Trade Policy and Access to Intermediate Inputs: Quantifying the Welfare Costs of a Fertilizer Shortage[1]

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[1]The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors and do not necessarily represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors or the countries they represent. All errors are our responsibility.

Fertilizer access and trade

- Chemical **Fertilizers**: one of the **most critical intermediate inputs** in the world
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  - Support $\sim$48% of world population (Erisman et al., 2008)

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- **Big role of trade:** Over 80% of countries import at least 75% of their fertilizers. FAOSTAT

- Trade restrictions and geopolitical shocks can create **large-scale** disruptions to fertilizer access.

Recent large-scale disruptions to fertilizer access

Iranian attacks have knocked out swaths of Middle Eastern production of urea, the world's most widely used nitrogen fertiliser, while gas shortages have forced fertiliser producers across south Asia to cut output.

That means that of the 2.1mn tonnes of urea — the world's most widely used nitrogen fertiliser — that would normally have been loaded for export over the past two weeks, about half has been disrupted.

At the same time, more than 1.1mn tonnes of fertiliser and fertiliser inputs, including 570,000 tonnes of urea, is currently stuck in the Gulf, either being loaded or already on ships, according to Kpler data.

The New York Times

ar in the Middle East | LIVE Updates 4m ago | Photos | Maps | Pakistan as Mediator | Kurds on Iran's Frontier | Strait of Hormuz

Global Food Supply Faces a Dangerous Bottleneck as Iran War Persists

Fertilizer prices are climbing as a result of disruptions in the Middle East, putting global food supplies at risk.

Listen · 8:24 min | Share full article | 483

Reuters

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US, Canadian farmers face soaring fertilizer prices amid Trump trade war

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Ukraine War Hits Farmers as Russia Cuts Fertilizer Supplies

Shortages and higher costs take a toll on the major crop producer, threatening to spur global food inflation

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  - Labor market: wage changes, sectoral reallocation
  - Public finances: taxes and subsidies
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***This paper**: answers these questions (accounting for GE adjustments) by taking advantage of an unusual episode...*

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An **ideal setting**: trade policy-driven **economy-wide** fertilizer shortage

Preview of results

1. Combine multiple data sources to document **3 stylized facts**:
   - Fertilizer imports: $\downarrow$ 99%
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    - An example application: Strait of Hormuz disruption

Contribution to literature

- **Effects of fertilizer on agricultural productivity using RCTs** (Carter et al., 2021; Beaman et al., 2013; Duflo et al., 2008, 2011). Hard to assess GE effects using small-scale experiments (Bergquist et al., 2023; Muralidharan and Niehaus, 2017; Artuc et al., 2023)
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- **Industrial policy** Import ban highly distortive (McDonald et al., 2024), fertilizer subsidy common industrial policy (Brooks and Donovan, 2026)
  Contribution: No fertilizer subsidy under the ban mitigates worker losses

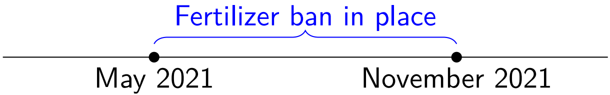
Outline

1. Background
2. Data
3. Stylized Facts
4. Quantitative Spatial Model of Agro Production and Trade
5. Estimation
6. Counterfactuals

Outline

Background

- **Timeline**: Abrupt, unexpected ban



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  - Alleged goal: transition to organic (health & environmental concerns).
  - Suspected goal: saving ForEx (USDA, 2021).

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  Fertilizer ban in place

  May 2021 — November 2021

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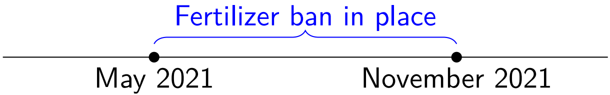

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- **Organic fertilizer can only supplement not substitute chemical fertilizer**: Organic fertilizer
  - President of Lanka Organic Agriculture Movement:

The [...] committee [...] had no knowledge of organic farming [...] It needs two to three seasons to develop microbes that enhance soil quality. It is during this time that the farmers needed governmental support. But that support was missing.

Fertilizer production is geographically concentrated — making imports essential

Nitrogen fertilizer needs gas-intensive ammonia plants
China, Russia, US, Qatar, Saudi Arabia

Phosphate fertilizer needs phosphate rock deposits
Morocco, China, US, Russia

Potash fertilizer needs potash deposits
Canada, Russia, Belarus

- Most countries, including Sri Lanka, lack both cheap gas and mineral deposits, making them structurally dependent on fertilizer imports.

Outline

I. Trade policy data: Digitization

- Hand-code gazettes with imports and exports regulations (March 2020-October 2022) identifying banned products Details
- Global NTM datasets (e.g. TRAINS) do not capture import bans that **start and stop within same year**

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The Gazette of the Democratic Socialist Republic of Sri Lanka
EXTRAORDINARY

අංක 2226/48 - 2021 මැයි මස 06 වැනි බ්‍රහස්පතින්දා - 2021.05.06
No. 2226/48 - THURSDAY, MAY 06, 2021

(Published by Authority)

PART I : SECTION (I) — GENERAL

Government Notifications

Imports and Exports (Control) Act, No. 1 of 1969

IN terms of the powers vested in me by Section 20 read together with Sub-Section 4(1) and Section 14 of the Imports and Exports (Control) Act, No. 1 of 1969 as amended by Act, No. 48 of 1985 and Act, No. 28 of 1987, I, Mahinda Rajapaksa, the Minister of Finance, promulgate following Regulations.

Mahinda Rajapaksa,
Minister of Finance.

Ministry of Finance,
Colombo 01,
06 May 2021.

2A PART I : SEC. (I) - GAZETTE EXTRAORDINARY OF THE DEMOCRATIC SOCIALIST REPUBLIC OF SRI LANKA - 06.05.2021

	Column I HS Heading	*Column II HS Code*		*Column III Description*	*Column IV Import Control License (L)*
251	**29.16**			**Unsaturated acyclic monocarboxylic acids, cyclic monocarboxylic acids, their anhydrides, halides, peroxides and peroxyacids; their halogenated, sulphonated, nitrated or nitrosated derivatives.**	
		2916.20.00	-	Cyclanic, cyclenic or cycloterpenic monocarboxylic acids, their anhydrides, halides, peroxides, peroxiacids and their derivatives:	
		2916.20.40	---	Transfluthrin	**L**
252	**29.30**			**Organo-sulphur compounds.**	
		2930.20.00	-	Thiocarbamates and dithiocarbamates:	
		2930.20.10	---	Thiobencarb	**L**
		2930.90.00	-	Other:	
		2930.90.20	---	Edifenphos	**L**

II. Trade, agricultural yields, fertilizer and household survey

1. Sri Lanka's monthly **import/export** transactions (2017-22) Details

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3. **Household Surveys** (2016, 2019): regional variables Details

4. **Government agricultural data + (private) Tea Board**: Details
    - Production and cultivated area, by region, pre- and post-ban.
    - Producer prices by region, pre-ban.
    - Rice (paddy), maize, peanut, potato, onion, cinnamon, cloves, tea.

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5. Rice yields at pixel level (2000-2022) computed using state-of-the-art remote sensing methods based on satellite imagery (Ozdogan et al., 2025). Similar procedure for tea yields (2014-22). Details

Remote sensing: Paddy rice area mapping method (Ozdogan et al., 2025)

Use expert-based image classification algorithm on satellite observations (from Landsat and Sentinel-2), enhanced to isolate rice signal

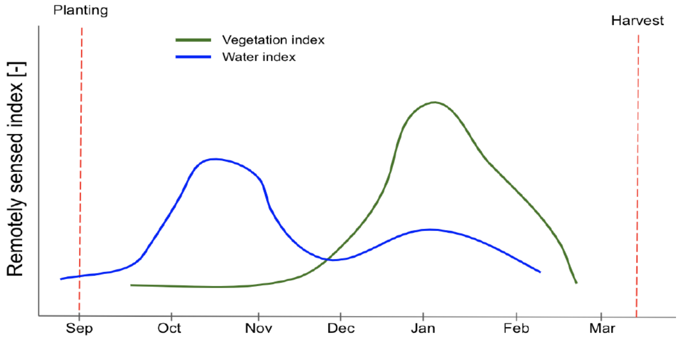

Figure: Wetness and greenness index for Hettipola

More Details

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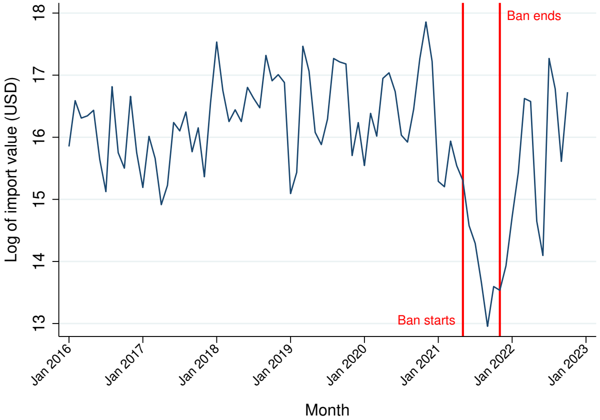


Figure: Value of fertilizer imports, by month (all fertilizer products)

Details

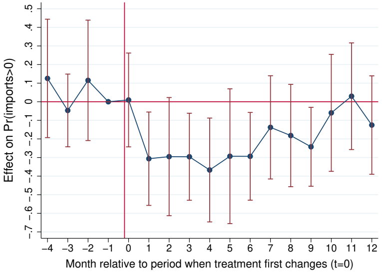
Fertilizer imports: Event study

De Chaisemartin and d'Haultfoeuille (2022) event study design to account for ban switching on and off:

$$y_{ct} = \sum_{\tau \neq -1} \beta_\tau \times ban^{\tau}_{ct} + \omega_t + \omega_c + \epsilon_{ct}$$

- y_{ct}: log imports (intensive) or dummy for positive imports (extensive)
- c : HS8 product, t: month-year, ban^{τ}_{ct}: dummy indicating whether an import ban on product c was first imposed τ periods before period t.

Fertilizer imports ↓ after the ban: Monthly event study



(a) Dynamic Ban Effects on Imports (Extensive Margin)

Notes: De Chaisemartin and d'Haultfoeuille (2022) event study design at HS8 product-month level. The treatment variable is a ban dummy. **Control group**: all non-banned products.

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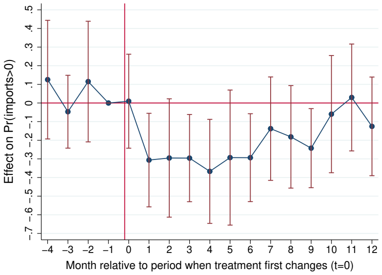

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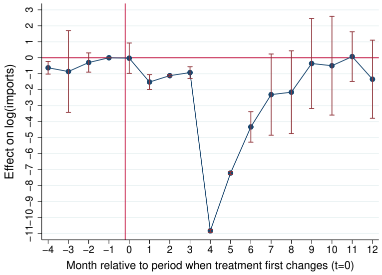

(b) Dynamic Ban Effects on Imports (Intensive Margin)

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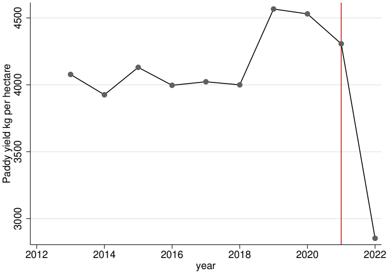
Fertilizer only | Robustness to seasonality and null effects for COVID-19 placebo

2. Rice production ↓ and rice imports ↑ after the ban: Raw data



(a) Annual Maha yield

Notes: The left panel shows the Maha (September-March) rice yield in 2012-2022. The right panel shows the monthly imports of rice. Red lines mark the import ban's beginning and end.

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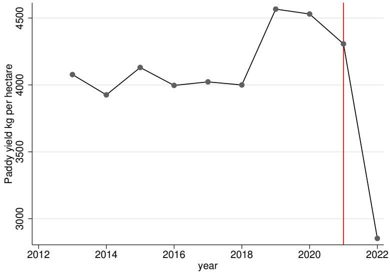

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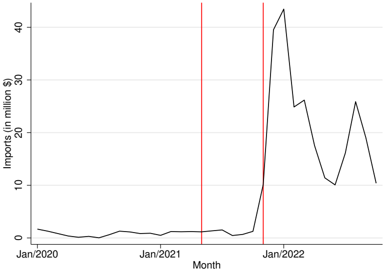

(b) Monthly rice imports

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Production decline not weather related | Yield maps | Decline in tea yields

3. Fertilizer-intensive agro exports $\downarrow$ after the ban: Quarterly event study

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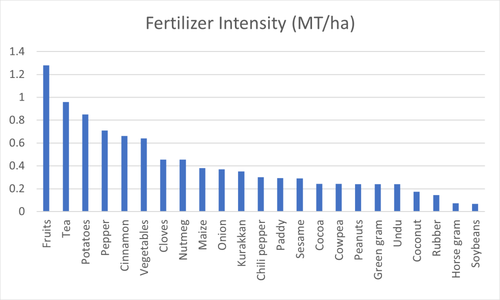
Firm-quarter-level export regression

- Define Fertilizer Usage of each agro exporting firm: average fertilizer intensity of crops exported by the firm pre-ban (in 2017-19 data).



- Treated Firm: a firm above 75th pctile of Fertilizer Usage.

