The Dynamic Effects of Weather Shocks on Agricultural Production

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Motivation

IPCC (2022)

- Ongoing rise in global surface temperatures, frequency, and intensity of extreme weather events, and expected to increase in the near term: Physical risk.
- Many implications for economies, especially for developing economies, mostly located in warmer and more vulnerable regions.
- Impact on productivity, health, development, conflicts, etc

Motivation

Important economic impacts of weather variations in the Agricultural sector (Dell et al., 2014)

- Increased detrimental effect in developing countries.
    - Effects on output.
    - Effects on employment.

Objective of the paper

Measure quantitatively the dynamic effects of abnormal weather realizations on the supply of agricultural production over time.

Why Peru ?

- Upper middle-income country (World Bank classification)
- Agricultural sector (World Bank, 2015) :
  - 7.04 % of GDP
  - 28.26% of total employment
  - 18.23% of total land
- Exposed to the strong weather variations affecting differently the various regions of the country.

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Literature Review

Economic growth and climate nexus

- Reduction of economic growth with higher temperatures. [Dell et al., 2012; Colacito et al., 2019; Hsiang, 2010]

- Impacts of climate change over productivity [Ortiz-Bobea et al. (2021)]

Effects of weather and climate change on agriculture

- Agronomic models based on crop simulations (see, *e.g.*, Rosenzweig et al., 2013; Asseng et al., 2014

- Annual panel data approach [Welch et al., 2010; Powell and Reinhard, 2016; Schmitt et al., 2022; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; D'Agostino and Schlenker, 2016]

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Databases

Agricultural data

Monthly statistical reports "EL AGRO EN CIFRAS" from the Ministry of Agriculture and Irrigation of Peru (MINAGRI) from 01/2001 to 12/2015. (180 months)
Monthly data on production, economic indicators, planted and harvested area, prices, (...) by region and culture.

Macroeconomic data

Banco Central de Reserva del Peru:

- Peruvian CPI
- Sol/US Exchange rate
- National interest rate
- Industrial production index

Databases

Meteorological data[1]

- PISCOt V1.1 database: gridded daily temperature data set, (1981 - 2016)
- CHIRPS v2.0 database: gridded daily rainfall data set (1981 to present)
- Copernicus, a set of dynamic land cover maps

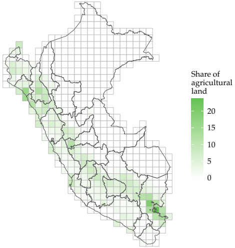

Figure: Agricultural area for each grid cell

[1] Exact sources in appendix

Variables of interest

Agricultural production

$$y_{cim}^{raw} = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \varepsilon_{cim}$$

where c: crop type, i: the region, and $\varepsilon_{cim} \sim \mathcal{N}(0, 1)$.
Let y^{det} denote the detrended expression, we deseasonalize the production by dividing each month by its monthly average as follows:

$$y_{c,i,t} = \ln\left(y_{c,i,t}^{det}\right) - \ln\left(\overline{y}_{c,i,m}^{det}\right), \tag{1}$$

where $\overline{y}_{c,i,m}^{det}$ is the monthly average of detrended production of crop c in region i at specific month m.

Variables of interest

Weather anomalies

$$\mathcal{W}_{i,y,m} = \overline{\left(\{\mathcal{W}_{i,y,m,d}\}_{d=1}^{31}\right)}.$$

We use the distance of the weather variable from its monthly average:

$$W_{i,t} = W_{i,y,m} = \mathcal{W}_{i,y,m} - \overline{\mathcal{W}}_{i,m},$$

where $\overline{\mathcal{W}}_{i,y,m} := (y_T - y_0)^{-1} \sum_{y=y_0}^{y_T} \mathcal{W}_{i,y,m}$.

Temperatures anomaly $T_{i,t}$:

$$T_{i,t} = \mathcal{T}_{i,y,m} - \overline{\mathcal{T}}_{i,m} \tag{2}$$

Precipitations anomaly $P_{i,t}$:

$$P_{i,t} = \mathcal{P}_{i,y,m} - \overline{\mathcal{P}}_{i,m} \tag{3}$$

Descriptive statistics

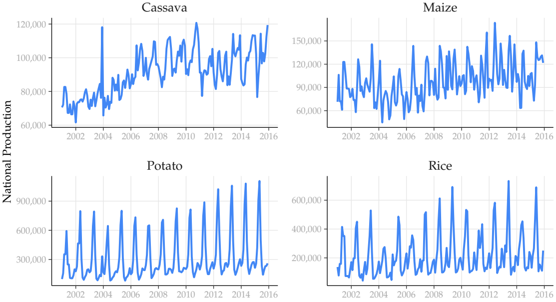

Figure: National monthly crop production for selected cultures (in tons)

