The Dynamic Effects of Weather Shocks on Agricultural Production

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1. Introduction

Motivations (1/3)

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- Particularly harmful for developing countries.
- Quantitatively assessing physical risk is important as temperature continues to increase.
- Anticipating the cost of physical risk important to implement adaptation policies.

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2. Temporal aggregation of weather data: annual weather data underestimate physical risk as extreme positive and negative weather events average out throughout the year (Colacito, Hoffmann, and Phan (2019)).
3. Heterogenous effects across seasons, crops, and space: effects of the weather different during growing season (vs. harvesting), or per type of crops (eg., maize vs. rice).

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- Usual quantitative assessments rely on annual data (Jagnani et al. 2020; DAgostino and Schlenker 2016; Burke and Emerick 2016; Deschênes and Greenstone 2007).
- This leads to underestimated risks (Cui et al. (2024)): possibly large implications for misanticipating future food shortages.

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4. No temporal aggregation of weather data: only monthly extremes considered (caveat #2).

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  - A micro to macro analysis.

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    - a 1.5% decline in exports
    - a modest reduction in inflation.

2. Data

Agricultural Data

- Rice, Maize, Potatoes, Cassava

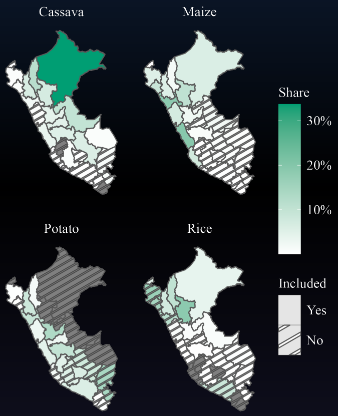

Figure 1: Regional distribution of crop production by administrative regions

Agricultural Data

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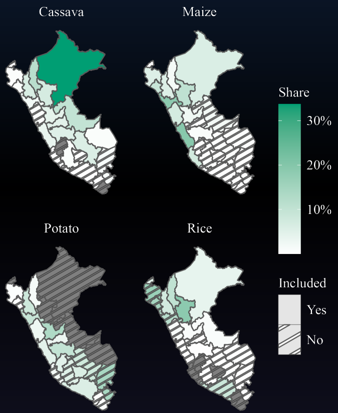

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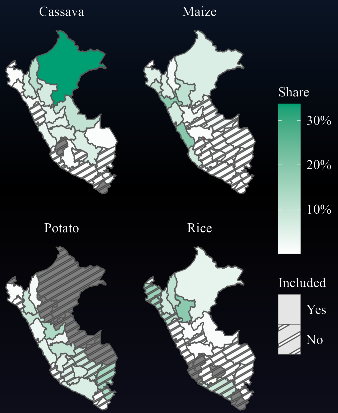

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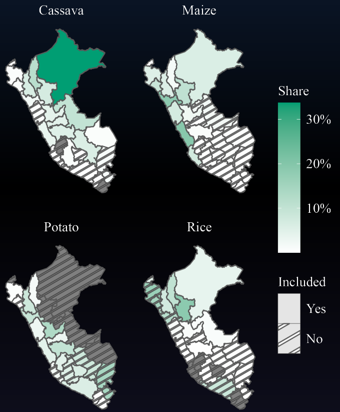

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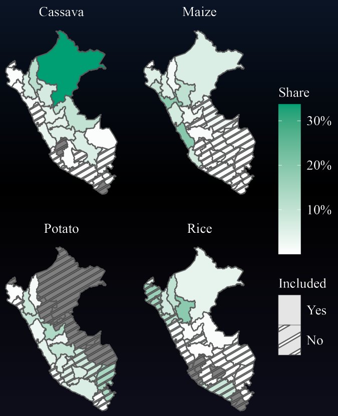