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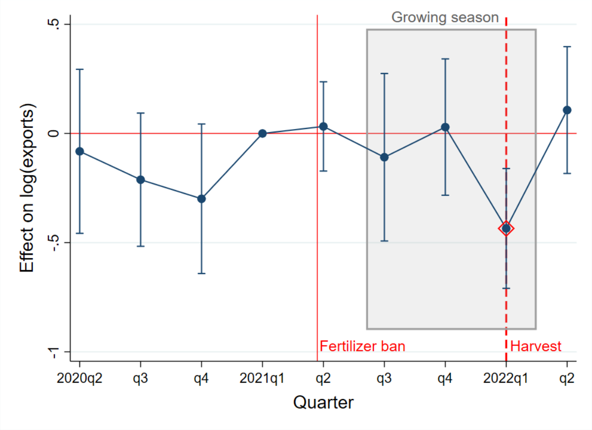

(a) Dynamic Ban Effects on Firm-level Exports

Notes: Treatment group consists of firms above 75th percentile of pre-ban Fertilizer Usage across all agricultural exporters

Robustness to seasonality and null effects for COVID-19 placebo

Broader lessons on large-scale fertilizer disruptions

Specific to Sri Lanka:

- Average welfare loss? Distribution (regions, occupations)?
- Role of adjustments in labor/goods markets, taxes, subsidies?

General lessons: cost of a large-scale disruption to fertilizer supply?

- What happens when policy-driven restrictions are less extreme?

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- What happens when policy-driven restrictions are less extreme?
- What happens when shock is external, e.g. geopolitical conflict (Iran war, Russo-Ukrainian war)?
- When is the PE effect a good approximation?

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General lessons: cost of a large-scale disruption to fertilizer supply?

- What happens when policy-driven restrictions are less extreme?
- What happens when shock is external, e.g. geopolitical conflict (Iran war, Russo-Ukrainian war)?
- When is the PE effect a good approximation?

To answer these questions and quantify other effects, we develop a ***quantitative GE model of trade, space, and agriculture****.*

Outline

Model overview

- **Geography**: 25 domestic regions + 1 foreign Rest-of-World (RoW).
    - Fixed population and land.

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    - Government subsidizes fertilizer, funded by flat income tax.
  - **Agriculture** (**A**): K crops, with region-specific varieties (Armington).

Agricultural sector

- Region i has L_{ik} hectares of land suitable for growing crop k.
  - Cobb-Douglas production function in plot ω:

$$q_{ik}(\omega) = T_{ik}^{A}(n_{ik}(\omega))^{\gamma_k^n}(f_{ik}(\omega))^{\gamma_k^f}(l_{ik}(\omega))^{\gamma_k^l} \quad (1)$$

  - n: labor; f: fertilizer; l: land; T_{ik}^{A}: productivity parameter
  - CRS: $\gamma_k^n + \gamma_k^f + \gamma_k^l = 1$
  - We aggregate crop production from plot to regional level
- **Key data features**:
  - Importance of fertilizer (γ_k^f) can vary across crops (k).
  - T_{ik}^{A} captures suitability of land in region i for growing crop k.

Aggregate regional production function

Fertilizers, subsidies, and taxes

- **Fertilizer subsidies:**
  - Farmers face subsidized fertilizer prices (crop-specific):

$$p_i^{f,k} = (1 - s_k)\, p_{LKA}^f$$

- **Financing (taxes):**
  - Subsidies funded via a uniform income tax t adjusted to balance government budget
- **Fertilizer imports (QRs):**
  - Government restricts imports via quantitative restrictions (up to $\bar{f}$)
  - With restrictions, domestic price exceeds world price:

$$p_{LKA}^f > p_{RoW}^f$$

  - License rents accrue to middlemen:

$$QR^{rent} = (p_{LKA}^f - p_{RoW}^f)\, \bar{f}$$

Agents in the economy

1. Middlemen

Own fertilizer endowment and import licenses; earn fertilizer sales revenue, license rents

2. Mobile workers

Earn w_n^m, mobile across sectors

3. Tea estate workers

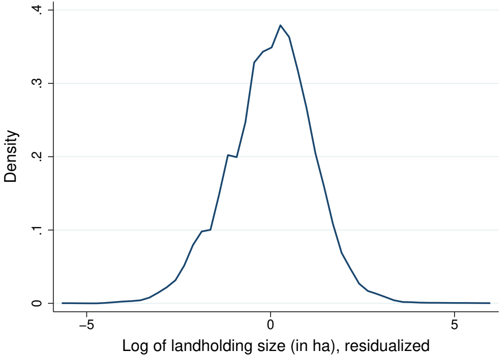
Earn w_n^e, must work in tea farms

4. Farmers

Own land L_n^h; earn rents R_n^h

Farmers and land inequality

- **Log-normal distribution of landholding size** : $L_n^h \sim \log \mathcal{N}(\mu_n, \sigma_{Ln}^2)$



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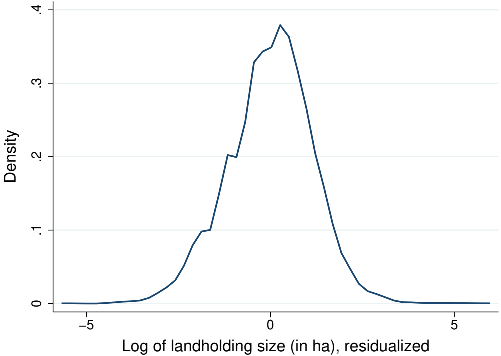
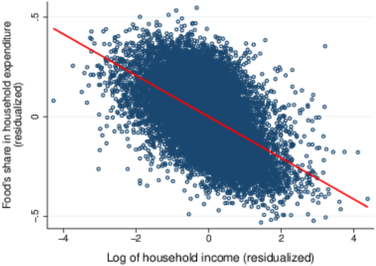


- **Land rent of farmer h also log-normal:** $\Rightarrow$
  $R_n^h = L_n^h \cdot \frac{R_n}{L_n} \sim \log \mathcal{N}(\mu_n + \ln R_n - \ln L_n, \sigma_{Ln}^2)$

Consumer preferences

- Between **A** and **M**: non-homothetic (PIGL) $\rightarrow$ Food larger share for poorer households

$$\xi^A(y, P^A, P^M) = \phi + \nu \left(\frac{y}{(P^A)^\phi (P^M)^{1-\phi}} \right)^{-\eta}$$



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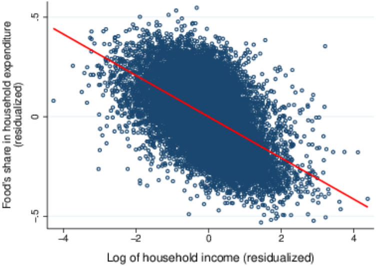

- Within **A** + within **M**: nested CES Preferences Market clearing

Developing country features & empirics → Theory

Empirical facts

1. Land inequality within districts.
2. Food share falls with income.
3. Near-complete fertilizer import ban.
4. World's highest crop-specific subsidies.

Theory ingredients

1. Log-normal land distribution within districts.
2. Non-homothetic preferences.
3. Rent-generating QRs in a quantitative spatial model.
4. Tax-funded crop-specific subsidies.

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---

(1)+(2) ⇒ aggregate food expenditure share depends on distribution of income

Challenge: aggregate over a **mixed income distribution**

- Farmers: log-normal (heterogeneous land ownership)
- Workers: degenerate (all earn same wage within type)

Proposition (Aggregate Agricultural Expenditure)

Under PIGL preferences and a log-normal distribution of land ownership, aggregate agricultural expenditure in district n has the closed form:

$$X_n^A = \underbrace{\phi(1-t)E_n}_{\text{homothetic baseline}} + \nu(1-t)^{1-\eta} \cdot \frac{\mathcal{N}_n}{\left[\underbrace{(P_n^A)^{\phi}(P_n^M)^{1-\phi}}_{\text{Cobb-Douglas price index}}\right]^{-\eta}}$$

where the numerator $\mathcal{N}_n$ is:

$$\mathcal{N}_n = \overbrace{N_n^m(w_n^m)^{1-\eta} + N_n^e(w_n^e)^{1-\eta}}^{\text{workers: homogeneous within type}} + \overbrace{N_n^F\, r_n^{1-\eta}\, e^{-\eta(1-\eta)\frac{\sigma_{Ln}^2}{2}}}^{\text{farmers (w/ inequality correction)}}$$

Proof Appendix G.A

Implications for welfare

- Two key features of most economies in the world:
  1. Poorer people spend a larger share of their income on food
  2. Land-inequality (income inequality) within and across districts

New ingredients in quantitative spatial model: Combination of non-homothetic preferences (Eckert and Peters, 2023; Boppart, 2014) and log-normal approximation of farm size (Allanson 1992; Bakucs Ferto, 2009)

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  New ingredients in quantitative spatial model: Combination of non-homothetic preferences (Eckert and Peters, 2023; Boppart, 2014) and log-normal approximation of farm size (Allanson 1992; Bakucs Ferto, 2009)

- More land/ income unequal district (given mean land /income) $\rightarrow$ low agro spending $\rightarrow$ smaller agro sector $\rightarrow$ larger manufacturing (outside option) $\rightarrow$ less negative effects of ban on welfare

- Quantitatively, non-homothetic model predicts 24.9% agro employment vs. 15% under homotheticity — matches ILO's 25%

Welfare across agents

Outline

Estimating demand-side parameters: Engel elasticity (η)

- From model, agro's share (ξ^A) within total expenditure is:

$$\xi^A(y, P^A, P^M) = \phi + \nu\Big(\frac{y}{(P^A)^{\phi}(P^M)^{1-\phi}}\Big)^{-\eta}$$

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$$\ln(\xi^A_{nh} - \phi) = -\eta \ln(y_{nh}) + \theta hhsize_{nh} + \omega_n + \epsilon_{nh}$$

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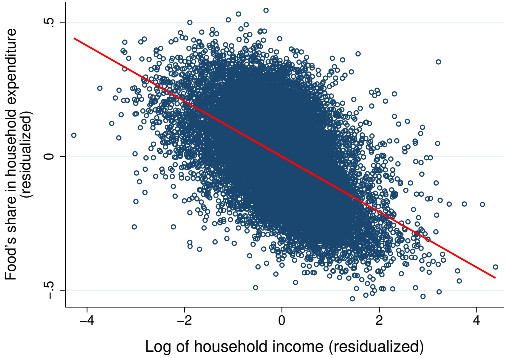
- **Concern**: endogeneity of income
  - e.g. seasonality in food prices and employment opportunities
  - **IV** approach: lottery earnings affecting income (not food prices)

Estimating demand-side parameters: Engel elasticity

Non-homotheticity i.e. Engel elasticity ($\hat{\eta} = 0.66$)

- Sensitivity of food expenditure share to income (**HH Survey**):



- IV for income: lottery earnings Details Results table

Estimating demand-side parameters: Elasticity of substitution across crops (σ_A)

- Sensitivity of (relative) crop demand to (relative) crop price

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- From the model, derive the estimating equation:

$$\ln(\beta^A_{nhk}) = -(\sigma_A - 1)\ln(P_{nhk}) + \omega_k + \omega_h + \epsilon^A_{nhk}$$

  - k: indexes crops; h: indexes households; n: indexes regions
  - β^A: crop's expenditure share; P: crop price

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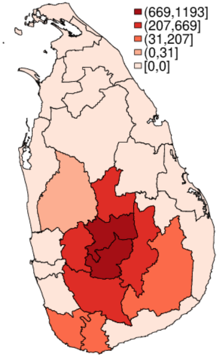
  - k: indexes crops; h: indexes households; n: indexes regions
  - β^A: crop's expenditure share; P: crop price

- **Concern**: endogeneity of crop prices
  - e.g. due to regional tastes
  - IV for price: Exogenous variations in geography & climate from FAO-GAEZ data affecting production (not directly demand)

Details Results table Values

An example variation: Potential tea yield (kg/ha per year)

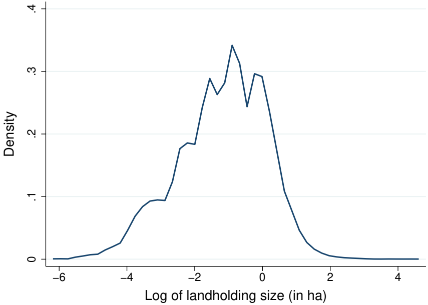
- Supply-side IV for price (Sotelo, 2020): geography-driven potential yields (FAO-GAEZ), by crop and region. E.g. for **tea**:



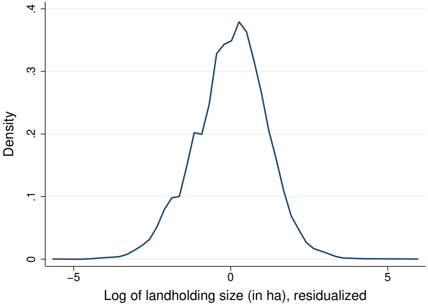
Elasticity of substitution across crops ($\hat{\sigma}_A = 1.71$)

Estimation: Land distribution parameters

Figure: Distribution of Log Landholding Size (**HH Survey**, 2016)



(a) Unadjusted



(b) Deviation from regional average

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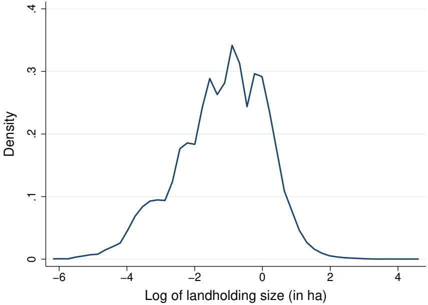

