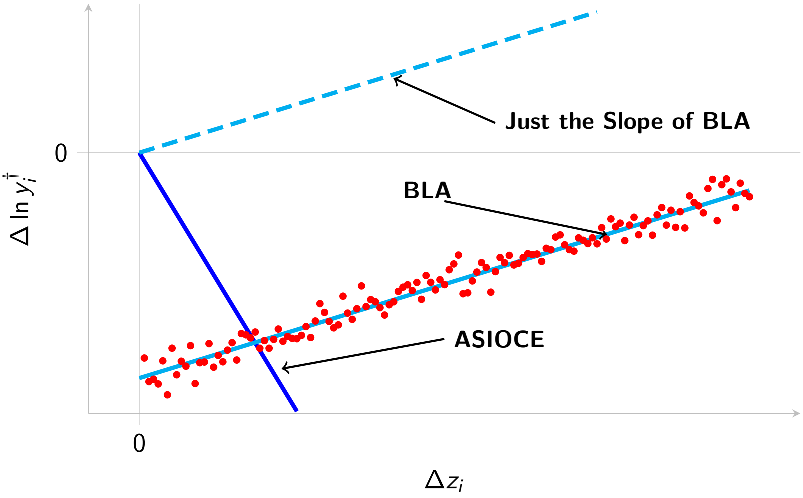
Best Linear Approximation vs ASIOCE with a Sign Reversal



Best Linear Approximation vs ASIOCE with a Sign Reversal



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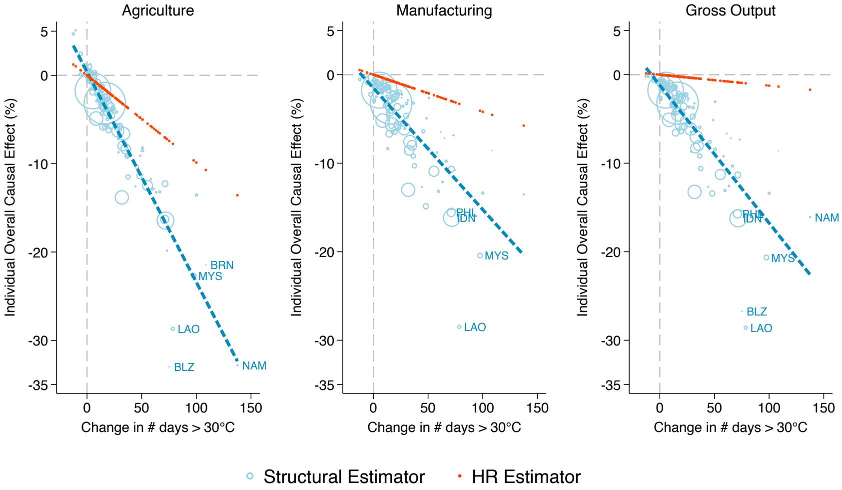
Evaluating the conditions for identification

- Take the single-sector, single shock, perfect competition version of the model and take a first order approximation of ΔlnY_{it}
- Individual elements of B matrix are

