Extreme weather shocks and potentials effects on agri-food markets

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Virtual session
(day 2)
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Summary of previous session

- Overview of temperature effects on food market
- Different proxies of weather-related shocks
- Short-run price adjustment and long-run price equilibrium
- Asymmetric price adjustment and market performance
- Short-run and long-run effects of temperature variation

Outline (2nd session)

- Group assignment
- Threshold model
- Identifying temperature extreme events
- Case studies
- Temperature volatilities
- Summary of price dynamics

Cross-sectional Dependence Test

Assume,

$$y_{it} = \alpha_i + \beta x_{it} + \mu_{it} \;\; , i = 1, .., N \; t = 1, ..., T$$

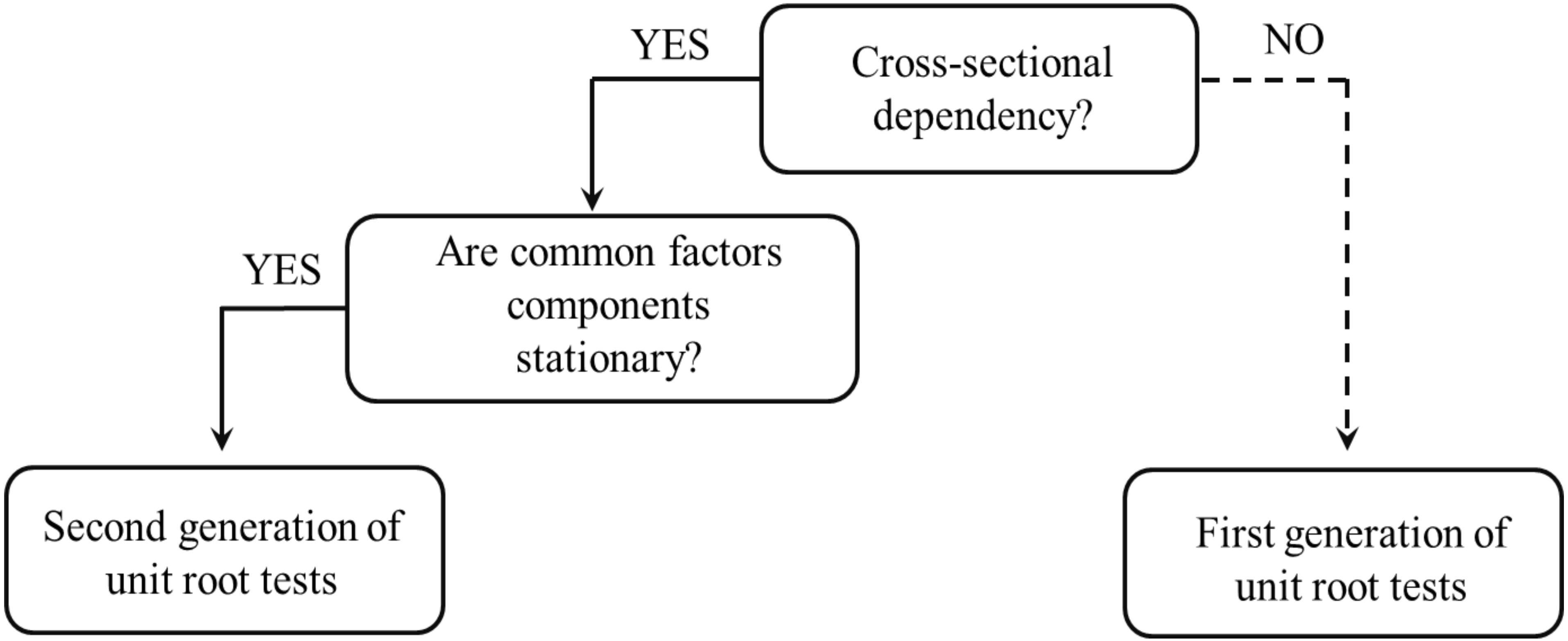
$$H_0: \; \rho_{ij} = \mathrm{cor}\left(u_{it}, u_{jt}\right) = 0 \text{ for } i \neq j$$
$$H_1: \; \rho_{ij} = \mathrm{cor}\left(u_{it}, u_{jt}\right) \neq 0 \text{ for } i \neq j$$

ρ_{ij}: the product-moment correlation coefficients of the residuals

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_t^T \hat{u}_{it}\hat{u}_{jt}}{(\sum_t^T \hat{u}_{it}^2)^{0.5} \; (\sum_t^T \hat{u}_{jt}^2)^{0.5}}$$