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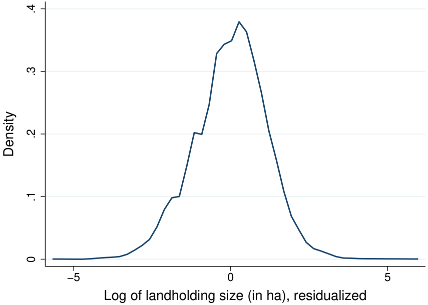

(b) Deviation from regional average

- **Parameters of log-normal distribution**: Formulae
  1. Dispersion parameter: (log) land size SD
  2. Scale parameter: match average farm size

Estimation: Other parameters and unobservables

- **Supply side: Cobb-Douglas production function parameters**
  1. Fertilizer share in crop production costs (LKA government data)
  2. Land and labor cost shares (LKA input-output tables) Formulae

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  - **Intuition**: set value of unobservables to explain "gaps"
  - Heavy use of LKA's **regional data** (2019): wages, # of workers and farmers, agricultural production/area/prices. System of equations

Estimation: Summary

Table: Demand-side Parameters

Parameter	Description	Value	SE	Source
ϕ	Asymptotic agricultural share	0.0105	.	Household Survey (HIES)
ν	PIGL parameter	0.12	.	Eckert Peters (2023)*
η	Engel elasticity	0.656	0.129	Estimated on HIES data
σ_M	EoS across origins (manuf)	2.528	.	Feenstra et al (2018)*
σ_A	EoS across crops	1.714	0.153	Estimated on HIES data
σ_K	EoS across origins (within crop)	2.377	.	Match crop price increase

*taken from the literature

*this presentation

Table: Supply-side: Cobb-Douglas production function parameters

Crop	Fertilizer (γ_k^f)	Labor (γ_k^n)	Land (γ_k^l)
Cinnamon	0.032	0.429	0.539
Cloves	0.043	0.424	0.533
Groundnuts	0.066	0.414	0.520
Maize	0.177	0.365	0.458
Onions	0.075	0.410	0.515
Potatoes	0.129	0.394	0.477
Rice	0.110	0.469	0.421
Tea	0.109	0.487	0.404

Outline

Counterfactual results: Full ban of fertilizer imports

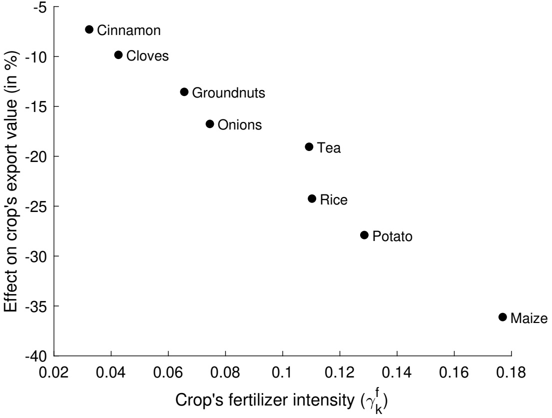
Table: Country-level effects

Variable	Effect	% Effect
Fertilizer imports ($)	-$1,253 MM	-100%
Fertilizer imports (kg)	-4,043 MM kg	-100%
Fertilizer usage (kg)	-4,043 MM kg	-96.5%
Agro exports ($)	-$596 MM	-22.6%

- Stylized Fact: "1. Fertilizer imports declined after the import ban"
- Trade deficit? -$1,253 MM *versus* +$596 MM
  - "Offset factor": 48% $(=\frac{596}{1{,}253}) \rightarrow$ limits effectiveness in saving ForEx
  - Without subsidies, more than 100% offset

Effect on crop yields and exports: Counterfactual results

Agricultural exports



- Stylized Fact: "3. Fertilizer-intensive agro exports declined significantly after the ban on fertilizer imports"

PE vs GE decomposition: Elasticity of yields to fertilizer

$$\textbf{GE:} \quad d\ln(Y_{ik}) = \underbrace{-\frac{\gamma_k^f}{\gamma_k^l} d\ln(p_i^{f,k})}_{\text{PE}} \overbrace{-\frac{\gamma_k^n}{\gamma_k^l} d\ln(w_i^k)}^{\text{GE wage effect}} + \overbrace{\left(\frac{1}{\gamma_k^l} - 1\right) d\ln(p_{ik})}^{\text{GE crop price effect}}$$

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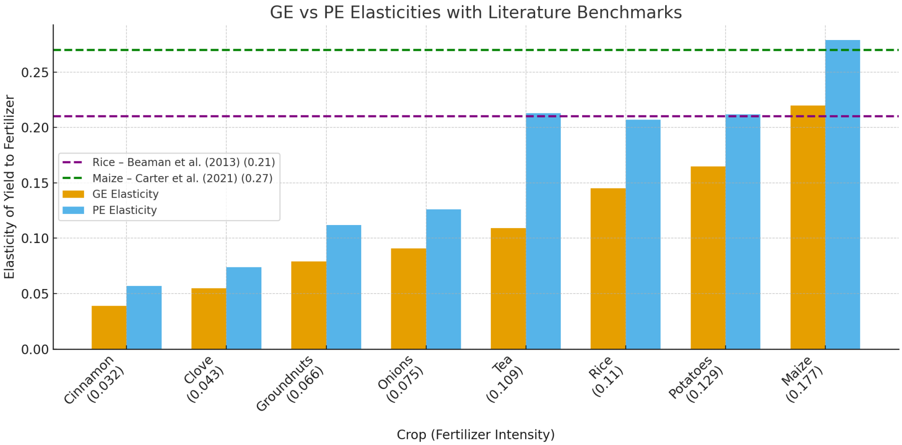
Divide by Δ fertilizer intensity to derive elasticity of yield wrt fertilizer

GE elasticity < PE elasticity



Model Validation GE vs PE Elasticities formulae

Scaling up fertilizer shocks: from PE to GE

Experiment: Exclude share λ of land from international fertilizer market.

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Result: as $\lambda \to 0$, GE/PE $\to 1$ on treated land.

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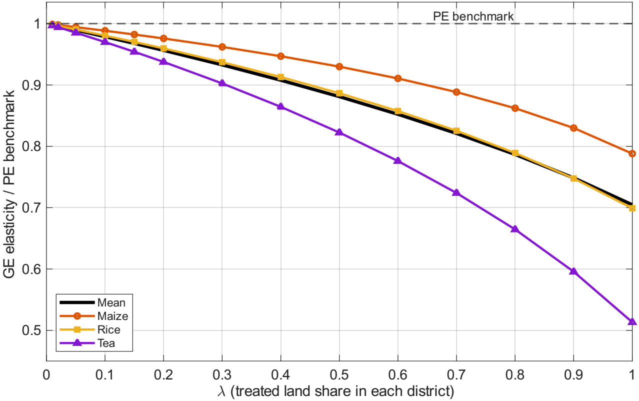

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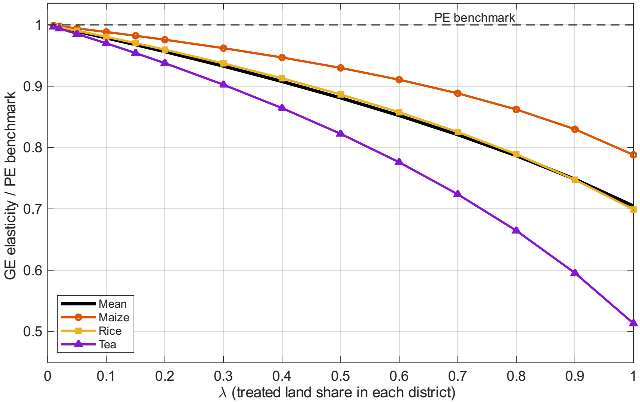
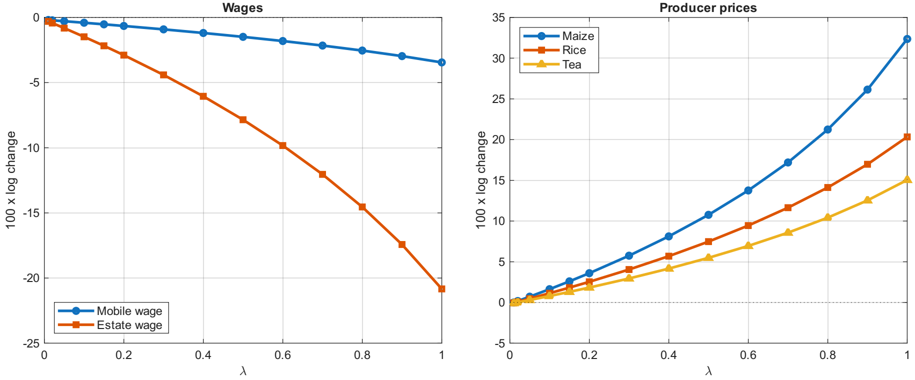


Small, localized shocks are PE-like; nationwide disruptions are not.

Why the GE wedge grows with coverage



Mechanism:

Larger coverage λ moves economy-wide wages ($\downarrow$) and crop prices ($\uparrow$) $\Rightarrow$ treated-land yield losses smaller than predicted by PE

Effect on welfare: Counterfactual results

Overall welfare effects

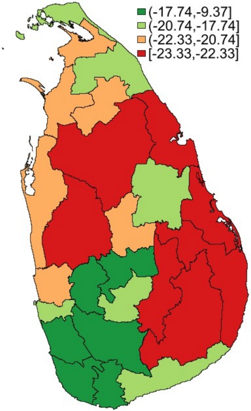
Table: Welfare effects (cross-district average)

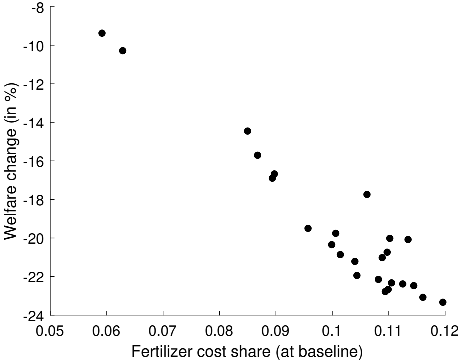
Agent type	**Equivalent Variation (EV)**
Mobile Worker	-0.67%
Estate Worker	-16.58%
Repr. Farmer	-19.51%
Cross-type Average	-7.33%

- Farmer and estate worker (whose incomes are attached to agriculture) suffer more.
- Mobile worker (can move across sectors) suffers less.

EV definitions Composition effect

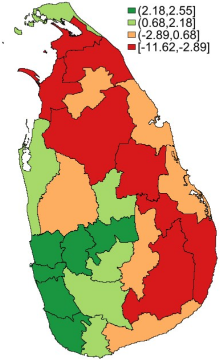
Welfare effects on farmers

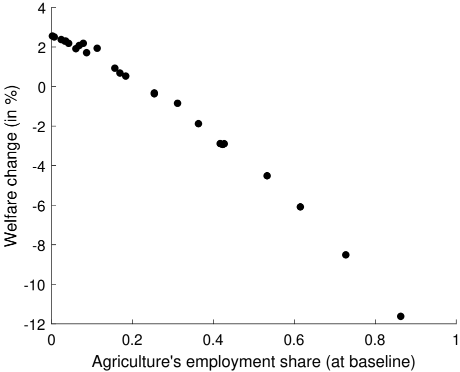




Geographic Heterogeneity #1: Worse effects in regions specialized in fertilizer-intensive crops ($\rho = -0.95$).

Welfare effects on mobile workers





Geographic Heterogeneity #2: Worker suffers little if her region has large manufacturing employment "buffer" that can easily absorb her.

Importance of context-specific features in GE

Table: Ban Effects on Welfare (EV), by agent type

Agent type	Main CF (1)
Mobile Worker	-0.67%
Estate Worker	-16.58%
Representative Farmer	-19.51%
Average across types	-7.33%

Context-relevant features affect welfare estimates:

Importance of context-specific features in GE

Table: Ban Effects on Welfare (EV), by agent type

Agent type	Main CF (1)	Homothetic preferences (2)
Mobile Worker	-0.67%	-0.46%
Estate Worker	-16.58%	-17.71%
Representative Farmer	-19.51%	-21.01%
Average across types	-7.33%	-7.84%

Context-relevant features affect welfare estimates:

- **Non-homothetic preferences**: accurately predict agro labor share

Importance of context-specific features in GE

Table: Ban Effects on Welfare (EV), by agent type

Agent type	Main CF (1)	Homothetic preferences (2)	No subsidies (3)
Mobile Worker	-0.67%	-0.46%	-1.52%
Estate Worker	-16.58%	-17.71%	-9.84%
Representative Farmer	-19.51%	-21.01%	-11.43%
Average across types	-7.33%	-7.84%	-5.04%

Context-relevant features affect welfare estimates:

- **Non-homothetic preferences**: accurately predict agro labor share
- **Fertilizer subsidies**: an implied income redistribution scheme (from non-farm to farm sector)

Importance of context-specific features in GE

Table: Ban Effects on Welfare (EV), by agent type

Agent type	Main CF (1)	Homothetic preferences (2)	No subsidies (3)	Halving (QR) (4)	Halving (TC) (5)
Mobile Worker	-0.67%	-0.46%	-1.52%	+0.13%	-0.25%
Estate Worker	-16.58%	-17.71%	-9.84%	-3.19%	-3.54%
Representative Farmer	-19.51%	-21.01%	-11.43%	-3.9%	-4.24%
Average across types	-7.33%	-7.84%	-5.04%	-1.30%	-1.66%

Context-relevant features affect welfare estimates:

- **Non-homothetic preferences**: accurately predict agro labor share
- **Fertilizer subsidies**: an implied income redistribution scheme (from non-farm to farm sector)
- **Modeling trade policy as QRs**: price wedges correspond to rents, which are not entirely lost (for less than full ban)

2026 Iran War: global shortage $\neq$ domestic cutoff

Counterfactual Exercise:

Reduce fertilizer endowments by 36% worldwide (Strait of Hormuz crisis).