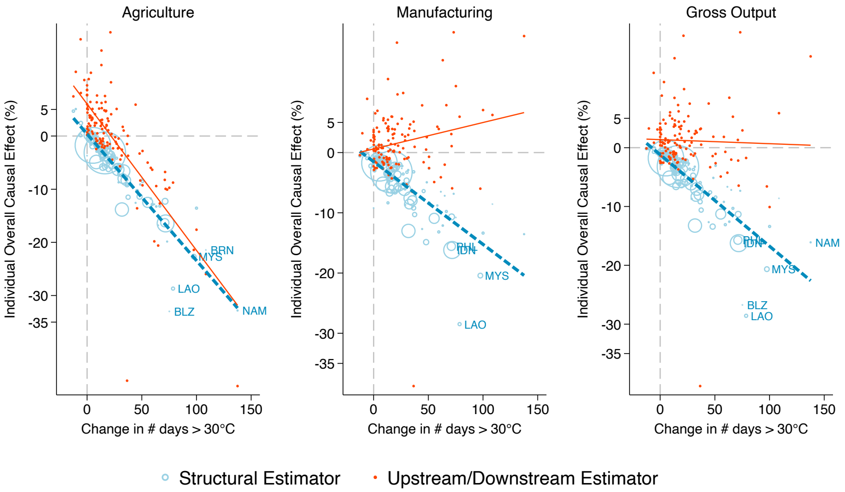
$$
\begin{aligned}
b_{ij} \quad = \quad & \sum_{K=0}^{\infty} \sum_{m_1,\ldots,m_K} \prod_{\ell=1}^{K} \Bigg(\beta_{\Phi}^{m_{\ell-1}} \pi_{m_{\ell-1},m_\ell} + (\beta_{\Omega}^{m_{\ell-1}} - 1)(\beta_{\Phi}^{m_{\ell-1}} - 1) \\
& \times \sum_r \pi_{m_{\ell-1},r} \sum_{d=0}^{\infty} \sum_{s_1,\ldots,s_d} (\beta_{\Omega}^{m_{\ell-1}})^d \gamma_{rs_1}\gamma_{s_1 s_2}\ldots\gamma_{s_d,m_\ell} \Bigg) \\
& \times \Bigg(\pi_{m_K,j} + (\beta_{\Omega}^{m_K} - 1) \sum_r \pi_{m_K,r} \sum_{d=0}^{\infty} \sum_{s_1,\ldots,s_d} (\beta_{\Omega}^{m_K})^d \gamma_{rs_1}\gamma_{s_1 s_2}\ldots\gamma_{s_d,j} \Bigg) .
\end{aligned}
$$

- If constant trade shares and labor shares across units, then
  - TWFE recovers best fit line
  - global time-series estimator correctly specified

Comparing Structural vs Heterogeneous-Robust Estimates



Comparing Structural vs Upstream/Downstream Estimates



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What do we learn from the TWFE?

- TWFE:

$$\Delta \ln y_i = \underbrace{\Delta \ln y_i^{\dagger}(\boldsymbol{z_1}, \boldsymbol{z_0}; \boldsymbol{\epsilon_1})}_{\text{individual overall causal effect}} + \underbrace{f_i(\boldsymbol{z_0}, \boldsymbol{\epsilon_1}) - f_i(\boldsymbol{z_0}, \boldsymbol{\epsilon_0})}_{\text{influence of unobserved shocks}}$$

$$\check{\beta}^{FE} = \sum_i \zeta_i \left[\frac{\Delta \ln y_i^{\dagger}}{\Delta z_i} + \frac{f_i(\boldsymbol{z_0}, \boldsymbol{\epsilon_1}) - f_i(\boldsymbol{z_0}, \boldsymbol{\epsilon_0})}{\Delta z_i} \right]$$

with $\zeta_i \equiv \frac{\Delta z_i (\Delta z_i - \overline{\Delta z})}{\sum_k \Delta z_k (\Delta z_k - \overline{\Delta z})}$

- Best Linear Approximation (BLA):

$$(\alpha^{BLA}, \beta^{BLA}) \equiv \arg\min_{a,b} \sum_{i=1}^{N} \left(\Delta \ln y_i^{\dagger} - a - b \Delta z_i \right)^2.$$

$$\beta^{BLA} = \sum_i \zeta_i \left[\frac{\Delta \ln y_i^{\dagger}}{\Delta z_i} \right], \quad \alpha^{BLA} = \overline{\Delta \ln y^{\dagger}} - \overline{\Delta z} \times \beta^{BLA}.$$

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Point Estimates, Baseline θs ($\theta^{ag} = 1.4$, $\theta^{manuf} = 4.6$)

	Agriculture				Manufacturing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta z_{it}^{>30}$	-0.00274	-0.00340	-0.00273	-0.00379	-0.00045	-0.00017	-0.00045	0.00006
	(0.00052)	(0.00309)	(0.00052)	(0.00323)	(0.00065)	(0.00185)	(0.00065)	(0.00181)
$\Delta z_{it}^{>30} \times \overline{z_i}$		0.00003		0.00005		-0.00001		-0.00002
		(0.00013)		(0.00014)		(0.00010)		(0.00010)
$\Delta z_{it}^{<0}$			0.00299	0.00706			-0.00118	-0.00407
			(0.00124)	(0.00238)			(0.00104)	(0.00177)
$\Delta z_{it}^{<0} \times \overline{z_i}$				-0.00050				0.00035
				(0.00031)				(0.00019)