Possible tests: Pesaran’s CD test, Friedman’s test, Frees’ test,

Panel Unit Root Test



Consider cross sectional dependencies, Hadri (2002)

Ignore cross sectional dependencies, …

Short-run vs. Long-run Effects

Figure 2. Increase in Average Global Temperature and Contributions of Key Factors
(Deviations from 1880–1910 average, degrees Celsius)

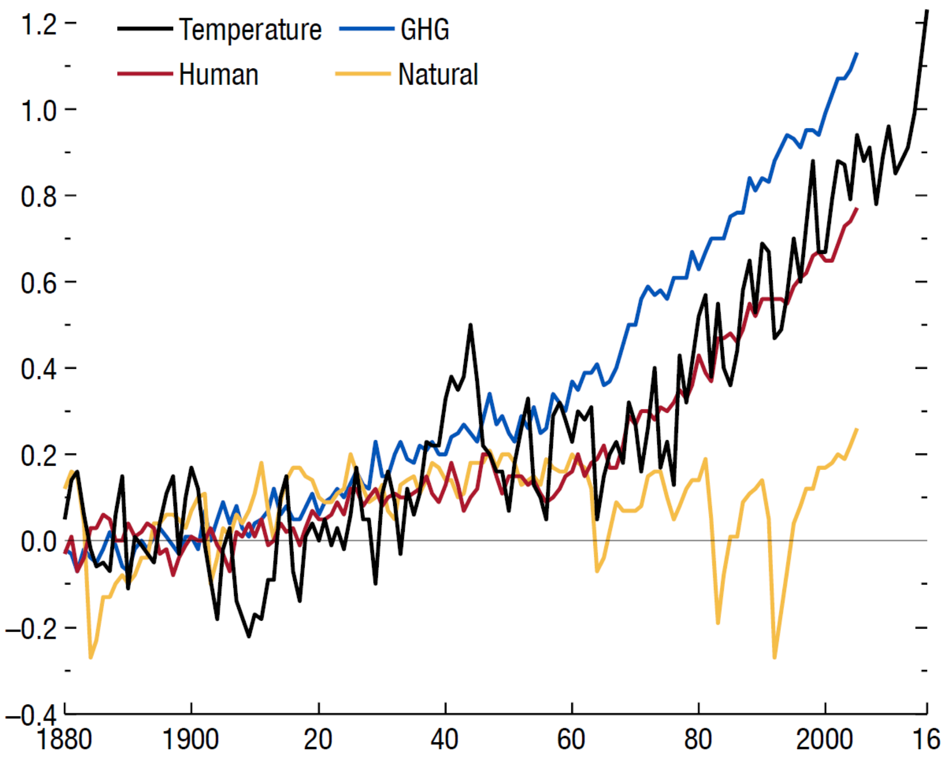
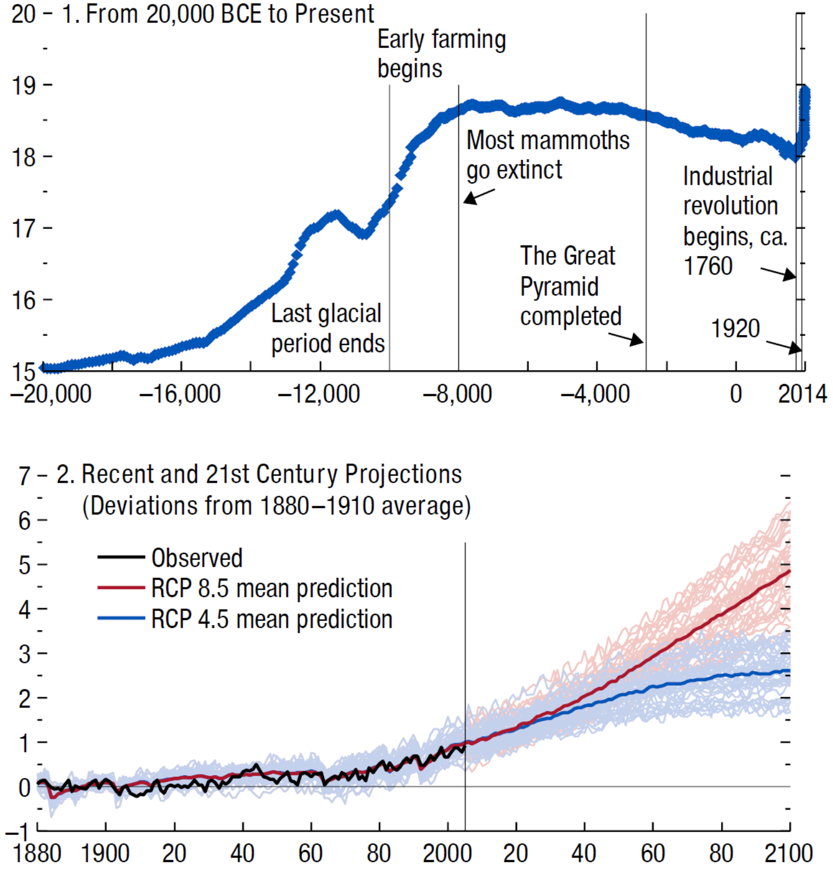