Metric	Full import ban	Iran War CF
Fertilizer use in Sri Lanka	−96.5%	−35.6%
Avg. welfare (EV)	−7.33%	−0.20%
Rep. farmer EV	−19.51%	−0.17%

2026 Iran War: global shortage $\neq$ domestic cutoff

Counterfactual Exercise:

Reduce fertilizer endowments by 36% worldwide (Strait of Hormuz crisis).

Metric	**Full import ban**	**Iran War CF**
Fertilizer use in Sri Lanka	-96.5%	-35.6%
Avg. welfare (EV)	-7.33%	-0.20%
Rep. farmer EV	-19.51%	-0.17%
Gross agro export value	-22.6%	$+0.4\%$
Tax rate	-27.3%	$+0.37\%$

- Same agronomic force: fertilizer-intensive crops and districts still lose more.
- Different GE incidence: **higher crop prices** worldwide cushion agriculture compared to full fertilizer ban.

Conclusion

- **Sri Lanka's fertilizer import ban**: an episode of trade policy-induced, large-scale disruption to fertilizer access.
- Extrapolating from PE estimates would lead to overestimating impacts of large-scale disruptions.
- Trade policy **interacts** with domestic (agricultural) policy:
  - Pre-existing input subsidies **shift distributional burden** of disruption.
- Average **welfare cost** equivalent to a **7.3%** income loss but **unevenly distributed** across regions and between farmers and workers.
  - Informs welfare policy **targeting** in face of shocks.
- Terms-of-trade effects on agricultural prices are larger for global fertilizer shocks than domestic fertilizer restrictions, and therefore different distributional effects.

Thank You. For comments/ questions/ suggestions:

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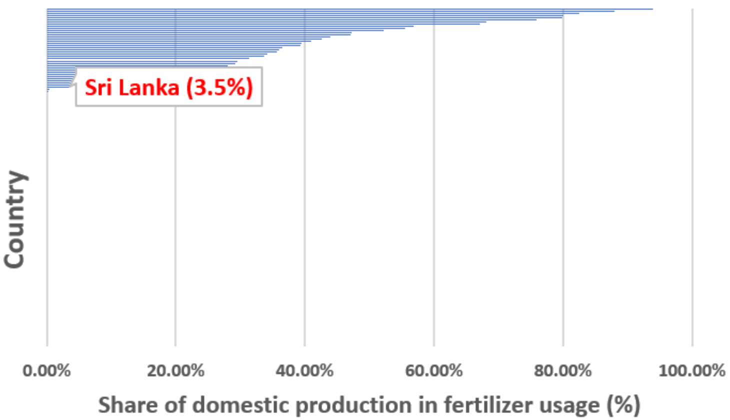
Share of domestic production in fertilizer usage



Only 19% of countries are net exporters of fertilizer and bulk of it comes from Russia and Belarus. back

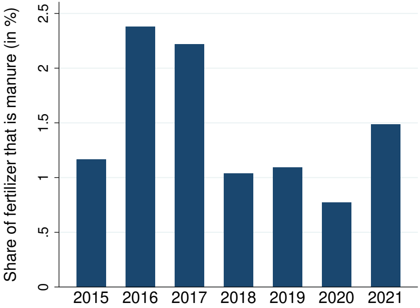
Fertilizer: Organic vs inorganic (1/2)

- Fertilizers supply plant with nutrient needs (mostly N, P, K) that are not sufficiently (naturally) occurring in soil.
- **Organic**: slow-releasing.
  - Requires some heat/moisture to extract nutrients during the time of plant need because nutrient release requires some breakdown.
  - Plant need is met with almost the right timing and amounts, so leaching (removal of excess nutrients from the plant/soil system) is minimized.
- **Inorganic** (chemical): rapid use of nutrients, which are already in plant uptake-ready form.
  - But could come at the expense of leaching, especially if not timed right.
- Both types can meet plant needs, but amounts and timing matter.

Back

Fertilizer: Organic vs inorganic (2/2)

- The share of organic fertilizer (manure) was lower than 2.5% (before and after ban).



Notes: the figure shows the percentage of fertilizer used in Sri Lankan agriculture (by total nitrogen content) that is composed of manure in each year. Data is from the FAO. Back

Data: Trade policy

- **Source**: Sri Lanka's Extraordinary Gazettes on Imports and Exports (Control Regulations) from March 2020 to October 2022.
- Digitize gazettes, manually inspect all entries, create product database with start/end dates of each import ban.
  - Products defined at the level of the 8-digit codes of the Harmonized System (HS).
- Fertilizer import bans started in May 2021. Most ended by July 2021, with the rest eliminated in November 2021.
- Combining with trade data, we observe that banned products accounted for:
  - 16-19% of total imports in 2017-2019 (pre-ban)
  - 12% in 2020 and 10% in 2021 (ban effects?)

Back

Data: International trade

- **Source**: S&P Global Market Intelligence's **Panjiva** data platform:
  - Novel high-frequency granular data covering universe of export/import transactions of Sri Lanka from January 2017 to October 2022.
  - Bills of landing (BoL) show name/address of shipper (exporter) and consignee (importer).
  - Variables: value (in USD), weight, and quantity (with unit of measurement), HS8 product code.
- Firms identified by name (BoL does not require tax ID number):
  - Noisy names: use machine learning and text analysis techniques to clean names and assign unique firm identifier to each name.
- Aggregate data to the level of Sri Lankan exporting/importing firm-HS8 product-partner country-month-year.
- Focus on fertilizer products (HS chapter 31) and agricultural products (HS chapters 06 up to 24).

Back

Data: Fertilizer use (1/2)

- **Source**: Sri Lanka's National Fertilizer Secretariat.
  - Crop-level chemical fertilizer requirements (in kilograms per hectare) for 23 crops.
  - Crop-level total cultivated area (in hectares).
  - Fertilizer prices (in $ per tonne).

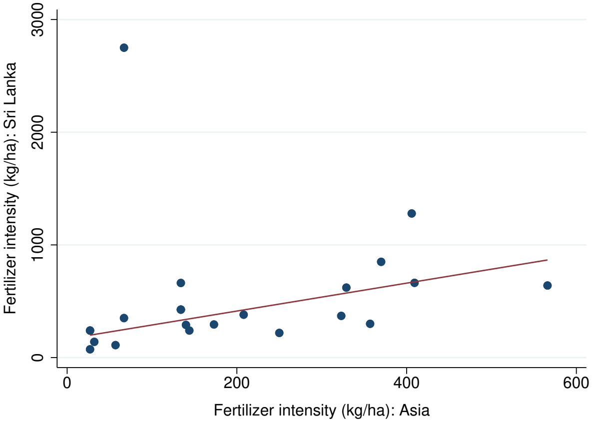
- Compute each crop's country-level expenditure on fertilizer.

C-D parameter estimation

- To validate and complement: **International Fertilizer Development Center** and **International Fertilizer Association**
  - Its fertilizer requirements (for Asia) has a correlation is 0.677 with NFS (excluding soy outlier).
  - Replace NFS data with IFDC/IFA for soy only.

Back

Data: Fertilizer use (2/2)



Notes: the figure plots the fertilizer intensity (in kg/ha) of 22 crops from two alternative data sources: Sri Lanka's National Fertilizer Secretariat (vertical axis) and the International Fertilizer Development Center and the International Fertilizer Association (on the horizontal axis). The regression line (computed excluding the outlier point) is shown in red. Back

Data: Household survey (1/2)

- **Source**: 2016/2019 waves of **Household Income and Expenditure Survey (HIES)**
  - From Sri Lanka's Department of Census and Statistics.
  - Yearlong survey conducted in consecutive monthly rounds.
  - Nationally representative sample enumerated in each round (**weights**)
- District's average monthly **wages** in 2019 (w_i^m, w_i^e):
  - Worker: household member who is a "paid employees during last 4 weeks/last calendar month".
  - Use compensation (sum of "wages/salaries" and "tips, commissions, overtime pay etc") in main occupation.
  - Wages computed separately for estate and non-estate (mobile) workers.
    - Estate workers: live and work in tea plantations.
    - Housing tied to their tea estate, so cannot change jobs in the short run.

Back

Data: Household survey (2/2)

- District's **number of workers (N_i^m, N_i^e) and farmers (N_i^F)** in 2019:
  - Locate households with positive **landholdings** ($L_i^h > 0$) in 2016 data.
    Land distr. estimation Land density
  - Count numbers of "farmer households" and "worker households".
  - Multiply # of households by average # of economically active agents per household.
  - To obtain number of non-estate (i.e. mobile) workers, subtract number of estate workers from total number of workers.
  - Inflate by 2.8% to reflect Sri Lanka's 2016-2019 population growth.
- Household earnings and spending: Inequality and aggregate food expenditure
  - **Income**, total **food expenditure**. Non-homotheticity
  - Value/quantity of purchased crops $\Rightarrow$ **crop prices**. EoS estimation
  - **"Lottery" winnings**: "income by chance or ad hoc gains".

Back

Data: Agro production and cultivated area

From **Sri Lanka's Department of Census and Statistics**:

- **Rice ("Paddy Statistics")**:
  - Production (in kg) and cultivated area (in ha) for each district.
  - All growing seasons between 2012-13 Maha and 2022 Yala.
- **Other crops** (maize, peanut, potato, onion, cinnamon, cloves, tea):
  - Production (in kg) and area (in ha), by Divisional Secretariat (DS).
  - All growing seasons between 2019-20 Maha and 2022 Yala.
  - Aggregate data from DS level to district level.
  - For tea: production data from Sri Lanka Tea Board's **annual reports**.
- Crops with harvests in both Yala and Maha (maize, rice, groundnuts): sum production and area across two seasons.
- **National** production data: from **Economic Statistics of Sri Lanka 2023 report** C-D parameter estimation
  - For each crop, use total 2022 production (in metric tons).

Back Land distr. estimation

Data: Producer prices

- **Source**: Bulletin of Selected Retail and Producer Prices 2016-2019.
  - Published Sep/2020 by Department of Census and Statistics.
- Average 2019 producer prices (in Sri Lankan rupees per kilogram), by district.
  - Crops: coconut, potatoes, cinnamon, cloves, onions, soybeans, peanuts, maize.
  - No tea: use data from UN's Food and Agriculture Organization (FAO), assuming Sri Lanka's tea price holds across districts.
- Impute missings using crop's average price in other districts.
  - Price missing for 45% of district-crop pairs that have non-zero agricultural production.
  - But imputation biases likely small because producer prices vary little across districts:
    - Coefficient of variation is 0.009-0.058 depending on the crop (average=0.032).

Back

Data: Remote sensing

- Estimates of **rice cultivated area** and **rice yield** (2000-2022) at highly spatially granular level.
  - Then aggregate up to the divisional secretariat (DS) level.
- **Methodology** (in companion paper: Ozdogan et al., 2025):
  - **Remote sensing**: expert-based image classification algorithm on satellite observations (from Landsat and Sentinel-2), enhanced to isolate rice signal.
  - **Rice yield estimation**: statistical model correlates regional yields from government statistics with satellite-derived vegetation index (green chlorophyll index). Then add random forest-based machine learning model to incorporate additional environmental variables.
- Measures are highly consistent with government statistics:
  - Area: survey-based crop cutting experiments.
  - Yield: production statistics.

Back Rice regressions

Remote sensing step 1: An example image

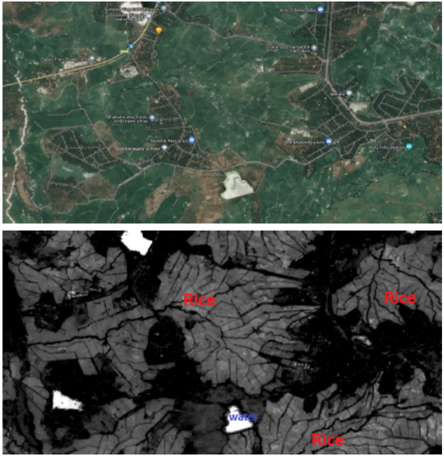


Figure: Areas identified as rice

back

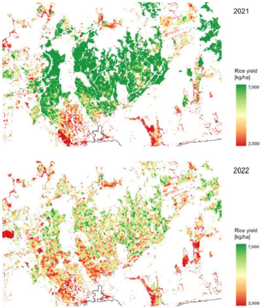
Remote sensing step 2: Paddy rice area mapping method (for pixels identified as rice)

- Correlate district-level yields from government with satellite-derived vegetation index (green chlorophyll index). Use random forest-based ML model to incorporate additional environmental variables.

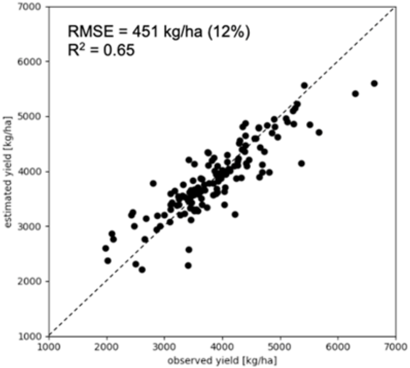
Table: List of variables used in pixel-level paddy rice yield estimation.