Point Estimates, Preferred Spec ($\theta^{ag} = 1.4$, $\theta^{manuf} = 4.6$)

	Agriculture				Manufacturing				Gross Output			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TWFE												
$\Delta z_{it}^{>30}$	-0.0020	-0.0037	-0.0020	-0.0037	-0.0003	-0.0031	-0.0003	-0.0027	-0.0005	-0.0035	-0.0005	-0.0032
	(0.0004)	(0.0031)	(0.0005)	(0.0031)	(0.0004)	(0.0023)	(0.0004)	(0.0021)	(0.0005)	(0.0021)	(0.0004)	(0.0019)
$\Delta z_{it}^{>30} \times \overline{z_i}$		0.0001		0.0001		0.0001		0.0001		0.0001		0.0001
		(0.0001)		(0.0001)		(0.0001)		(0.0001)		(0.0001)		(0.0001)
$\Delta z_{it}^{<0}$			-0.0006	-0.0061			0.0013	-0.0030			0.0013	-0.0033
			(0.0014)	(0.0019)			(0.0011)	(0.0013)			(0.0010)	(0.0011)
$\Delta z_{it}^{<0} \times \overline{z_i}$				0.0007				0.0005				0.0005
				(0.0002)				(0.0002)				(0.0002)
Structural Model												
$\Delta z_{it}^{>30}$	-0.0027	-0.0034	-0.0027	-0.0038	-0.0004	-0.0002	-0.0004	0.0001				
	(0.0005)	(0.0031)	(0.0005)	(0.0032)	(0.0006)	(0.0018)	(0.0007)	(0.0018)				
$\Delta z_{it}^{>30} \times \overline{z_i}$		0.0000		0.0000		0.0000		0.0000				
		(0.0001)		(0.0001)		(0.0001)		(0.0001)				
$\Delta z_{it}^{<0}$			0.0030	0.0071			-0.0012	-0.0041				
			(0.0012)	(0.0024)			(0.0010)	(0.0018)				
$\Delta z_{it}^{<0} \times \overline{z_i}$				-0.0005				0.0003				
				(0.0003)				(0.0002)				

Point Estimates, Avg Temp °C

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	Agriculture		Manufacturing	
	(1)	(2)	(3)	(4)
TWFE				
Δz_{it}	-0.0202	0.0472	-0.0072	-0.0038
	(0.0232)	(0.0348)	(0.0156)	(0.0236)
$\Delta z \times \overline{z_i}$		-0.0048		-0.0002
		(0.0020)		(0.0013)
Preferred Specification ($\theta^{ag} = 1.37$, $\theta^{manuf} = 4.66$)				
Δz_{it}	-0.0696	0.0034	-0.0021	0.0611
	(0.0183)	(0.0376)	(0.0142)	(0.0272)
$\Delta z \times \overline{z_i}$		-0.0052		-0.0043
		(0.0028)		(0.0024)
Boehm et al (2023) ($\theta^{ag} = 0.8$, $\theta^{manuf} = 1.1$)				
Δz_{it}	-0.0582	-0.0034	0.0001	0.0763
	(0.0159)	(0.0326)	(0.0178)	(0.0309)
$\Delta z \times \overline{z_i}$		-0.0039		-0.0052
		(0.0024)		(0.0027)
Shapiro (2016) ($\theta^{ag} = 3.3$, $\theta^{manuf} = 8.5$)				
Δz_{it}	-0.0664	0.0160	-0.0090	0.0769
	(0.0224)	(0.0422)	(0.0221)	(0.0374)
$\Delta z \times \overline{z_i}$		-0.0058		-0.0059
		(0.0030)		(0.0030)
Fontagné (2022) ($\theta^{ag} = 6.9$, $\theta^{manuf} = 8.3$)				
Δz_{it}	-0.0912	0.0612	-0.0142	0.0684
	(0.0388)	(0.0678)	(0.0217)	(0.0387)
$\Delta z \times \overline{z_i}$		-0.0108		-0.0057
		(0.0050)		(0.0030)