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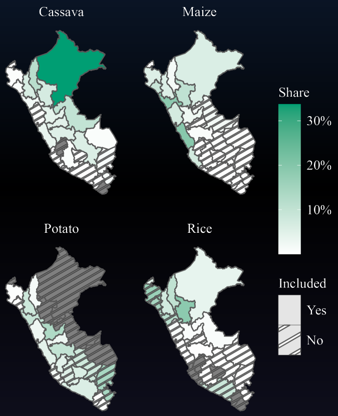

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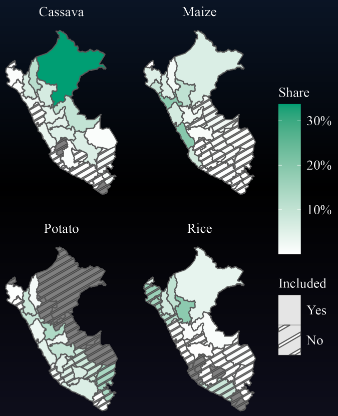
- Percentage deviation from monthly average (details).



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Weather Data (1/4)

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Weather Data (2/4)

Step 1: Weather at the Monthly Grid Level

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For grid cell ℓ and for a specific month m in year y, we compute:

Average maximum temperature:

$$\mathcal{T}_{\ell,y,m} = \frac{1}{N_{dm}} \sum_{d=1}^{N_{dm}} \mathcal{T}_{\ell,y,m,d}$$

where N_{dm} is the number of days in month m.

Total rainfall:

$$\mathcal{P}_{c,y,m} = \sum_{d=1}^{N_{dm}} \mathcal{P}_{c,y,m,d}$$

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For $\mathcal{W}_{c,y,m}$ (temperatures and precipitations):

A. Climate Normals

For each month m: average monthly values over the 30-year period from 1986 to 2015:

$$\overline{\mathcal{W}}_{\ell,\bullet,m} = \frac{1}{y_T - y_0 + 1} \sum_{y=y_0}^{y_T} \mathcal{W}_{\ell,y,m}.$$

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B. Deviations from Normals

We compute the deviations from the monthly climate normals:

$$W_{\ell,m,y} = \mathcal{W}_{\ell,y,m} - \overline{\mathcal{W}}_{\ell,\bullet,m}.$$

Weather Data (4/4)

Step 3: Regional Aggregation

From the monthly grid-level weather data, we compute monthly regional aggregates at date t (year y and month m) using a weighted mean:

$$W_{i,t} = \frac{\sum_{c \in \mathcal{R}_i} \omega_c^{\text{area}} \omega_c^{\text{cropland}} W_{c,t}}{\sum_{c \in \mathcal{R}_i} \omega_c^{\text{area}} \omega_c^{\text{cropland}}},$$

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ω_c^{area}: proportion of the cell to the total surface area of the region

$\omega_c^{\text{cropland}}$: proportion that the cell represents in the agricultural production of the region.

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3. Weather data: temperature anomalies and precipitation anomalies (deviation from historical monthly average), same period, aggregated at the regional scale.

3. Empirical Analysis

Local Projections

How sensitive agricultural output is to exogenous changes in the weather?

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Model of Local Projections (Jordà 2005), in a panel dimension (Acevedo et al. 2020) (region x time), estimated independently for each crop:

$$\begin{aligned} \underbrace{y_{c,i,t+h}}_{\text{Production}} = \underbrace{\alpha_{c,i,h}}_{\text{Reg. fixed effect}} + \beta^T_{c,h} T_{i,t} + \beta^P_{c,h} P_{i,t} \\ + \delta_{c,i,h} \underbrace{X_t}_{\text{Controls}} + \varepsilon_{c,i,t+h} \end{aligned} \quad . \tag{1}$$

We are interested in the estimated coefficients associated with temperature and precipitation shocks for various time horizons $h = \{0, 1, ..., T_c\}$ with T_c the IRF time length (or the crop's natural time of growth from planting to harvesting ~6 to 8 months).