Predictor	**Source**	**Spatial resolution**
GCI	Landsat / Sentinel-2	10-30 meters
Seasonal rain [mm]	ERA5	10 km
Rainy days	ERA5	10 km
VPD	ERA5	10km
Dry spells	ERA5	10km
Days with temp $>$ 30 C	ERA5	10km
Elevation	SRTM	30 meters
District boundary	GADM	30 meters [rasterized]

Example rice yield map: Central part of the Hambantota district



Validation: Rice yield



Notes: Validation results of the random forest yield model including both the remotely sensed and environmental variables. The validation is based on roughly 25 percent of the training held back for testing purposes in a cross-validation. Each data point represents a district-year in the test set.

back

Data: Input-output tables

- **Source**: Institute of Policy Studies (Amarasinghe and Bandara, 2005).
- For year 2000.
- Relevant variables: employee compensation and value added (at factor cost prices) for multiple agricultural sectors:
  - Paddy, minor export crops, highland crops, coconut/toddy, potatoes.
  - Tea growing (combining high, medium, and low elevations).
- Usage: estimate labor and land coefficients of model's Cobb-Douglas agricultural production functions. C-D parameter estimation

Back

Data: Potential yields

- **Source**: Global Agro-Ecological Zones (**GAEZ**) project of the Food and Agriculture Organization of the United Nations (**FAO**)
  - Grid cell-level potential attainable yields (for 38 crops).
  - Often used in agro trade literature (Costinot et al., 2016; Bustos et al., 2016; Sotelo, 2020; Farrokhi and Pellegrina, 2022).
  - Advantage: spatial variation in agro productivity due to exogenous geography (e.g. climate, geology) helps create IV. IV estimation
- Variables: potential yield (in kilograms per hectare) at grid cell level:
  - Crops: rice, maize, peanuts, potatoes, onions, cinnamon, cloves, tea.
  - Growing conditions chosen to reflect relevant place/time:
    - Rain-fed (except for rice, which is irrigated).
    - "Historical" climate conditions of 1981-2010 (without climate change).
- Aggregate up from grid cell to district level.

Back

Data: Weather

- **Source #1**: Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)
  - Quasi-global gridded **rainfall** time series combining high-resolution satellite imagery and in-situ station data.
  - Variables: total rainfall (mm/season); rainy days (# days in season receiving >2mm of rain); dry spells (maximum # consecutive days in season receiving <1mm of rain).
  - For each growing season (Maha/Yala) between 1999 and 2022.
- **Source #2**: ERA5-Land dataset
  - High-resolution data on evolution of Earth's land surface since 1950.
  - Variables: average incoming shortwave solar **radiation** (watts per square meter); total **vapor pressure deficit** (hectopascals); average max/min **temperatures** (degrees Celsius).
  - For each growing season (Maha/Yale) between 1999 and 2022.
- Aggregate data up from grid cell to district level.

Back Rice regressions

Data: Rest of World (RoW)

- **World Bank's World Development Indicators**: global 2019 GDP per capita (in current USD): w_{RoW}=\$11,330.5.
- **Food and Agriculture Organization of the UN (FAO), 2019**:
  - Production quantities (ton) and harvested area (ha) by country-crop.
  - Producer prices (in USD/tonne): median across available countries.
- **International Labour Organization (ILO)**: size of global labor force in 2019 (3.45 billion) used as number of workers.
- **Number of farmers** (260 million) estimated in two steps:
  1. Multiply 3.45 billion by agro's share of global employment (26%, from ILO) to get number of agro workers.
  2. Multiply number of agro workers by ratio of farmers to agro workers (0.29, from Brazilian Agricultural Census)
- **Google Finance**: exchange rate between USD and Sri Lankan Rupee (LKR): E_{2019}=176 LKR/USD and E_{2022}=360 LKR/USD.

Back

1B. Fertilizer imports ↓ after the ban: Raw data

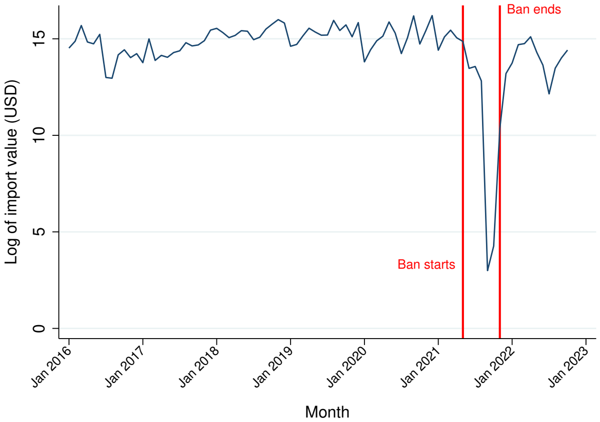


Figure: Value of fertilizer imports, by month (only banned fertilizer products)

1C. Decline driven by quantities of fertilizer imports

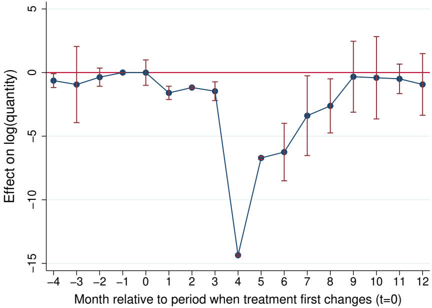
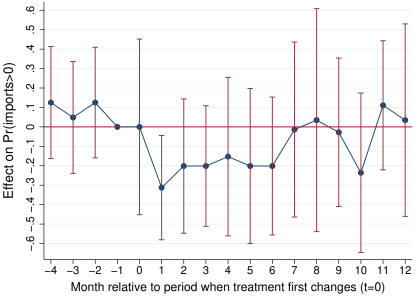


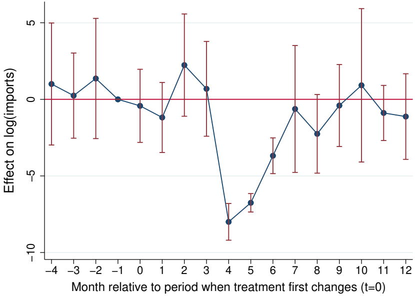
Figure: Fertilizer quantity

Notes: the treatment variable is a dummy indicating whether fertilizer product c had its imports banned in month t, and the not-yet-treated products serve as the control group, which includes non-banned fertilizers as well as other products.

1D. Fertilizer imports ↓ after the ban (within fertilizer class)



(a) Dynamic Ban Effects on Imports, fertilizer only (Extensive Margin)



(b) Dynamic Ban Effects on Imports, fertilizer only (Intensive Margin)

Notes: The treatment variable is a dummy indicating whether fertilizer product c had its imports banned in month t, and the never-treated fertilizer products serve as the control group.

Back

2B. Rice Yield and Cultivated Area, by year (1/2)

- **Concern**: was post-ban rice yield decrease due to bad weather?
  - Leverage remote-sensing data (highly spatially granular). RS data
  - Allows us to control for **local** weather. Weather data

- Run panel regression at the season-DS level.
  - **DS** (divisional secretariat): third-level administrative divisions.

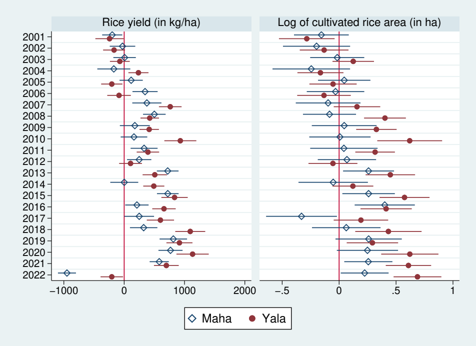
$$Y_{dy}^{s} = \theta_{y}^{s} + \omega_{d}^{s} + \mathbf{B}_{\mathbf{W}}^{\mathbf{s}} \mathbf{W}_{\mathbf{dy}} + \epsilon_{dy}^{s}$$

- d: indexes DSs; s: indexes seasons (Maha/Yala); y: indexes years
- Y: outcome variable (rice yield or cultivated area)
- θ, ω: season and DS fixed effects
- $\mathbf{W}$: vector of weather variables (rainfall, rainy days, dry spells, solar radiation, VPD, average min/max temperatures)

Back

2B. Rice Yield and Cultivated Area, by year (2/2)

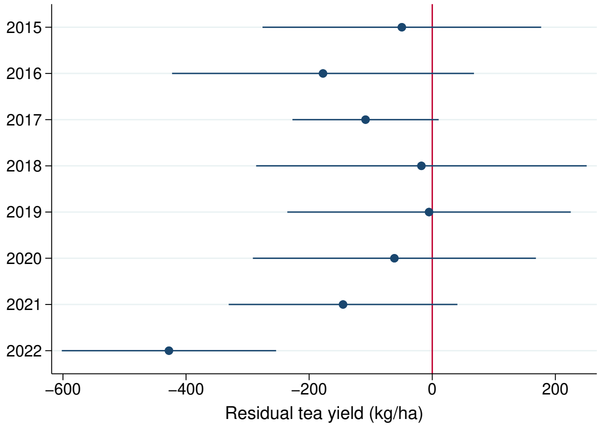
$$Y_{dy}^{s} = \theta_{y}^{s} + \omega_{d}^{s} + \mathbf{B_W^s W_{dy}} + \epsilon_{dy}^{s}$$



A 26.9% yield ↓ relative to the 2000 baseline, but no ↓ in area. Decline is not driven by weather-related variables Back

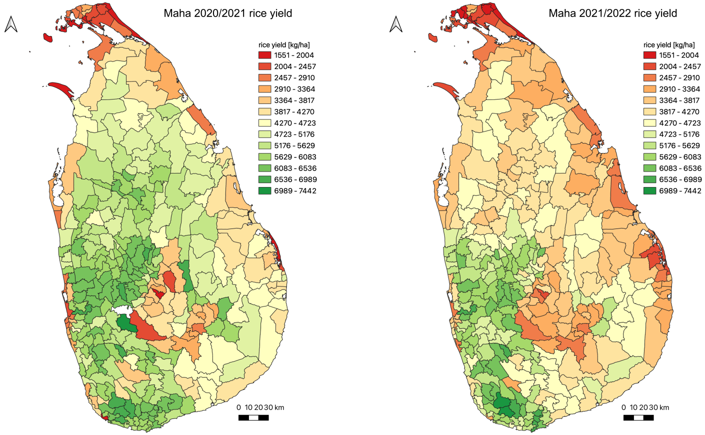
2C. Tea Yield registers similar decline after controlling for weather-related variables

Figure: Tea Yields, by year



Back

2D. Regional rice yields (pre- and post-ban)



Notes: The figures show rice yields (in kg/ha) at the Divisional Secretariat (DS) level for the 2020/21 Maha season (left panel) and the 2021/22 Maha season (right panel). The Maha season rice runs from September of a year to March of the following year. Back

3A. Firm-quarter-level export regressions

- For each firm f, define fertilizer usage U_f as:

$$U_f = \sum_{v=1}^{23} FIC_v \times \left(\frac{X_{fv}^{2017-2019}}{\sum_{v'} X_{fv'}^{2017-2019}} \right),$$

  - v: crop index; FIC: crop-specific fertilizer intensity (in kg/ha)
  - $X_{fv}^{2017-2019}$: firm exports of crop v between 2017-2019

3A. Firm-quarter-level export regressions

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  - v: crop index; FIC: crop-specific fertilizer intensity (in kg/ha)
  - $X_{fv}^{2017-2019}$: firm exports of crop v between 2017-2019

- The event study specification is then given by:

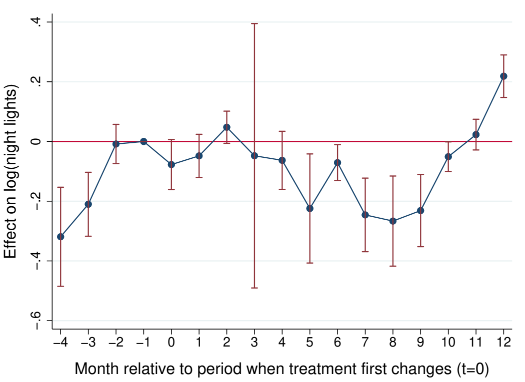
$$\ln(X_{ft}) = \sum_{\tau \neq -1} \gamma_\tau \times \mathbb{1}\{t = T_0 + \tau\} \times \underbrace{\mathbb{1}\{U_f > U_{p75}\}}_{\text{T group dummy}} + \Omega_t + \Omega_f + \mu_{ft}$$

  - t: quarter index; X: agricultural exports
  - U_{p75}: 75th percentile of U_f across firms
  - T_0: first quarter of the fertilizer import ban (Q2/2021)
  - (Ω_t, Ω_f): quarter/firm fixed effects

Back

Overall effects on income: Evidence from nightlights

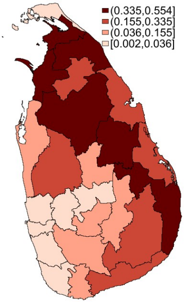
Figure: Dynamic Ban Effects on Nightlights



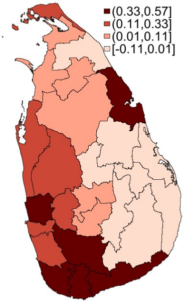
Notes: The treatment group consists of districts that are above-median in terms of fertilizer importance at baseline (2019). Below-median districts serve as the control group. The outcome variable is the log of nightlights at the district-month level.

Back

"Placebo" test: Covid and nightlights



(a) Fertilizer's importance in local economy



(b) Reduction in log(NL), Feb/2020 - Nov/2020

Notes: Panel (a) shows fertilizer importance index (which accounts for size of agro sector and fertilizer intensity of grown crops), by district. Panel (b) shows the reduction in the log of average night light intensity between February 2020 and November 2020, by district.