Figure 1. Average Global Temperature
(Degrees Celsius)



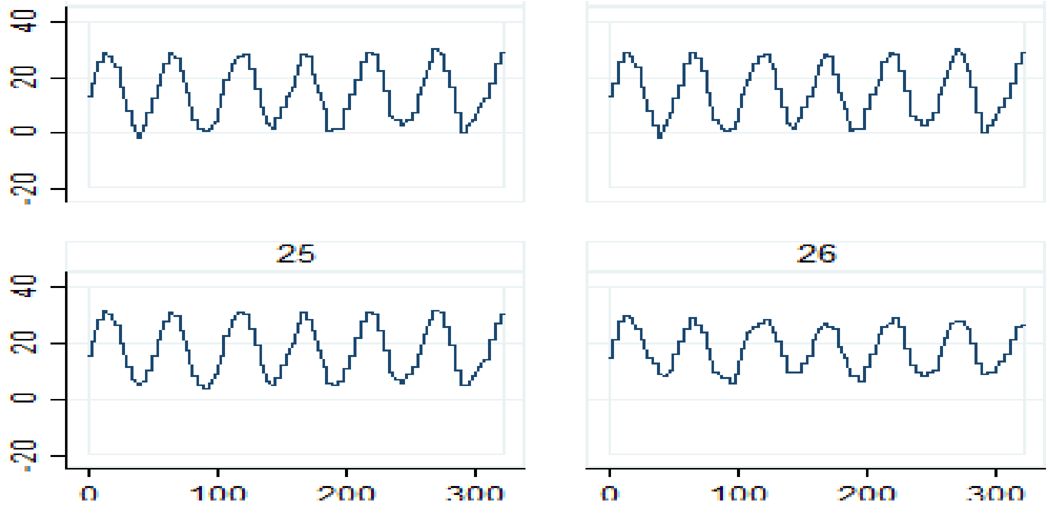
Source: IMF, 2018

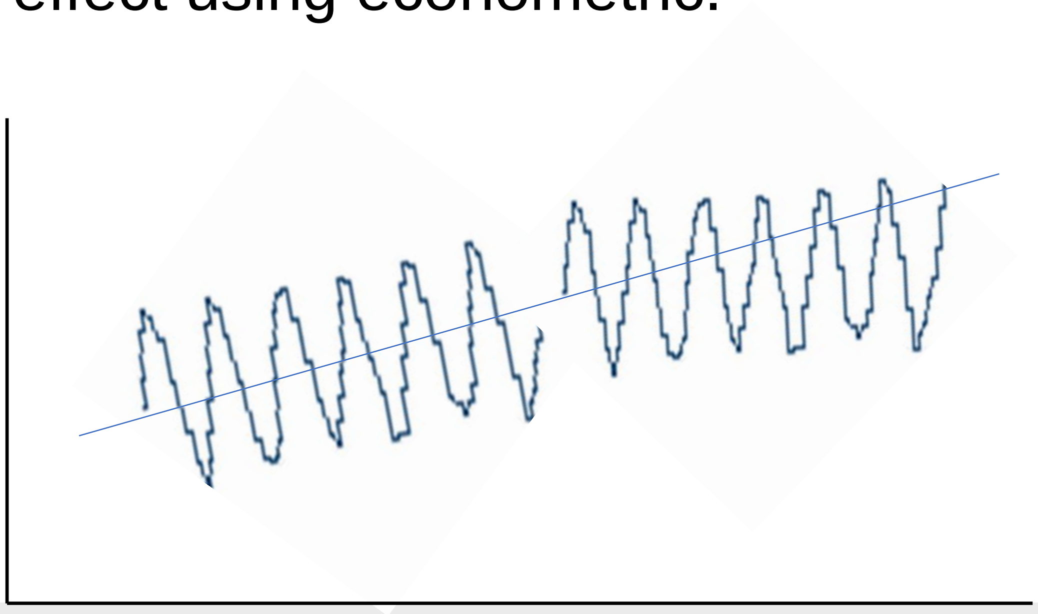
Threshold Effects of Temperature

- Temperature→ seasonally.