Local Projections

$$y_{c,i,t+0} = \alpha_{c,i,0} + \beta^T_{c,0} T_{i,t} + \beta^P_{c,0} P_{i,t} + \delta_{c,i,0} X_t + \varepsilon_{c,i,t+0}$$

$$y_{c,i,t+1} = \alpha_{c,i,1} + \beta^T_{c,1} T_{i,t} + \beta^P_{c,1} P_{i,t} + \delta_{c,i,1} X_t + \varepsilon_{c,i,t+1}$$

$$y_{c,i,t+2} = \alpha_{c,i,2} + \beta^T_{c,2} T_{i,t} + \beta^P_{c,2} P_{i,t} + \delta_{c,i,2} X_t + \varepsilon_{c,i,t+2}$$

$$\ldots$$

$$y_{c,i,t+H} = \alpha_{c,i,H} + \beta^T_{c,H} T_{i,t} + \beta^P_{c,H} P_{i,t} + \delta_{c,i,H} X_t + \varepsilon_{c,i,t+H}$$

- We are interested in the coefficients: $\{\beta^T_{c,0}, \beta^T_{c,1}, \beta^T_{c,2}, \ldots \beta^T_{c,H}\}$ and $\{\beta^P_{c,0}, \beta^P_{c,1}, \beta^P_{c,2}, \ldots \beta^P_{c,H}\}$

Linear Response

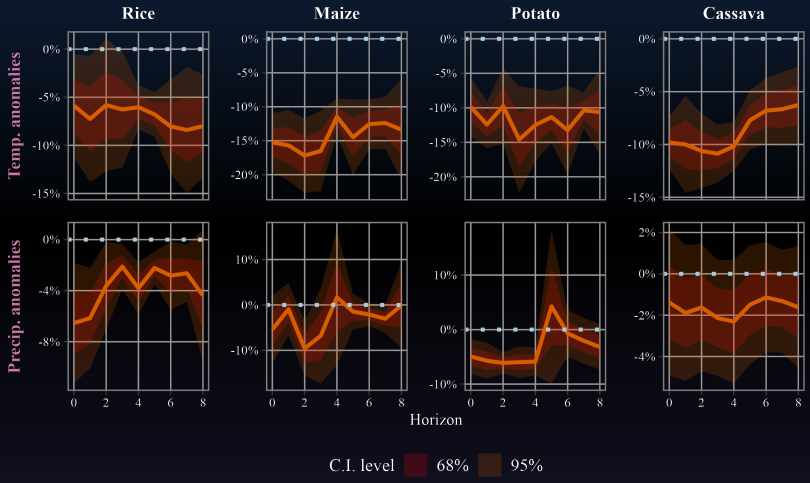

Figure 3: Agricultural production response to a weather shock

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  How do time-dependency of weather shocks shape propagation patterns?

Seasonal Effect (2/3)

Similarly to Auerbach and Gorodnichenko (2011), we accomodate the LP framework for time-dependency.

$$\begin{aligned} y_{c,i,t+h} =& \Phi\left(\hat{z}_{c,i,t}\right)\left[\alpha^{G}_{c,i,h} + \beta^{G,T}_{c,h} T_{i,t} + \beta^{G,P}_{c,h} P_{i,t} + \delta^{G}_{c,i,h} X_t\right] \\ &+ \left(1 - \Phi\left(\hat{z}_{c,i,t}\right)\right)\left[\alpha^{H}_{c,i,h} + \beta^{H,T}_{c,h} T_{i,t} + \beta^{H,P}_{c,h} P_{i,t} + \delta^{H}_{c,i,h} X_t\right] \\ &+ \varepsilon_{c,i,t+h} \end{aligned}$$

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- Two states: Growing season and Harvesting season
- Transition function: CDF of the standard normal distribution.
- When $\hat{z}_{c,i,t}$ high –> surface is planted –> $\Phi\left(\hat{z}_{c,i,t}\right)$ close to one –> informative of $\beta^{G,T}_{c,h} T_{i,t}$ and $\beta^{G,P}_{c,h} P_{i,t}$.