Back

Robustness

- **Seasonality**
  - **Concern**: agriculture is seasonal.
    - Since bans happened in a specific part of the year, results could be driven by seasonality in fertilizer imports and agro exports.
  - Re-estimate event studies with deseasonalized outcome variables.
  - Little change in results. Results

Robustness

- **Seasonality**
  - **Concern**: agriculture is seasonal.
    - Since bans happened in a specific part of the year, results could be driven by seasonality in fertilizer imports and agro exports.
  - Re-estimate event studies with deseasonalized outcome variables.
  - Little change in results. Results
- **Covid-19 Pandemic**
  - **Concern**: bans happened during the pandemic, so our estimates could be capturing its effects.
    - Requires pandemic effects to differ between banned and non-banned products.
  - Run "falsification test":
    - Re-estimate event studies with treatment period starting in Mar/2020.
    - Keep treatment/control group assignments.
  - If anything, imports of eventually-banned fertilizers *increased* relative to other products early in the pandemic. Results

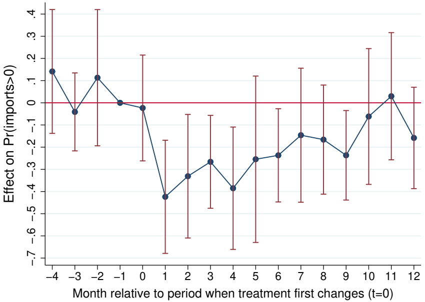
Back

Results: Seasonality (1/4)

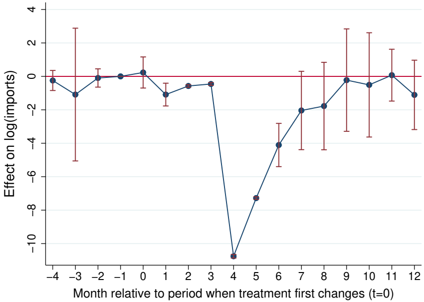
- **Concern**: seasonality as a potential confounder.
  - Already addressed by time fixed effects?
- Extra check: **deseasonalize** outcome variables. Example:
  - For each product p and month $m = \{1, ..., 12\}$, compute average imports between 2017 and 2019.
  - Then subtract this average from import variable M_{pt} wherever t corresponds to month m.
  - Then re-run the regressions using the new, transformed import variable.
- Analogous procedure for extensive margin.
  - Outcome variable is dummy for positive imports.
- Analogous procedures for:
  - Regressions at quarterly (not monthly) level.
  - Regressions at firm (not product) level.

Back

Results: Seasonality (2/4)



(a) Effect on Deseasonalized Imports (Extensive Margin)

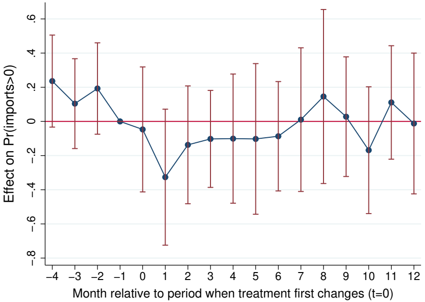


(b) Effect on Deseasonalized Imports (Intensive Margin)

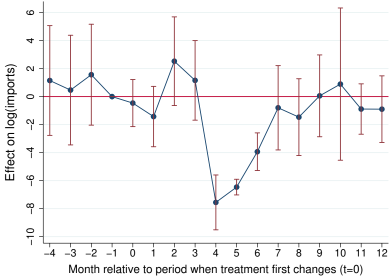
Notes: The treatment variable is a dummy indicating whether fertilizer product c had its imports banned in month t, and the not-yet-treated products serve as the control group, which includes non-banned fertilizers as well as other products.

Back

Results: Seasonality (3/4)



(a) Effect on Deseasonalized Imports, fertilizer only (Extensive Margin)



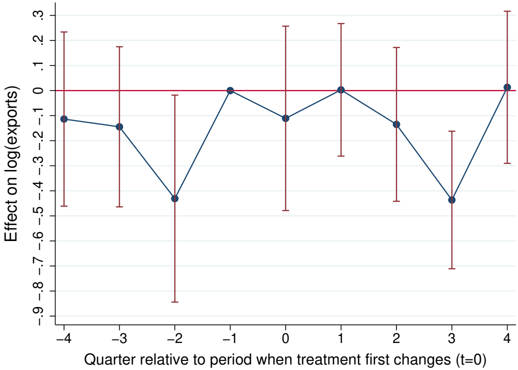
(b) Effect on Deseasonalized Imports, fertilizer only (Intensive Margin)

Notes: The treatment variable is a dummy indicating whether fertilizer product c had its imports banned in month t, and the never-treated fertilizer products serve as the control group.

Back

Results: Seasonality (4/4)

Effect on Deseasonalized Exports (Firm-level)



Notes: Treatment variable is a dummy indicating whether import bans on the fertilizer inputs required by firm f exports in quarter t were above the 75th percentile for all firms.

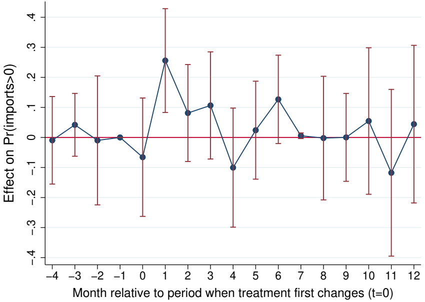
Back

Results: Pandemic (1/3)

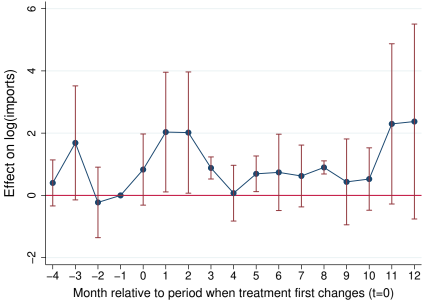
- **Concern**: import bans happened during Covid pandemic.
- Could our estimated ban effects actually be Covid effects in disguise?
  - No bias unless the pandemic affects banned products more than non-banned products.
- Extra check: when Covid arrived in March/2020, did imports of **“futurely banned”** fertilizers fall **disproportionately**?
  - Similar in spirit to a “placebo/falsification test”.
- **Results**: no evidence of negative Covid “effects” on ”futurely banned” fertilizer imports.

Back

Results: Pandemic (2/3)



(a) Covid's "Effect" on Imports (Extensive Margin)

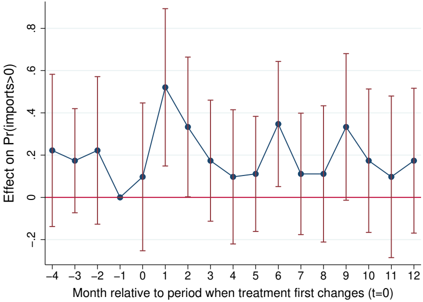


(b) Covid's "Effect" on Imports (Intensive Margin)

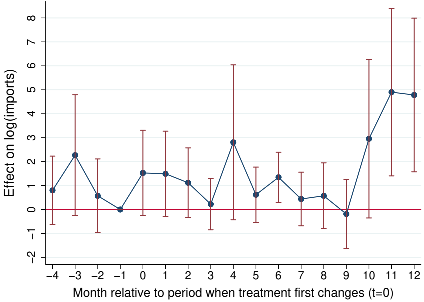
Notes: The treatment group consists of fertilizer products that would eventually be banned in 2021. Never-banned products (both non-banned fertilizers and other types of product) serve as the control group. The treatment period is defined as starting in March 2020.

Back

Results: Pandemic (3/3)



(a) Covid's "Effect" on Imports, fertilizer only (Extensive Margin)



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Notes: The treatment group consists of fertilizer products that would eventually be banned in 2021. Never-banned fertilizer products serve as the control group. The treatment period is defined as starting in March 2020.

Back

Model: Income Sources

- Agents types in region i: **mobile workers**, **estate workers**, **farmers**
  - N_i^m mobile workers provide labor (except in tea), earn wage w_i^m
  - N_i^e tea estate workers provide labor (in tea agriculture), earn wage w_i^e
  - N_i^F farmers rent out land, earn rent
- A set of **middlemen** (with measure-zero):
  - Earn income from license rents (if any) and sales of fertilizer (F_i).

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- Aggregate income E_i in region i is:

$$E_i = w_i^m N_i^m + w_i^e N_i^e + + \overbrace{\sum_k \gamma_k^l p_{ik} Q_{ik}}^{\text{land rent } (R_i)} + p_i^f F_i + QR_i^{rent}$$

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- Aggregate land **rent** distributed **in proportion to landholding size**.
  - Land **size** distribution assumed **log-normal(μ_i, σ_{Li}^2)**.

    $\Rightarrow$ Land **rent** distribution is **log-normal($\mu_i + \ln(\frac{R_i}{L_i})$, σ_{Li}^2)**

Back

Model: Consumer Demand (1/3)

- **A** vs **M**: PIGL (price-independent generalized linear) preferences:

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$$V(y, P^A, P^M) = \frac{1}{\eta}\left(\frac{y}{(P^A)^{\phi}(P^M)^{1-\phi}}\right)^{\eta} - \nu \ln\left(\frac{P^A}{P^M}\right)$$

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- Agro's expenditure share ξ^A is then given by:

$$\xi^A(y, P^A, P^M) = \phi + \nu\left(\frac{y}{(P^A)^{\phi}(P^M)^{1-\phi}}\right)^{-\eta}$$

Back

Model: Consumer Demand (2/3)

- Within agriculture, CES preferences across crops (k):

$$\beta_{nk}^{A} = b_k (P_{nk}/P_n^A)^{1-\sigma_A}, \text{ for } k \in \{1, ..., K\}$$

$$P_n^A = \Big(\sum_k b_k P_{nk}^{1-\sigma_A} \Big)^{\frac{1}{1-\sigma_A}}$$

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$$P^A_n = \left(\sum_k b_k P_{nk}^{1-\sigma_A} \right)^{\frac{1}{1-\sigma_A}}$$

- Within each crop, CES preferences across origins (i):

$$\beta^A_{ni,k} = b_{i,k} (p_{ik} \tau^A_{ni,k} / P_{nk})^{1-\sigma_K}$$

$$P_{nk} = \left(\sum_i b_{i,k} (p_{ik} \tau^A_{ni,k})^{1-\sigma_K} \right)^{\frac{1}{1-\sigma_K}}$$

  - $(\beta^A_{nk}, \beta^A_{ni,k})$: expenditure shares; (P^A_n, P_{nk}): price indices
  - $(b_k, b_{i,k})$: exogenous taste shifters; (p_{ik}): crop prices

Back

Model: Consumer Demand (3/3)

- Within manufacturing, CES preferences across origins (i):

$$\beta_{ni}^M = (p_{ni}^M / P_n^M)^{1-\sigma_M}$$

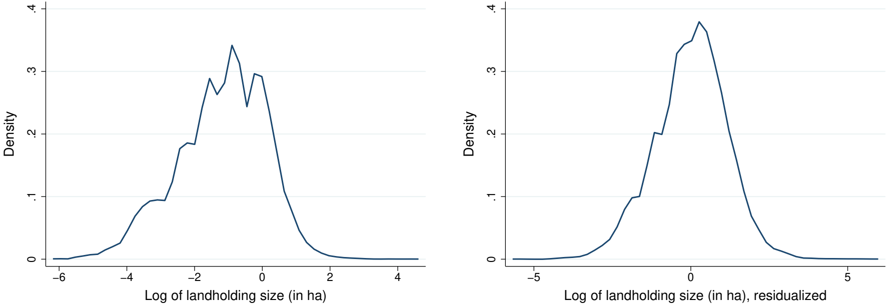
$$P_n^M = (\sum_i (p_{ni}^M)^{1-\sigma_M})^{\frac{1}{1-\sigma_M}}$$

  - β_{ni}^M: expenditure share (within manufacturing) on origin i
  - p_{ni}^M: price in n of the variety from i

Back

Empirics: Land inequality

Figure: Distribution of (Log) Landholding Sizes



(a) Unadjusted (b) Deviation from regional average

Notes: The figure shows kernel density estimates for the log of the size (in hectares) of households' landownings. Estimation uses Epanechnikov kernels with optimal bandwidth (0.2021 and 0.1647 for the left and right panels, respectively). Back Data

Empirics: Food expenditure and land inequality

- Aggregate agro expenditures in region n:

$$X_n^A = \phi E_n + \nu((P_n^A)^{\phi}(P_n^M)^{1-\phi})^{\eta}(N_n^m(w_n^m)^{1-\eta} + N_n^e(w_n^e)^{1-\eta} + (N_n^F)^{\eta} R_n^{1-\eta} e^{-\eta(1-\eta)\frac{\sigma_{Ln}^2}{2}})$$

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- Test: X_n^A decreasing in σ_{Ln}^2 (conditional on aggregate income):

	Dependent variable: Log of food expenditures	
	(1)	(2)
Land inequality ($\hat{\sigma}_{Ln}^2$)	-0.0035	-0.0036
	(0.004)	(0.0041)
Log of total expenditures ($\ln(E_n)$)	0.893***	0.890***
	(0.0259)	(0.0265)
Constant	1.700***	1.745**
	(0.6305)	(0.6469)
Adjusted $\ln(X_n^A)$?	NO	YES
Observations	25	25

Notes: *** denotes significance at 1% level, ** at 5% level. The outcome variable of the district-level regressions is log of aggregate food expenditure ($\ln(X_n^A)$) in Column (1) and its adjusted version ($\ln(X_n^A - \hat{\phi}E_n)$) in Column (2), with $\hat{\phi} = 0.0105$. Back Data

Model: Fertilizer Endowments

- Fertilizer is not produced, but simply given as an endowment:

$$Q_i^f = F_i$$

  - Q_i^f: fertilizer production in region i.
  - F_i: fertilizer endowment in region i.