Simulations, TWFE Errors

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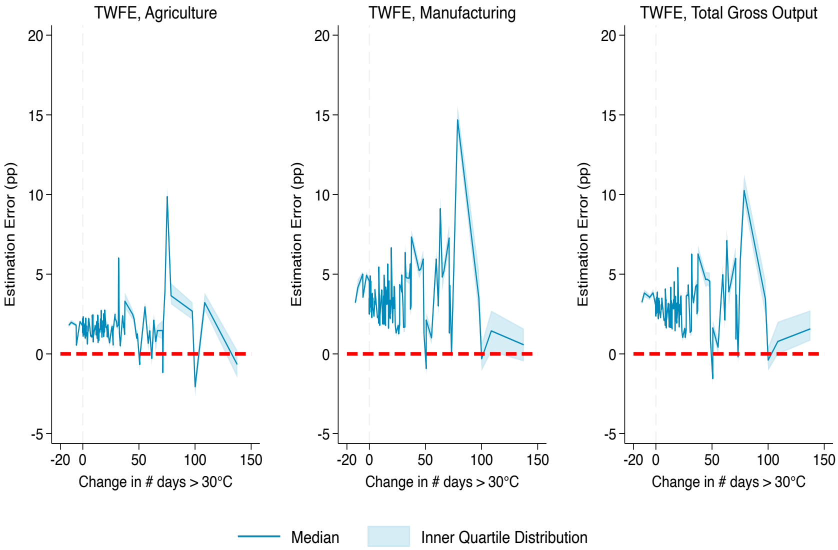
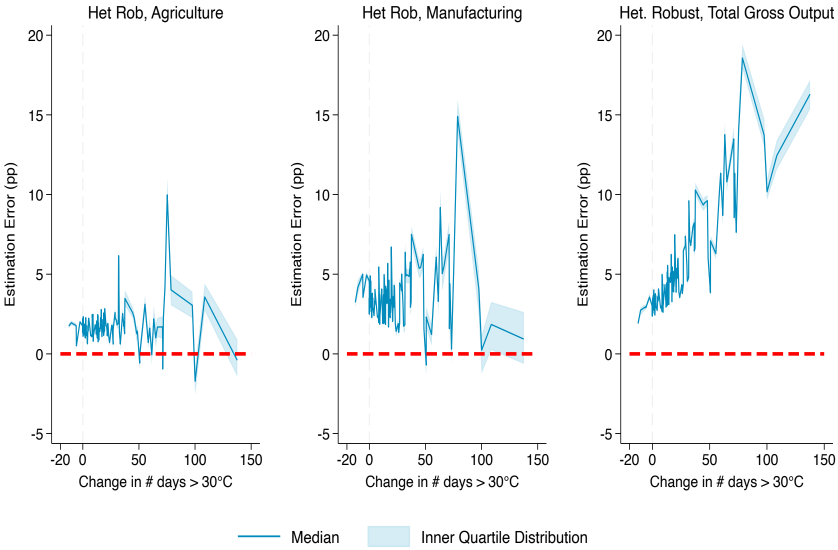