Seasonnal Effect (3/3)

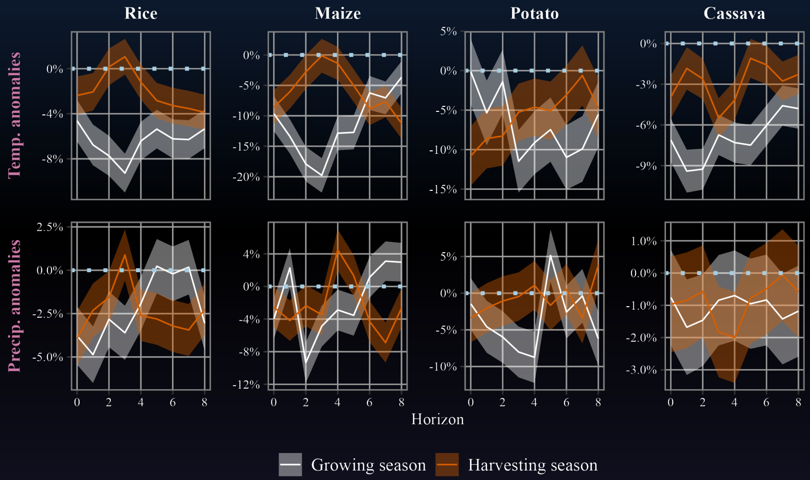

Figure 4: Agricultural prod. response to a weather shock contrasting for growing vs. harvesting season

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We compute national weather-adjusted agricultural production:

$$y_t^{\omega} = \frac{1}{\sum_c \omega_{c,t}} \sum_c \sum_h \sum_i \frac{1_{\text{signif}_{c,i,t,h}} \times \left(\beta_{c,h}^{T} T_{i,t-h} + \beta_{c,h}^{P} P_{i,t-h} \right) \times \omega_{c,t}}{\text{card}(I_{c,t})}, \qquad (2)$$

where $\omega_{c,t} = \sum_i y_{c,t,i}^{\text{raw}} \times p_c$ is a quantity weight for crop c at time t, with p_c the average selling price of crop c.

Aggregate Fluctuations (2/3)

The agricultural production is then expressed as the deviation (loss) from the expected trend: the 'weather component of agricultural losses'

$$WCAL_t = -100 \times (y_t^\omega - \overline{y_t^\omega}). \tag{3}$$

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A Structural vector auto-regressive (SVAR) model with Choleski decomposition is a straightforward way to quantitatively assess dynamic interactions across time series:

$$Y_t = \phi_0 + \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t \tag{4}$$

with $Y_t = \left[WCAL_t,\, RER_t,\, \pi_t^A,\, \pi_t,\, X_t,\, y_t^A,\, r_t,\, y_t \right]$.

Aggregate Fluctuations (3/3)

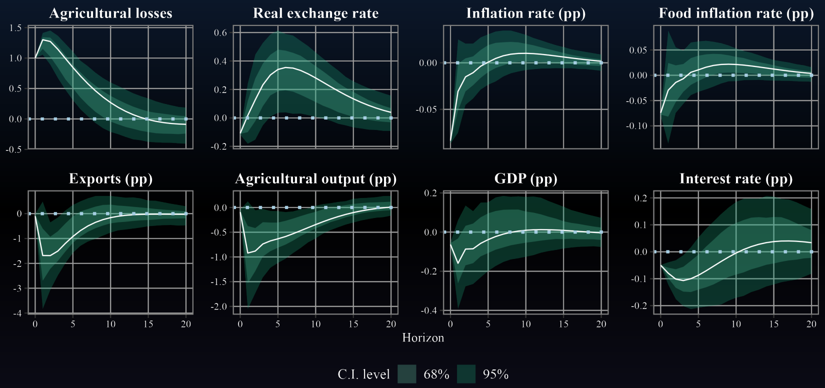

Figure 5: VAR(2) system response to one standard deviation orthogonal shock to the weather aggregate cost equation

4. Conclusion

Wrap-up

Objective: analyze the propagation mechanism of a weather shock on agricultural production at a monthly frequency, for various crops, in heterogeneous geographical and seasonal patterns.