- Temperature is the most critical factor to ensure quality and to reduce losses of perishable foods during transportation (Aung and Chang, 2014).

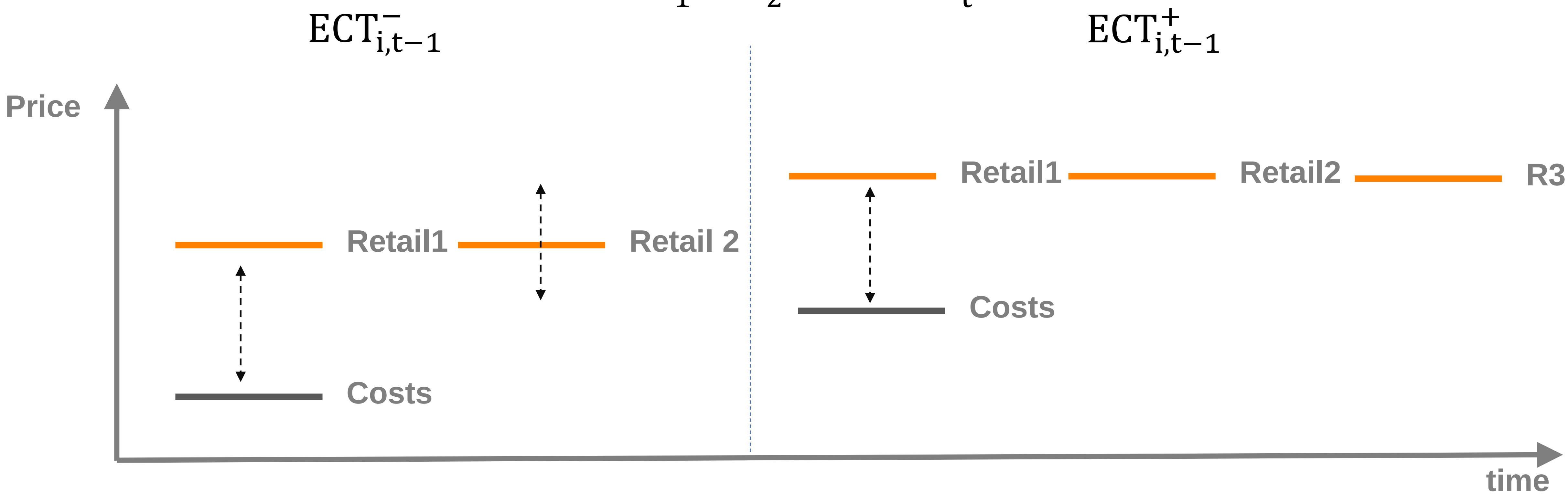
- Climate change is a long-run phenomena.
- How we can determine short or long-run effect using econometric.