- Within Sri Lanka, fertilizer endowments owned by measure-zero class of middlemen.

Back

Model: Manufacturing Production

- Manufacturing production function in region i is given by:

$$q_i^M = T_i^M n_i^M$$

  - n: labor input.
  - T_i^M: manufacturing productivity.

- Combined with CES demand, these assumptions imply:

$$\beta_{ni}^M = \frac{(w_i \tau_{ni}^M / T_i^M)^{1-\sigma_M}}{\sum_j (w_j \tau_{nj}^M / T_j^M)^{1-\sigma_M}}$$

  - β_{ni}^M: expenditure share (within manufacturing) on goods from region i
  - w_i: wages in region i

Back

Model: Agro Production (2/2)

- In plot ω growing crop k, unit cost minimization is:

$$c_{ik}(\omega) \equiv \min_{n,l,m} w_i n + r_{ik}(\omega) l + p_i^f f, \text{ such that: } q(n, l, f, T_{ik}^A) \geq 1$$

$$\Rightarrow c_{ik}(\omega) = \kappa_k w_i^{\gamma_k^n} (r_{ik}(\omega))^{\gamma_k^l} (p_i^f)^{\gamma_k^f} (T_{ik}^A)^{-1}$$

  - $r_{ik}(\omega)$: land rent; p_i^f: fertilizer price

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- Price equals marginal cost ($c_{ik}(\omega) = p_{ik}$) due to PC, so we get:

$$r_{ik}(\omega) = (T_{ik}^A)^{\frac{1}{\gamma_k^l}} \underbrace{(p_{ik})^{\frac{1}{\gamma_k^l}} (w_i)^{\frac{-\gamma_k^n}{\gamma_k^l}} (p_i^f)^{\frac{-\gamma_k^f}{\gamma_k^l}} (\kappa_k)^{\frac{-1}{\gamma_k^l}}}_{\equiv h_{ik}} \quad (2)$$

  - h: composite of relevant prices

Back

Market Clearing (1/3): Fertilizer

- If there are no QRs, worldwide market clearing in fertilizer is:

$$\underbrace{\sum_{i=1}^{R} F_i}_{\text{global fertilizer supply}} = \sum_{i=1}^{R} \frac{1}{p^f_{RoW}} \underbrace{\sum_k \gamma^f_k p_{ik} Q_{ik}}_{\text{fertilizer expenditure in } i}$$

- If QRs in place (imported fertilizer quantity $\leq \bar{f}$), separate market clearing for international and domestic markets:

$$\underbrace{\bar{f} + \sum_{i=1}^{I} F_i}_{\text{domestic fertilizer availability}} = \frac{1}{p^f_{LKA}} \sum_{i=1}^{I} \underbrace{\sum_k \gamma^f_k p_{ik} Q_{ik}}_{\text{fertilizer expenditure in } i}$$

$$\underbrace{F_{RoW} - \bar{f}}_{\text{fertilizer availability outside Sri Lanka}} = \frac{1}{p^f_{RoW}} \underbrace{\sum_k \gamma^f_k p_{i,RoW} Q_{i,RoW}}_{\text{fertilizer expenditure in RoW}}$$

Back

Model: Aggregate regional production

We aggregate crop production from the plot level to the regional level:

$$Q_{ik} = \mathcal{K}(T_{ik}^{A})^{\frac{1}{\gamma_k^l}} L_{ik}(p_i^{f,k})^{\frac{-\gamma_k^f}{\gamma_k^l}} (w_i^k)^{\frac{-\gamma_k^n}{\gamma_k^l}} (p_{ik})^{\frac{1}{\gamma_k^l}-1}$$

Back

Market Clearing (2/3): Agricultural Crops

- Crop k market clearing in region i is:

$$\underbrace{Q_{ik}}_{\text{local production of } k} = \sum_n \frac{\tau^A_{ni,k}}{p_{ni,k}} \underbrace{X^A_n \beta^A_{nk} \beta^A_{ni,k}}_{\text{exports of } k \text{ to region } n}$$

with crop prices satisfying bilateral pricing for all n:

$$p_{ni,k} = \tau^A_{ni,k} p_{ik}$$

Back

Market Clearing (3/3): Labor

- Mobile labor market clearing in each region i is:

$$\underbrace{N_i^m}_{\text{mobile labor force}} = \frac{1}{w_i^m}\Big(\sum_{k\neq \text{tea}} \underbrace{\gamma_k^n p_{ik} Q_{ik}}_{\text{wage bill of crop-}k\text{ farms}} + \underbrace{\sum_n X_n^M \beta_{ni}^M}_{\text{manufacturing wage bill}}\Big)$$

- Estate labor market clearing is:

$$\underbrace{N_i^e}_{\text{estate labor force}} = \frac{1}{w_i^e} \underbrace{\left(\gamma_{tea}^n p_{i,tea} Q_{i,tea}\right)}_{\text{wage bill of tea farms}}$$

- Note:
  - Demand for mobile labor comes from both agriculture and manufacturing.
  - Manufacturing uses labor as its only input, so full revenue is paid to labor in the form of wages.

Back

Welfare across agents

Workers (mobile / estate):

$$V_i^w = \frac{1}{\eta}\left(\underbrace{\frac{(1-t)w_i}{(P_i^A)^{\phi}(P_i^M)^{1-\phi}}}_{\text{real income (homoth.)}}\right)^{\eta} \; - \; \nu \ln\left(\underbrace{\frac{P_i^A}{P_i^M}}_{\text{relative price of food}}\right)$$

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Farmers:

$$V_i^F = \frac{1}{\eta}\left(\frac{1}{(P_i^A)^{\phi}(P_i^M)^{1-\phi}}\right)^{\eta}$$
$$\times \exp\left[\eta \underbrace{\left(\mu_i + \ln((1-t)R_i/L_i) + \frac{\sigma_{Li}^2}{2}\right)}_{\text{log mean income}} - \underbrace{\eta(1-\eta)\frac{\sigma_{Li}^2}{2}}_{\text{ineq. adj.}}\right]$$
$$-\nu \ln\left(\frac{P_i^A}{P_i^M}\right)$$

- Closed-form aggregation over rents from different sized landholdings.
- Farmer welfare depends on mean and dispersion of land income

Back

Welfare expressions

Workers (mobile / estate):

$$V_i^m = \frac{1}{\eta}\left(\frac{(1-t)w_i^m}{(P_i^A)^{\phi}(P_i^M)^{1-\phi}}\right)^{\eta} - \nu \ln\left(\frac{P_i^A}{P_i^M}\right)$$

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- η, ϕ, ν: non-homothetic preference parameters
- σ^A, σ^K: EoS across crops and origins

Welfare expressions

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- η, ϕ, ν: non-homothetic preference parameters
- σ^A, σ^K: EoS across crops and origins
- γ_k^f, γ_k^n, γ_k^l: fertilizer, labor, land shares in production
- μ_i, σ_{Li}^2: location and scale parameters of land ownership

Back

Estimating Equations: Engel elascitity (η)

- From model, agro's share (ξ^A) within total expenditure is:

$$\xi^A(y, P^A, P^M) = \phi + \nu\Big(\frac{y}{(P^A)^{\phi}(P^M)^{1-\phi}}\Big)^{-\eta}$$

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  - Rearrange, add household (h) and region (n) subscripts:

$$\ln(\xi^A_{nh} - \phi) = \ln(\nu) - \eta \ln(y_{nh}) + \eta\phi \ln(P^A_n) + (1-\eta)\phi \ln(P^M_n)$$

  - Collect region fixed effects, add HH size control and error term:

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  - Standard errors clustered at Primary Sampling Unit (PSU) level.

Back

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Back

Estimation: Production function parameters

- Leverage **properties of Cobb-Douglas** function to estimate $\{\gamma_k^f\}$:

$$\gamma_k^f = \frac{M_k^{f,LKA}}{p_k^{LKA} Q_k^{LKA}}, \; k \in \{1, ..., K\}$$

  - $M_k^{f,LKA}$: **\$ of fertilizer**/year used in national crop-k production Data
  - p_k^{LKA}: average export **price** of crop k (in \$/kg) Data
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- Apportion residual cost share to land/labor using I-O matrix: I-O tables

$$\gamma_k^n = \frac{CEMP_{s(k)}}{VA_{s(k)}} \times (1 - \gamma_k^f) \text{ and } \gamma_k^l = 1 - \gamma_k^n - \gamma_k^f$$

  - $CEMP_s$: total employee compensation in sector s
  - VA_s: total value added (at factor cost price) in sector s
  - $s(k)$: category to which crop k belongs (paddy, minor export crops, highland crops, coconut and toddy, potatoes, tea growing)

Back

Estimation: Demand-side parameters (1/2)

Non-homotheticity i.e. Engel elasticity (η)

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3. **Concern**: endogeneity of income
   - e.g. due to seasonality in agricultural prices
   - IV for income: Lottery income (no direct effect on food prices)

Estimation: Demand-side parameters (1/2)

Non-homotheticity i.e. Engel elasticity (η)

1. Governs sensitivity of food's expenditure share to income
2. From the model, derive the estimating equation:

$$\ln(\xi^{A}_{nh} - \phi) = -\eta \ln(y_{nh}) + \theta hhsize_{nh} + \omega_n + \epsilon_{nh}$$

   - h: indexes households; n: indexes regions
   - ξ^{A}: food's expenditure share; y: income

3. **Concern**: endogeneity of income
   - e.g. due to seasonality in agricultural prices
   - IV for income: Lottery income (no direct effect on food prices)
4. 2SLS estimation on household survey data:
   - **Engel elasticity** $\hat{\eta} = 0.66$

Details Results table Values back

Preference Parameter Estimates (2SLS)

	Panel A: Second Stage	
	Dependent variable:	
	Log of food's expenditure share (1)	Log of crop's expenditure share (2)
Log of household income $[\hat{\eta}]$	-0.656*** (0.129)	
Log of crop price $[1-\hat{\sigma}_A]$		-0.714*** (0.153)
Household size	0.135*** (0.029)	
	Panel B: First Stage	
	Dependent variable:	
	Log of household income (1)	Log of crop price (2)
Lottery/ad hoc income	8.81e-07*** (1.37e-07)	
Disaster/other relief payments	8.16e-07*** (1.42e-07)	
Regional potential yield > 0		-.062*** (.0044)
F-statistic	37.2***	199.4***
p-value	0.0000	0.0000
Fixed Effects?	PSU	Crop, HH
Clustered SEs?	by PSU	by HH
Weighted?	Yes	Yes
Observations	19,910	91,416

Notes: *** denotes significance at the 1% level, ** at the 5% level. Standard Errors in parentheses.

Back

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  - Then estimate **dispersion parameter** σ^2_{Ln} in district n as:

$$\hat{\sigma}^2_{Ln} = \frac{|\mathbb{S}_n|}{|\mathbb{S}_n| - 1} \left(\frac{1}{\sum_{h' \in \mathbb{S}_n} w_{h'}}\right) \sum_{h \in \mathbb{S}_n} w_h \big(\ln(L^h) - \bar{lL}_n\big)^2$$

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- Log-normality implies average landholding size is $\exp(\mu_n + \sigma^2_{Ln}/2)$:
  - Set **scale parameter** μ_n to match data: $\hat{\mu}_n = \ln\left(L_n/N^F_n\right) - \hat{\sigma}^2_{Ln}/2$
  - **Data**: land area (L_n), # of farmers (N^F_n). Data: land Data: farmers

Back

Inversion (Definition)

Definition (Inversion)

Given the model's parameters, observable exogenous variables ($\boldsymbol{N}^m$, $\boldsymbol{N}^F$, $\boldsymbol{L}$, $\boldsymbol{\tau}$), and a specific value for a vector of observable endogenous variables ($\boldsymbol{w}$, $\boldsymbol{Q}$, $\boldsymbol{p^A}$, $\boldsymbol{p^f}$), an **inversion** is a set of unobservable exogenous variables ($\boldsymbol{T}$, $\boldsymbol{b}$, $\boldsymbol{N}^e$, $\boldsymbol{F}$) and unobservable endogenous variables ($\boldsymbol{p}^-$, $\boldsymbol{P}$, $\boldsymbol{R}$, $\boldsymbol{E}$, $\boldsymbol{X}$, β) such that the resulting set of endogenous variables is an equilibrium of the economy with the resulting set of exogenous variables and with no quantitative restrictions.