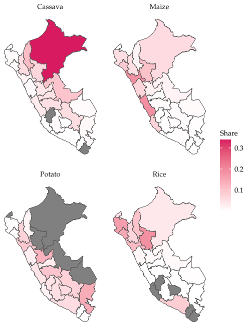

Figure: Regional distribution of crop production by administrative regions

Descriptive statistics

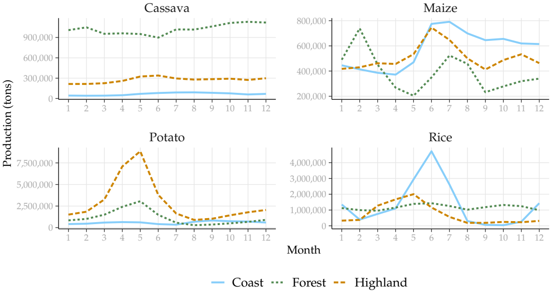

Figure: Crop production by months and natural regions (in tons)

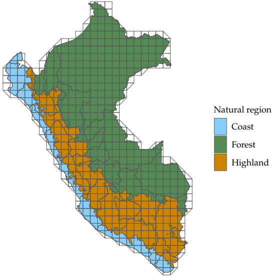

Figure: Natural regions in Peru

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Model – Linear effect

Model of Local Projections, developed in Jordà (2005), in a panel dimension, as Acevedo et al. (2020)

$$y_{c,i,t+h} = \alpha_{c,i,h} + \beta^T_{c,h} T_{i,t} + \beta^P_{c,h} P_{i,t} + \delta_{c,i,h} X_t + \varepsilon_{c,i,t+h}, \tag{4}$$

where :

- $y^c_{c,i,t+h}$ is the agricultural production of culture c in region i, deseasonalized and expressed in percentage deviation from a trend at predicted time $t+h$,
- $\beta^T_{c,h}$ and $\beta^P_{c,h}$ are the parameters vectors of interest,
- $T_{i,t}$ and $P_{i,t}$ are respectively the temperature and precipitations anomalies, used in the inference exercise at time t,
- X_t represents the set of the control variables and $\delta_{c,i,h}$ the corresponding estimated parameters,
- $\varepsilon_{c,i,t+h}$ is the error term for the estimation at the horizon h.

Linear Response

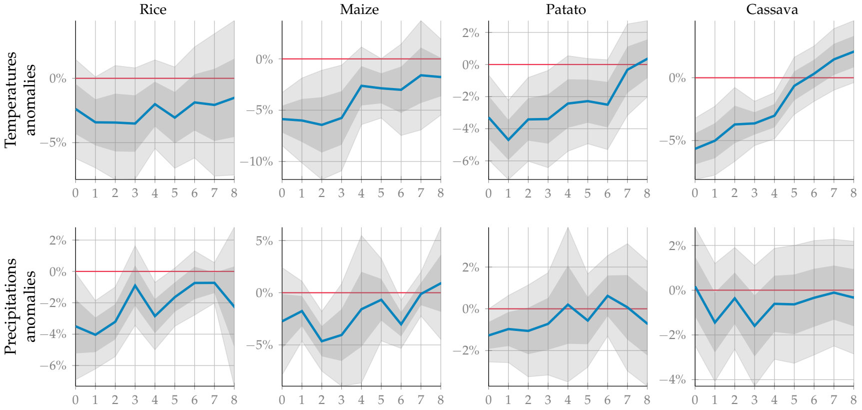

Figure: Agricultural production response to a weather shock

Model – Geographical effect

Model of Local Projections, weighted by geographical natural region distribution.

$$y_{c,i,t+h} = \alpha_{i,h} + \sum_{r \in \{\mathcal{C},\mathcal{H},\mathcal{F}\}} \gamma_{i,r} \left(\beta^{T}_{c,h,r} T_{i,t} + \beta^{P}_{c,h,r} P_{i,t} \right) + \delta_{i,h} X_t + \varepsilon_{c,i,t+h}, \qquad (5)$$

where :

- $\gamma_{i,r}$ is an observable value of regional distribution, computed based on the grid data covering Peru.

Geographical response

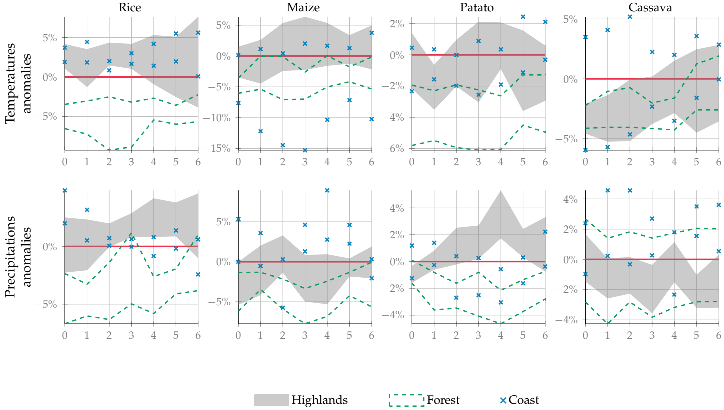

Figure: Agricultural production response to a weather shock by taking into account geographical patterns (Highlands, Forest and Coast)

Model – Seasonal effect

Model of Local Projections, augmented with a state-dependent variable with a panel data set to allow for non-linear response as in Auerbach and Gorodnichenko (2011).