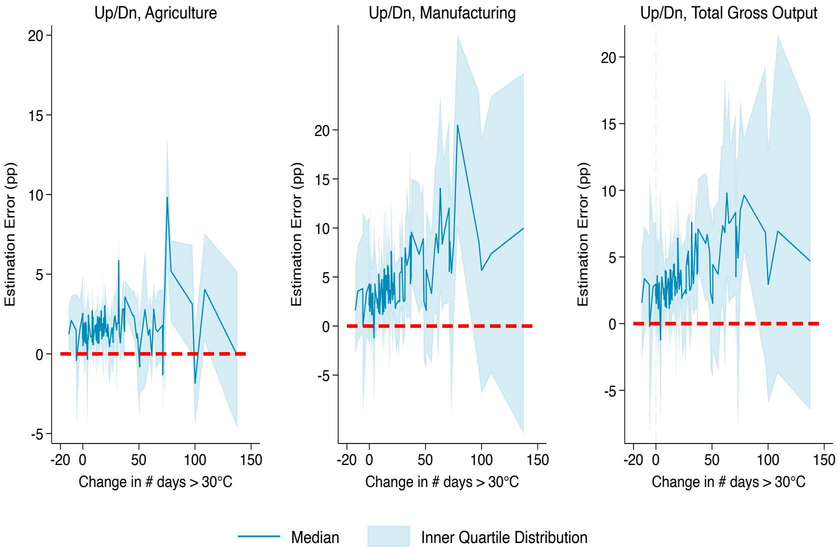
Simulations, HR Errors

back



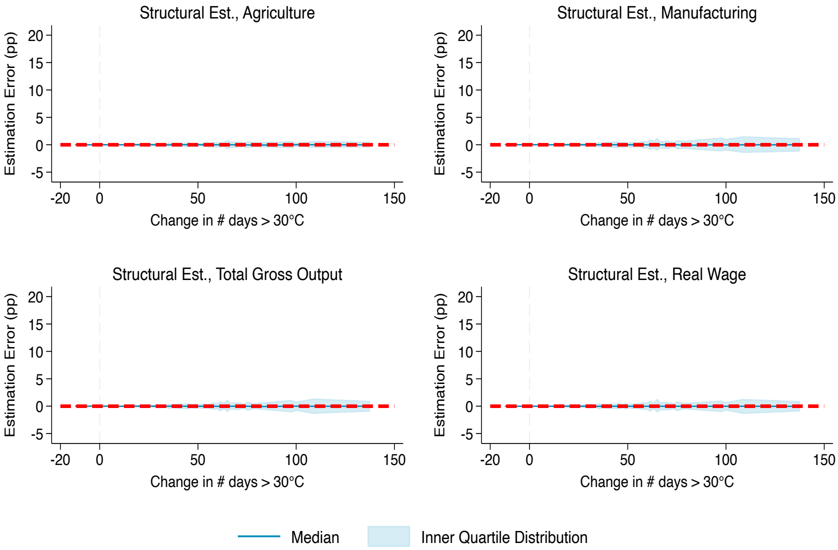
Simulations, UD Errors

back



Simulations, Grav Errors

back



Simulations, GMM Errors

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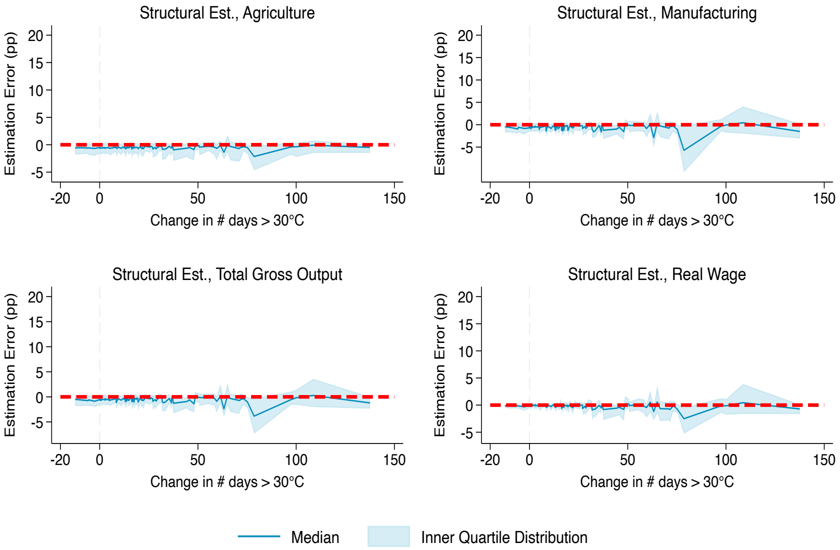