Rockets and Feathers Effects

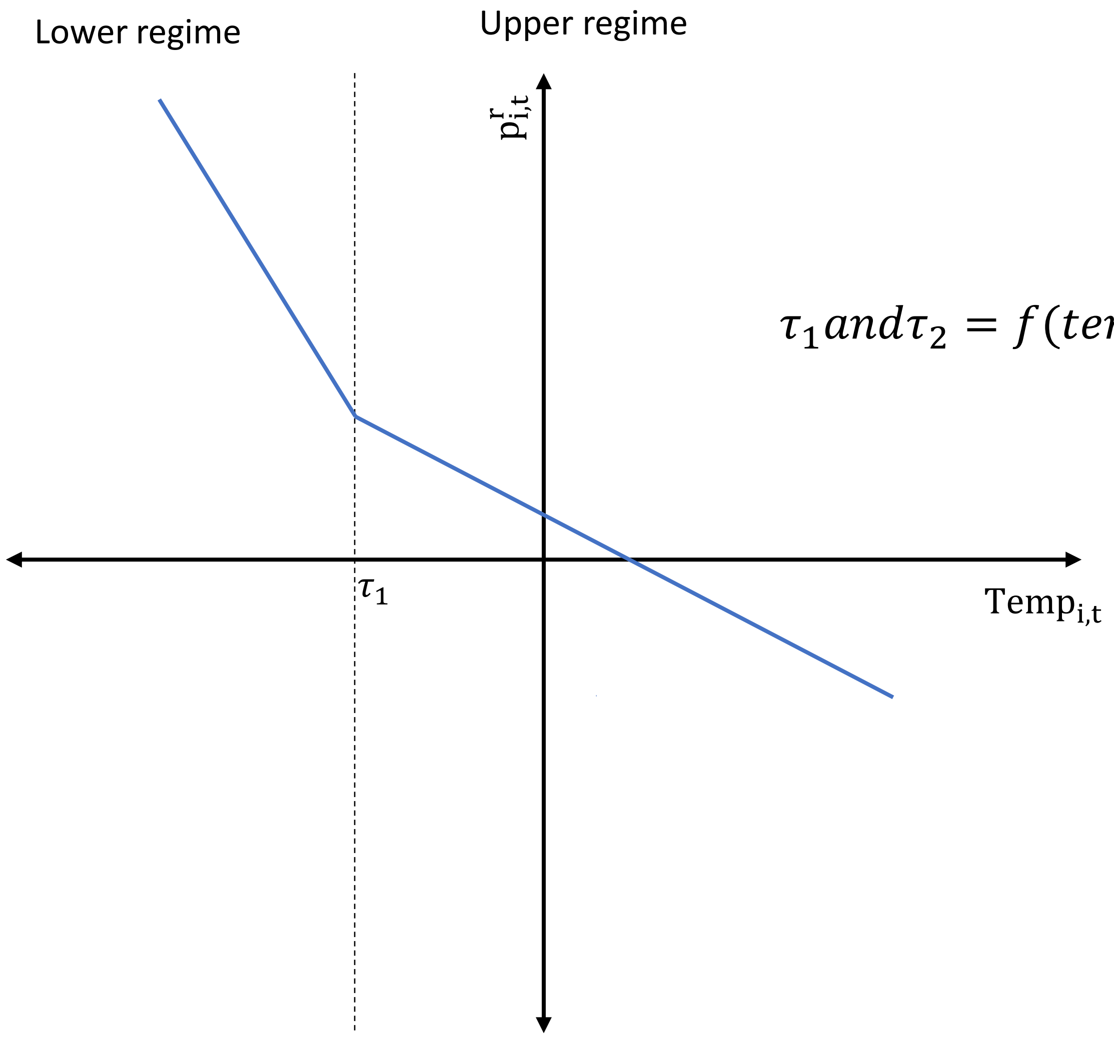
$$P^r - \alpha_1 + \alpha_2 P^w = \mathrm{ECT_t}$$



Fixed-effect Panel Threshold Model

- So far, we have assumed a linear relationship in the interaction terms!
- There might be a specific threshold above which the effects of whether is more obvious, e.g. extreme weather!
- The threshold model describes the jumping character or structural break in the relationship between variables.
  - E.g. above some thresholds (i.e. extreme weather shocks), the effects of temperature is more obvious.
- Hansen’s (1999) panel threshold model has a simple specification but obvious implications for economic policy.
- Threshold cointegration vs. threshold model.

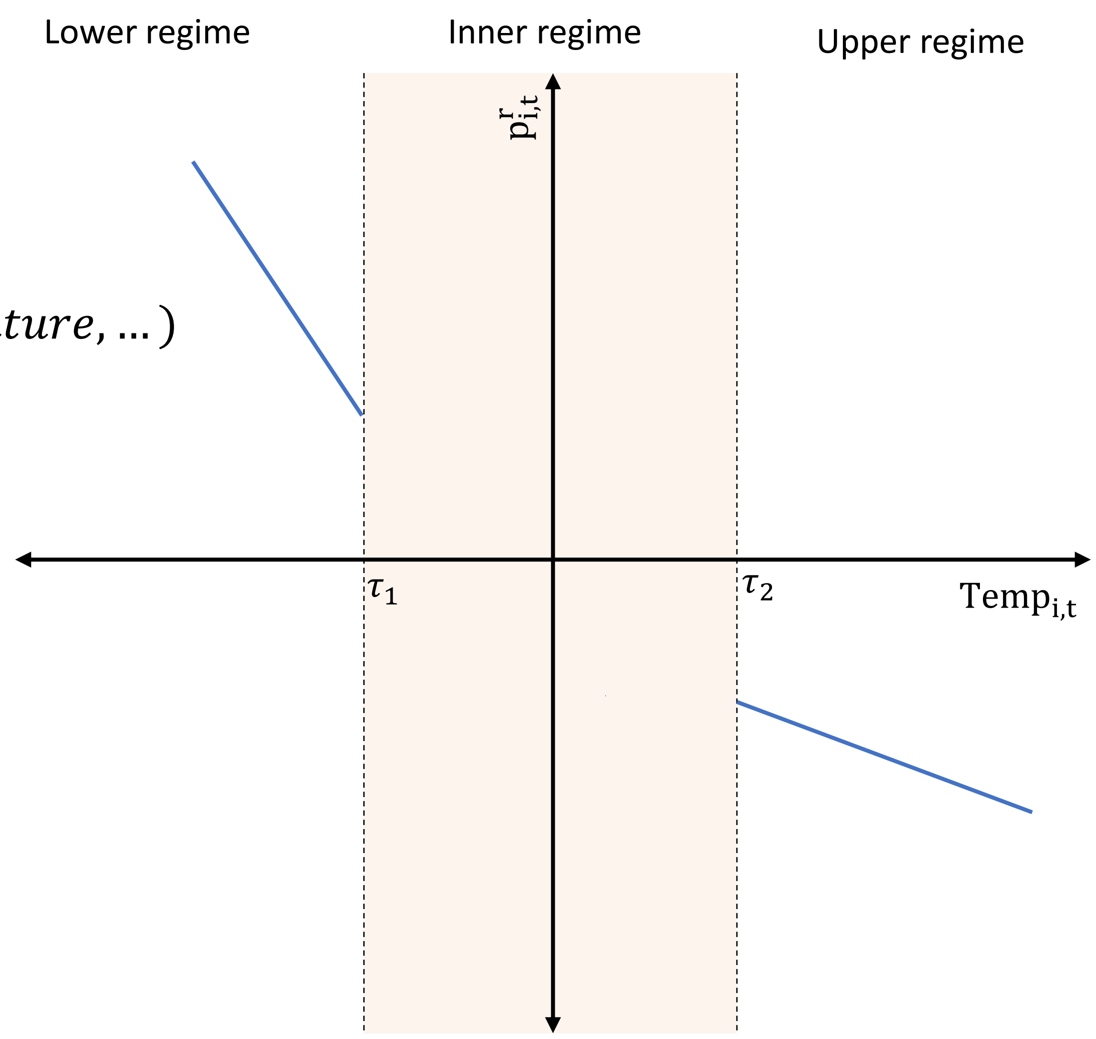
a)