1. Adverse weather shock: leads to a negative downturn in agricultural prod.:

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Comments are welcome: ewen.gallic@univ-amu.fr

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Appendix

Agricultural Data (1/4)

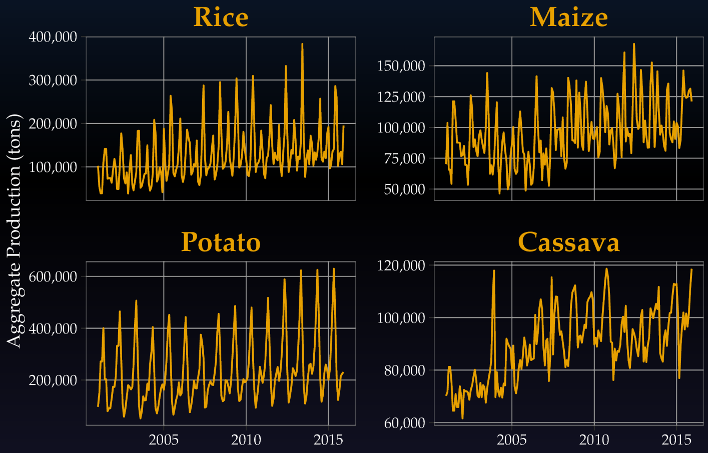

Figure 6: National monthly crop production for selected cultures (in tons)

Agricultural Data (2/4)

Table 1: Monthly production (in tons) per type of crop

Culture	Mean	Median	Std Dev.	Min.	Max.	# Regions	# Obs.
Cassava	6,004	3,878	7,792	0	16,080	15	2,631
Maize	7,170	4,336	8,490	0	2,705	13	2,271
Potato	17,252	5,801	30,155	6	360,070	12	2,091
Rice	13,128	4,441	16,213	3.9	8,863	7	1,212

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1. Demeaned data:

$$y_{c,i,m,t}^{\text{demeaned}} = \frac{y_{c,i,m,t}^{\text{raw}}}{n_T \sum_{t=1}^{T} y_{c,i,m}^{raw}} \tag{5}$$

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2. Estimate production with OLS, with a quadratic trend for crop c, in region i, in month m, by OLS:

$$y_{c,i,m}^{\text{demeaned}} = \beta_{c,i,m} t + \gamma_{c,i,m} t^2 + \varepsilon_{c,i,m} \tag{6}$$

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3. Define detrended value:

$$y_{c,i,m} = y^{demeaned}_{c,i,m} - (\hat{\beta}_{c,i,m} t + \hat{\gamma}_{c,i,m} t^2) \tag{7}$$

Agricultural Data (4/4)

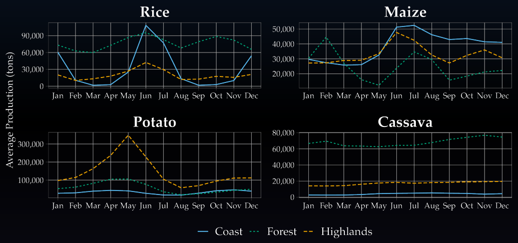

Figure 7: Crop production by months and natural regions (in tons)

Agricultural Share of each Cell within a Region

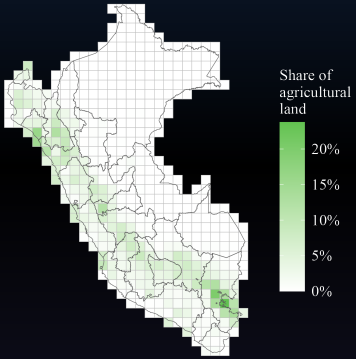

Figure 8: Regional agricultural area for each cell

Conceptual framework (1/3)