What do we learn from the TWFE? details

Expected influence of unobserved shocks: $\Delta\xi_i \equiv \sum_{k=1}^{\infty} \frac{m(k)}{k!} \sum_{j_1=1}^{N} \cdots \sum_{j_k=1}^{N} \frac{\partial^k f_i}{\partial\epsilon_{j_1}\cdots\partial\epsilon_{j_k}}\Big|_{(\mathbf{z_0},\boldsymbol{\epsilon_0})}$

If

i/ $\mathbb{E}_{\Delta\epsilon}\left[\prod_{r=1}^{k}\Delta\epsilon_{j_r}\middle| z_1, z_0, \epsilon_0\right] = m(k)$ for all $\{j_1,\cdots j_k\} \subseteq \{1,\cdots,N\}$, where $m(k) \in \mathbb{R}$

ii/ $\mathbb{E}\left[\sum_i \left(\Delta\xi_i - \frac{1}{N}\sum_k \Delta\xi_k\right)\left(\frac{\left(\Delta z_i - \overline{\Delta z}\right)}{\sum_k \Delta z_k\left(\Delta z_k - \overline{\Delta z}\right)}\right)\right] = 0,$

then

i/ $\mathbb{E}\left[\check{\beta}^{FE}\right] = \mathbb{E}\left[\sum_i \zeta_i \frac{\Delta \ln y_i^{\dagger}(\mathbf{z_1},\mathbf{z_0};\boldsymbol{\epsilon_1})}{\Delta z_i}\right] = \mathbb{E}\left[\beta^{BLA}\right]$

ii/ $\mathbb{E}\left[\check{\alpha}^{FE}\right] = \mathbb{E}\left[\overline{\Delta \ln y^{\dagger}} + \overline{\Delta\xi} - \check{\beta}^{FE}\overline{\Delta z}\right] = \mathbb{E}\left[\alpha^{BLA}\right] + \mathbb{E}\left[\overline{\Delta\xi}\right]$

What do we learn from the TWFE? details

Expected influence of unobserved shocks: $\Delta\xi_i \equiv \sum_{k=1}^{\infty} \frac{m(k)}{k!} \sum_{j_1=1}^{N} \cdots \sum_{j_k=1}^{N} \frac{\partial^k f_i}{\partial\epsilon_{j_1}\cdots\partial\epsilon_{j_k}}\Big|_{(\boldsymbol{z_0},\boldsymbol{\epsilon_0})}$

If

i/ $\mathbb{E}_{\Delta\epsilon}\left[\prod_{r=1}^{k} \Delta\epsilon_{j_r} \Big| z_1, z_0, \epsilon_0\right] = m(k)$ for all $\{j_1, \cdots j_k\} \subseteq \{1, \cdots, N\}$, where $m(k) \in \mathbb{R}$

ii/ $\mathbb{E}\left[\sum_i \left(\Delta\xi_i - \frac{1}{N}\sum_k \Delta\xi_k\right)\left(\frac{(\Delta z_i - \overline{\Delta z})}{\sum_k \Delta z_k (\Delta z_k - \overline{\Delta z})}\right)\right] = 0,$

then

i/ $\mathbb{E}\left[\check{\beta}^{FE}\right] = \mathbb{E}\left[\sum_i \zeta_i \frac{\Delta \ln y_i^{\dagger}(\boldsymbol{z_1},\boldsymbol{z_0};\boldsymbol{\epsilon_1})}{\Delta z_i}\right] = \mathbb{E}\left[\beta^{BLA}\right]$

ii/ $\mathbb{E}\left[\check{\alpha}^{FE}\right] = \mathbb{E}\left[\overline{\Delta \ln y^{\dagger}} + \overline{\Delta\xi} - \check{\beta}^{FE}\overline{\Delta z}\right] = \mathbb{E}\left[\alpha^{BLA}\right] + \mathbb{E}\left[\overline{\Delta\xi}\right]$

Ben Moll: *Research designs in applied microeconomics...exploit cross-sectional variation. As a result, they identify relative effects....To recover the missing intercept, and more accurately estimate aggregate impacts, research requires more structure.*