$$\begin{aligned} y_{i,c,t+h} = & F\left(\hat{z}_{i,c,t}\right)\left[\alpha^h_{G,i} + \beta^h_{G,T} T_{i,c,t} + \beta^h_{G,P} P_{i,c,t} + \delta^h_{G,i} X_t\right] \\ & + \left(1 - F\left(\hat{z}_{i,c,t}\right)\right)\left[\alpha^h_{H,i} + \beta^h_{H,T} T_{i,c,t} + \beta^h_{H,P} P_{i,c,t} + \delta^h_{H,i} X_t\right] + \varepsilon_{i,c,t+h}, \end{aligned} \tag{6}$$

where :

- $\hat{z}_{i,c,t}$ is an standardized index variable of utilized land surface, and F the cumulative density function defining the state of the season.
- $\beta^h_{S,T}$ and $\beta^h_{S,P}, S = G, H$ are the state-dependant parameter vectors of interest,
- $\delta^h_{S,T}, S = G, H$ are the state-dependent control variable parameter vectors of interest.x

Seasonal response

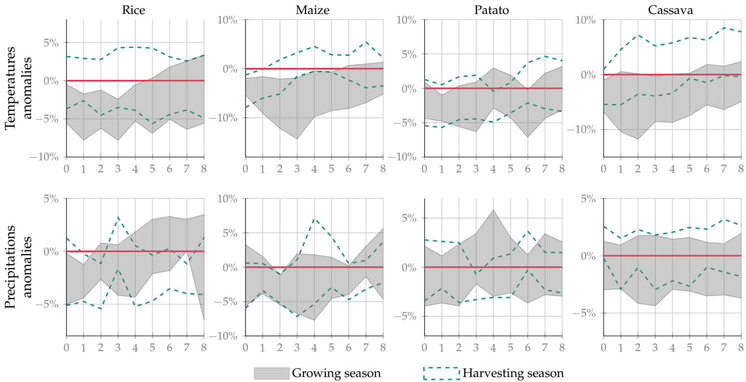

Figure: Agricultural production response to a weather shock contrasting for growing vs. harvesting season

Aggregate fluctuations

Aggregate measure of weather W_t:

$$W_t = \sum_{c=1}^{C} \omega_{c,t} \left[\sum_{h=0}^{H} \left(\hat{\beta}^h_{c,T} T_{i,c,t-h} + \hat{\beta}^h_{c,P} P_{i,c,t-h} \right) \right], \tag{7}$$

where :

- $\omega_{c,t}$ is a weight measuring the relative size of crop c in the total value added among all crops at time t
- $\hat{\beta}^h_{c,T}$ and $\hat{\beta}^h_{c,P}$ are the marginal effects estimated previously in the baseline LPs.

VAR Model:

$$Y_t = \phi_0 + \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t, \tag{8}$$

with:

$$Y_t = \begin{bmatrix} W_t, & RER_t, & \pi_t, & y^A_t, & y_t, & r_t \end{bmatrix}$$

.

Aggregate fluctuations

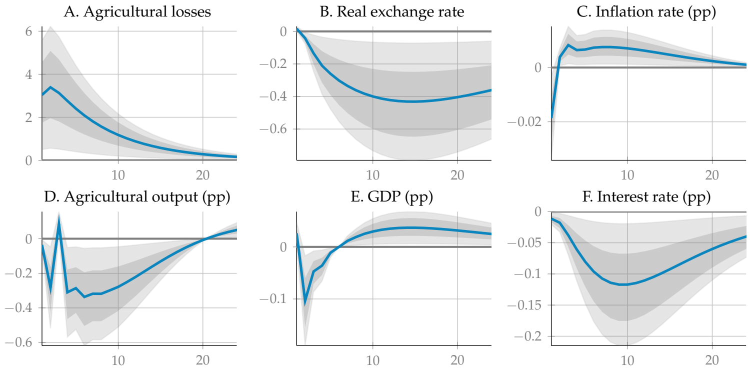

Figure: VAR(2) system response to one standard deviation orthogonal shock to the weather aggregate cost equation

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Objective

This paper aims to analyze the propagation mechanism of a weather shock on agricultural production at a monthly frequency, for various crops, in heterogeneous geographical and seasonal patterns.
Use of local projections models.

Findings

- An increase in both temperatures and precipitation leads to a decline in production, for up to four consecutive months for any crop in our sample.
- Negative effects are primarily driven by abnormally warm temperatures rather than increased precipitation.
  - Disparities in responses depending on the geographical climate and crop-specific responses when the shocks hit a zone rather than another.
  - Production is harmed when the weather shock happens during the growing period, but hardly during the harvesting phase.
- A representative shock in weather-driven loss shocks causes a 0.4% loss in agricultural output, leading to a 0.1% reduction in GDP.

Thank you for your attention!

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Meteorological data

- CHIRPS v2.0 database, made available by the Climate Hazards Center of the UC Santa Barbara: daily information on rainfall, from 1981 to present, 0.05° resolution satellite imagery.

- PISCOt V1.1, a data set of gridded daily temperatures data set, available from 1981 to 2016 at a 0.1° spatial resolution, from the SENAMHI (the National Service of Meteorology and Hydrology of Peru)