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For crop c in region i at time t:

$$Y_{c,i,t} = \underbrace{A_{c,i}}_{\text{TFP}} \quad \overbrace{N_{c,i,t}}^{\text{labour demand}} \quad \underbrace{H_{c,i,t}}_{\text{harvested area}} \tag{8}$$

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$$H_{c,i,t} \leq L_{c,i,t} \exp\left(\sum_{h=0}^{T_c} \beta_{c,h} W_{i,t-h}\right) \tag{9}$$

- $H_{c,i,t}$: Harvested area for crop c in region i at time t

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- $W_{i,t-h}$: Weather shocks realized in region i at time t-h

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- $ln(Y_{c,i,t}/L_{c,i,t})$: Percentage deviation of agricultural production from its potential value

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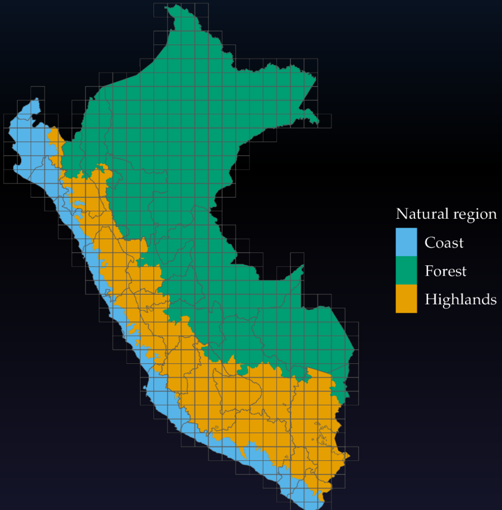
- $ln(N_{c,i,t})$: Log of labor demand

Natural Regions



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$$\Gamma_{c,i,t,h} = \beta^{T}_{c,h} T_{i,t-h} + \beta^{P}_{c,h} P_{i,t-h} \tag{11}$$

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2. Calculating Quantity Weights: production in monetary terms

$$\omega_{c,t} = \sum_{i} y^{\text{raw}}_{c,t,i} \times p_c, \tag{12}$$

$y^{\text{raw}}_{c,t,i}$: raw agricultural production in tons
p_c: average selling price of crop c

Weather-Driven Agricultural Loss (3/3)

3 Weather-Adjusted Agricultural Production:

$$y^{\omega}_{c,t} = \sum_h \sum_i \frac{1_{\text{signif}_{c,i,t,h}} \times \Gamma_{c,i,t,h} \times \omega_{c,t}}{\text{card}(I_{c,t})}, \tag{13}$$

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4. Aggregating Crop-Specific Production:

$$y^{\omega}_{t} = \frac{\sum_c y^{\omega}_{c,t}}{\sum_c \omega_{c,t}}, \tag{14}$$

$\omega_{c,t}$: the quantity weights computed in step 2

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5. Expressing Weather-Adjusted Production as a Deviation from Trend:

$$WCAL_t = -100 \times (y^{\omega}_t - \overline{y^{\omega}_t}). \qquad (15)$$

VAR Data

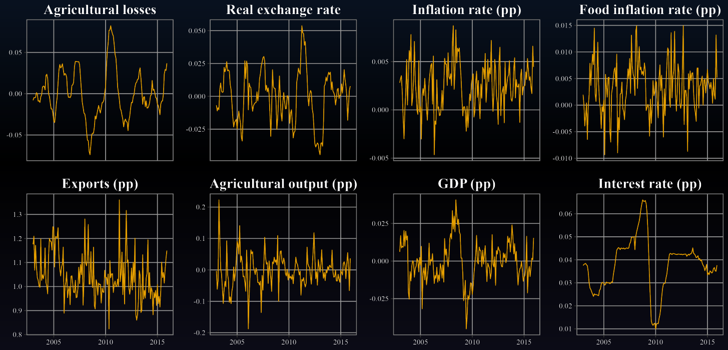

Figure 10: Series used in the Vector Auto-regressive Model