Single-threshold model

$$\tau_1 and \tau_2 = f(temperature, \dots)$$

b)



Multiple-thresholds model

Parameter Interpretation

$$\Delta P_{i,t} = \gamma_0^+ ECT_{i,t-1}^+ + \gamma_1^- ECT_{i,t-1}^- + \boldsymbol{\gamma_2^+} Temp_{i,t-1} ECT_{i,t-1}^+ + \boldsymbol{\gamma_3^-} Temp_{i,t-1} ECT_{i,t-1}^- + \cdots + \rho_i + \nu_{it}$$

More asymmetric pattern

$$\frac{\partial\, \Delta lnP_{it}^r}{\partial ECT_{i,t-1}^+} = \gamma_0^+ + \boldsymbol{\gamma_2^+}\mathrm{Temp}_{t-1} \rightarrow \text{ if } \gamma_2^+ > 0$$

$$\frac{\partial\, \Delta lnP_{it}^r}{\partial ECT_{i,t-1}^-} = \gamma_1^- + \boldsymbol{\gamma_3^-}\mathrm{Temp}_{t-1} \rightarrow \text{ if } \gamma_3^- < 0$$

More symmetric pattern

$$\gamma_2^+ < 0$$

$$\gamma_3^- > 0$$

- Rockets and feathers effect: $|\gamma_0^+| < |\gamma_0^-|$

Panel Threshold Model

- **Single-threshold model**

$$y_{\mathrm{it}} = \mu + X_{\mathrm{it}}(TEMP_{\mathrm{it}} < \gamma)\beta_1 + X_{\mathrm{it}}(TEMP_{\mathrm{it}} > \gamma)\beta_2 + \mu_{\mathrm{i}} + \varepsilon_{\mathrm{it}}$$

- **Multiple-threshold model**

$$y_{it} = \mu + X_{it}(TEMP_{it} < \gamma_1)\beta_1 + X_{it}(\gamma_1 \leq TEMP_{it} < \gamma_2)\beta_2 + X_{it}(TEMP_{it} \geq \gamma_2)\beta_3 + \mu_i + \varepsilon_{it}$$

Panel Threshold Model

Testing for a threshold effect is the same as testing for whether the coefficients are the same in each regime.

The null hypothesis and the alternative hypothesis (the linear versus the single-threshold model) are

$$H_0:\ \beta_1 = \beta_2$$
$$H_1:\ \beta_1 \neq \beta_2$$

$$F_2 = \frac{(S_1 - S_2)}{\hat{\sigma}^2}$$

Double-threshold Model

According to Bai (1997) and Bai and Perron (1998), the sequential estimator is consistent, so the thresholds are estimates in three-stage process:

Step 1: Fit the single-threshold model to obtain the threshold estimator $\boldsymbol{\gamma_1}$ and the Residual Sum of Square $S(\hat{\boldsymbol{\gamma}}_{\mathbf{1}})$.