Back

Inversion: System of equations

- Rewrite model's market clearing conditions into system of equations:

$$F^G \equiv \sum_{i=1}^{R} F_i = \frac{1}{p^f_{RoW}} \sum_{i=1}^{R} \sum_k \frac{\gamma_k^f}{S_k} p_{ik} Q_{ik}$$

$$Q_{ik} = \frac{1}{p_{ik}} \sum_n X_n^A b_k \left(\frac{P_{nk}}{P_n^A}\right)^{1-\sigma_A} b_{ik} \left(\frac{\tau^A_{ni,k} p_{ik}}{P_{nk}}\right)^{1-\sigma_K}$$

$$w_i^m N_i^m = \left(\sum_{k \neq \text{tea}} \frac{\gamma_k^n}{S_k} p_{ik} Q_{ik}\right) + \sum_n (E_n - X_n^A) \left(\frac{\tau^M_{ni} w_i}{T_i^M P_n^M}\right)^{1-\sigma_M}$$

$$w_i^e N_i^e = \frac{\gamma_k^n}{S_k} p_{i,\text{tea}} Q_{i,\text{tea}}$$

  - **Black** variables: directly observed or estimated in prior stage
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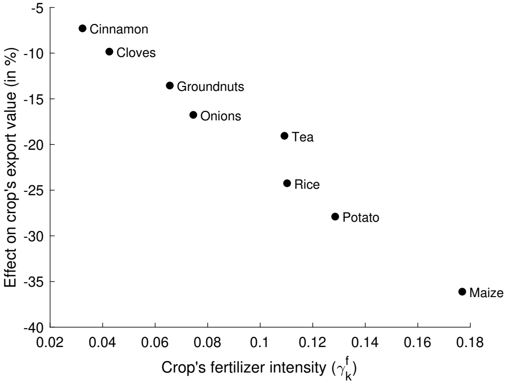
  - **Black** variables: directly observed or estimated in prior stage
  - **Red** variables: key unobserved variables
  - **Blue** variables: "intermediaries", functions of black/red only
- Solve numerically for red/blue, then recover agro productivity T_{ik}^A from land market clearing condition: $\gamma_k^l p_{ik} Q_{ik} = (T_{ik}^A)^{\frac{1}{\gamma_k^l}} h_{ik} L_{ik}$

Back

Counterfactual results: Effects on agricultural production and exports

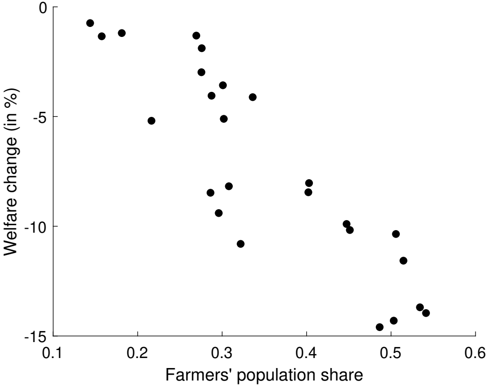


- Stylized Facts: "2. Rice production ↓ by 31.5% and 3. Fertilizer-intensive agro exports declined significantly after the ban on fertilizer imports"

Back

Counterfactual results: Increase in fertilizer import costs

Occupational composition and (average) welfare effects



Notes: The figure plots each district's farmer population share against the change in its cross-type average welfare (expressed as an equivalent % income variation) between the baseline equilibrium and the counterfactual equilibrium. The correlation coefficient between farmers' population share and % EV is -0.88. Back

Equivalent Variation

- Indexing baseline/counterfactual equilibria by 0/1 (respectively), the equivalent variation (EV) can generally be written as:

$$EV = V^{-1}(v_1; P_0^A, P_0^M) - y_0$$

  - V^{-1}: inverse of indirect utility function
  - v: utility level; y: income; (P^A, P^M): sectoral price indices

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- So, EV for a worker (of type $t \in \{m, e\}$) in region n is:

$$EV_n^t = V^{-1}(V_{n,1}^t; P_{n,0}^A, P_{n,0}^M) - w_{n,0}^t$$

- EV for representative farmer in region n:

$$EV_n^F = V^{-1}(V_{n,1}^F; P_{n,0}^A, P_{n,0}^M) - V^{-1}(V_{n,0}^F; P_{n,0}^A, P_{n,0}^M)$$

- Cross-type average (relative) EV in region n:

$$\tilde{EV}_n^{avg} = \left(\frac{N_n^m}{N_n}\right)\tilde{EV}_n^m + \left(\frac{N_n^e}{N_n}\right)\tilde{EV}_n^e + \left(\frac{N_n^F}{N_n}\right)\tilde{EV}_n^F$$

Back

Proof: Agro expenditure aggregation (1/2)

Prove that aggregated agro expenditure in region n (X_n^A) can be written as:

$$X_n^A = \phi E_n + \nu((P_n^A)^{\phi}(P_n^M)^{1-\phi})^{\eta}(N_n^m(w_n^m)^{1-\eta} + N_n^e(w_n^e)^{1-\eta} + N_n^F r_n^{1-\eta} e^{-\eta(1-\eta)\frac{\sigma_{Ln}^2}{2}})$$

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- Using PIGL agro share, write aggregate agro expenditure by workers as:

$$\begin{aligned} X_n^{A,W} &= N_n^m w_n^m \xi^A(w_n^m, P_n^A, P_n^M) + N_n^e w_n^e \xi^A(w_n^e, P_n^A, P_n^M) \\ &= \phi(N_n^m w_n^m + N_n^e w_n^e) + \nu((P_n^A)^{\phi}(P_n^M)^{1-\phi})^{\eta}(N_n^m(w_n^m)^{1-\eta} + N_n^e(w_n^e)^{1-\eta}) \end{aligned} \tag{3}$$

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- Individual farmer h with rent R^h spends $R^h \xi^A(R^h, P_n^A, P_n^M)$ on agro. Thus, average agro expenditure by farmers in n is:

$$\bar{X}_n^{A,F} = \phi r_n + \nu((P_n^A)^\phi (P_n^M)^{1-\phi})^\eta \mathbb{E}[(R^h)^{1-\eta}] \tag{4}$$

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- Log-normal distribution of R^h is inherited by $(R^h)^{1-\eta}$:

$$(R_n^h)^{1-\eta} \sim \text{log-N}((1-\eta)[\mu_n + \ln(R_n) - \ln(L_n)], (1-\eta)^2 \sigma_{Ln}^2)$$

Back

Proof: Agro expenditure aggregation (2/2)

- Using properties of the log-normal, expectation $\mathbb{E}[(R^h)^{1-\eta}]$ is:
$$\mathbb{E}[(R^h)^{1-\eta}] = \exp((1-\eta)[\mu_n + \ln(R_n) - \ln(L_n)] + (1-\eta)^2\sigma_{Ln}^2/2)$$

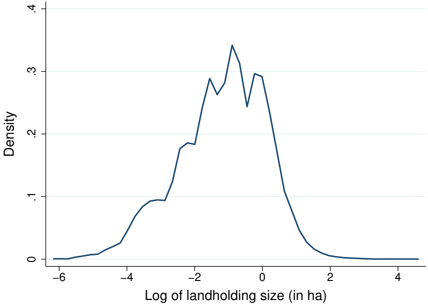
- Rearranging terms:
$$\mathbb{E}[(R^h)^{1-\eta}] = \left(\exp\left(\mu_n + \frac{\sigma_{Ln}^2}{2}\right)\frac{N_n^F}{L_n} \times \frac{R_n}{N_n^F} \times \exp\left(-\eta\frac{\sigma_{Ln}^2}{2}\right)\right)^{1-\eta}$$

- Noting that $\exp(\mu_n + \sigma_{Ln}^2/2)$ is the average land size in region n ($\frac{L_n}{N_n^F}$), cancel terms to get:
$$\mathbb{E}[(R^h)^{1-\eta}] = r_n^{1-\eta}\exp\left(-\eta(1-\eta)\frac{\sigma_{Ln}^2}{2}\right) \tag{5}$$

- To get aggregate agro expenditure, sum workers', farmers', and middlemen's:
$$X_n^A = X_n^{A,F} + X_n^{A,W} + X_n^{mm} = N_n^F\bar{X}_n^{A,F} + X_n^{A,W} + +X_n^{mm}$$
- To conclude the proof, apply equations (3), (4), (5), and income identity ($E_n = N_n^m w_n^m + N_n^e w_n^e + R_n + p_n^f F_n + QR_n^{rent}$) Back

Estimation: Land distribution parameters

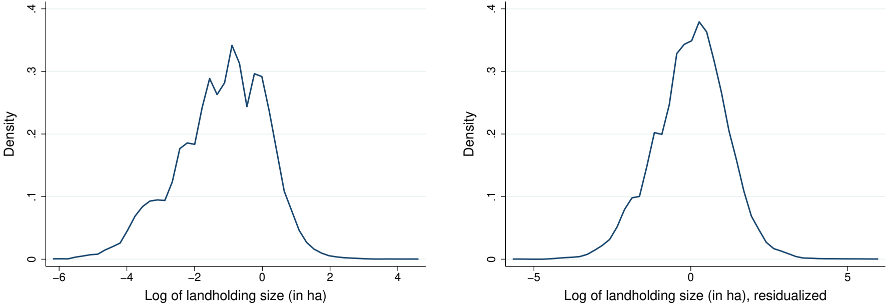
Figure: Distribution of (Log) Landholding Sizes



(a) Unadjusted

Estimation: Land distribution parameters

Figure: Distribution of (Log) Landholding Sizes



(a) Unadjusted

(b) Deviation from regional average

Estimation: Land distribution parameters

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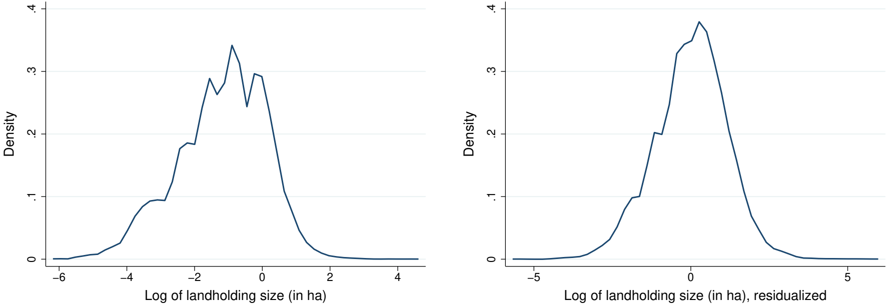

(a) Unadjusted

(b) Deviation from regional average

- **Land distribution parameters**: Formulae
    1. Dispersion parameter: land size dispersion (Househould survey)
    2. Scale parameter: set to match average farm size in the data

Estimation: Other parameters and unobservables

- **Supply side: Cobb-Douglas production function parameters**
  1. Share of fertilizer in crop production costs (National Fertilizer Secretariat) *Formulae* Values
  2. Relative land and labor cost shares (Input-output tables)

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  - **Intuition**: set unobservables to explain "gaps". Example:
    - Rice Q in Galle too high after accounting for land size, inputs prices
    - Explain gap by imposing sufficiently large productivity $T^{A}_{Galle,rice}$
  - **Data**: wages, # of mobile workers/farmers, fertilizer price, agro production/cultivated area/producer prices. System of equations

Validation: Night lights (NL)

1. Model predicts 6.3% income decline in fertilizer-intensive relative to less fertilizer-intensive districts (NL data: 7.7%) Covid placebo

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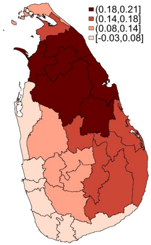
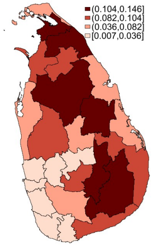


(a) Fall in (log) income implied by change in NL (4/2021 - 1/2022)



(b) Fall in (log) income predicted by model's counterfactual

2. Model replicates key stylized facts: 37.9% (model) vs 31.6% (data) decline in rice, sharp drops in crop yields and agricultural exports

Back

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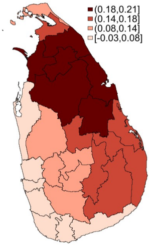

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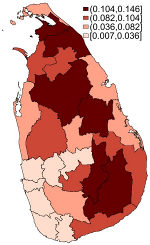

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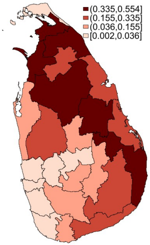

(c) Fertilizer's importance in local economy

2. Model replicates key stylized facts: 37.9% (model) vs 31.6% (data) decline in rice, sharp drops in crop yields and agricultural exports

Back

PE and GE Elasticities of Yield to Fertilizer

Yield response to any combination of price changes: Back

$$d \ln Y_{ik}(\omega) = -\frac{\gamma_k^f}{\gamma_k^l} d \ln p_i^{f,k} - \frac{\gamma_k^n}{\gamma_k^l} d \ln w_i^k + \left(\frac{1}{\gamma_k^l} - 1 \right) d \ln p_i^k \qquad (6)$$

Partial Equilibrium (only fertilizer price moves):

$$\epsilon_{ik}^{PE} \equiv \frac{\partial \ln Y_{ik}(\omega)}{\partial \ln FI_{ik}(\omega)} = \frac{\gamma_k^f}{\gamma_k^l + \gamma_k^f} \qquad (7)$$

General Equilibrium (wages and crop prices also adjust):

$$\epsilon_{ik}^{GE} \equiv \frac{\partial \ln(Q_{ik}/L_{ik})}{\partial \ln(f_{ik}/L_{ik})} = \frac{(\gamma_k^f + \gamma_k^l)\, d \ln p_i^{f,k} \cdot \frac{\gamma_k^f}{\gamma_k^f + \gamma_k^l} + \gamma_k^n\, d \ln w_i^k + (-1)\, d \ln p_i^k\, (1 - \gamma_k^l)}{(\gamma_k^f + \gamma_k^l)\, d \ln p_i^{f,k} + \gamma_k^n\, d \ln w_i^k + (-1)\, d \ln p_i^k} \qquad (8)$$

Since $d \ln w_i^k < 0$ and $d \ln p_i^k > 0$ under the ban: $\epsilon_{ik}^{GE} < \epsilon_{ik}^{PE}$