Step 2: Given $\hat{\boldsymbol{\gamma}}_{\mathbf{1}}$, the second threshold is determined as

$$\hat{\gamma}_2 = \underset{\gamma_2}{\operatorname{argmin}}\, S_2(\gamma_2)$$

tep 3: $\hat{\boldsymbol{\gamma}}_{\mathbf{2}}$ is efficient but $\hat{\boldsymbol{\gamma}}_{\mathbf{1}}$ is not. We re-estimate the first threshold as,

$$\hat{\gamma}_1 = \underset{\gamma_1}{\operatorname{argmin}}\, S_1(\gamma_1)$$

Double-threshold Model

If we reject the null hypothesis in a single-threshold model, then we should test the double-threshold model.

The null hypothesis is a single-threshold model, and the alternative hypothesis is a double-threshold model.

The F statistic is constructed as

$$F_2 = \frac{(S_1 - S_2)}{\hat{\sigma}_{22}^2}$$

Bootstrap is used on the critical values of the F statistic.

Different Types of Threshold Function

- Depends on how to move from one regime to another.

$$y_t = x_t\alpha + x_t\beta.\varphi(z_t;\tau,\gamma) + \varepsilon_t$$

β = regime specific slope parameters, $\varphi(z_t;\tau,\gamma)$ = is bounded between [0,1].

$Regim1\ Coef = \alpha,\qquad Regim2\ Coef = \alpha + \beta.\varphi(z_t;\tau,\gamma)$

- Linear model

$Regim1\ Coef = \alpha,\qquad Regim2\ Coef = \alpha + \beta$

Buncic, (2018)

Different Types of Threshold Function

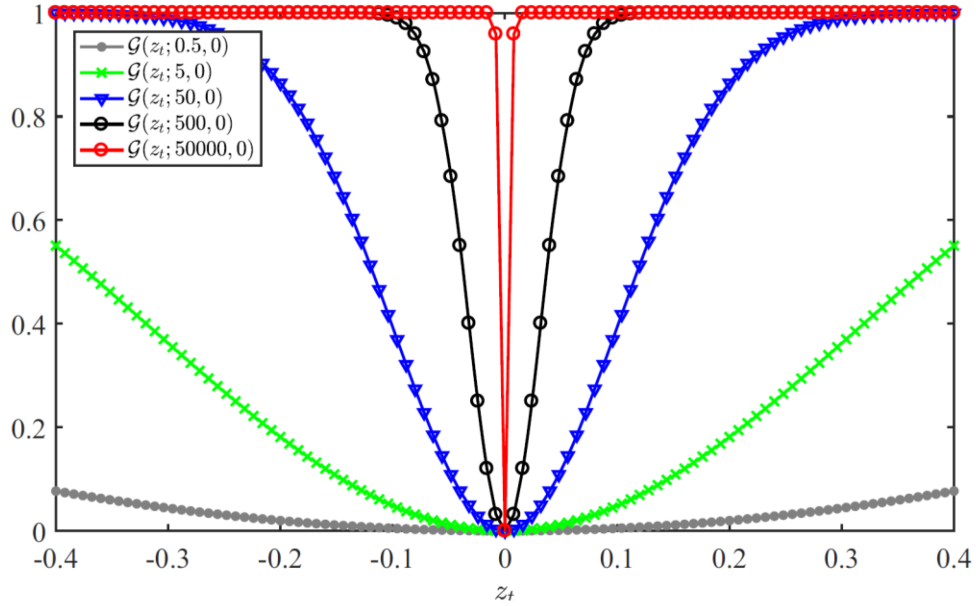
- Smooth transition function→ Logistic or exponential

Logistic STAR→ $\varphi(z_t;\tau,\gamma) = (1+\exp\{-\tau(z_t-\gamma)\})^{-1}$

Exponential STAR→ $\varphi(z_t;\tau,\gamma) = 1-\exp\{-\tau(z_t-\gamma)^2\}$

- Markov switching model

Switching between regiems are based on the transition probabilities.



Buncic, (2018)

Threshold Panel Model in Stata

- Please note that we need TPM to identify temperature thresholds → transition variable is temperature.

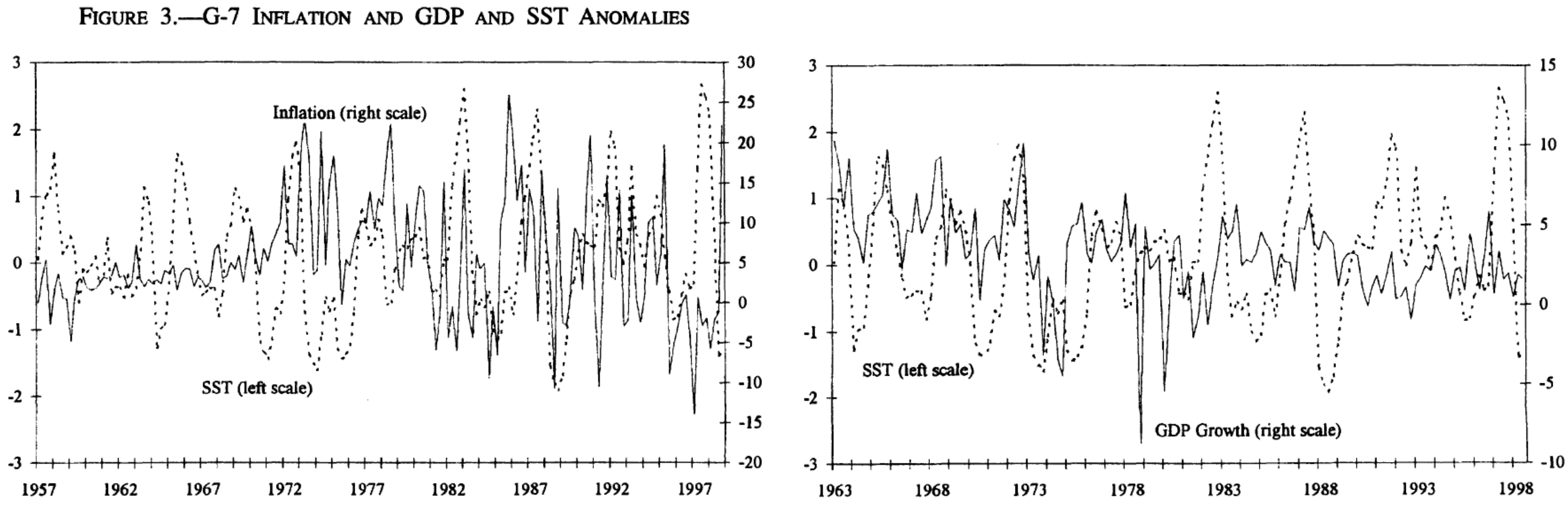
Case Study: El Niño, La Niña and Coffee Price

- Allan D. Brenner, 2002, **El Nino and World Primary Commodity Prices: Warm Water or Hot Air? The Review of Economics and Statistics.**

- The effects of ENSO on world prices and economic activity. The primary focus is on world real non-oil primary commodity prices, although the effects on G-7 consumer price inflation and GDP growth are also considered.

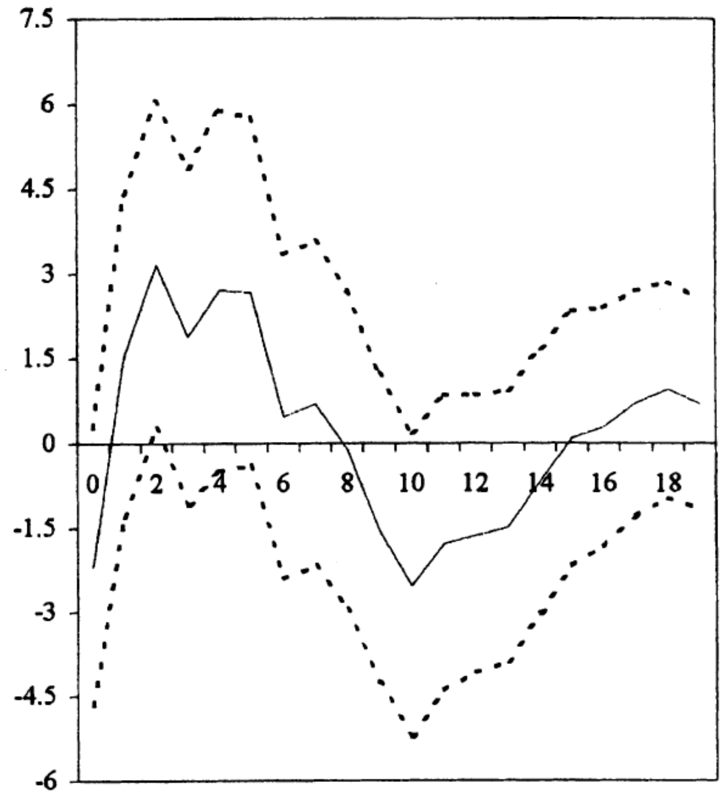
- Econometric framework: vector autoregressive (VAR) model.

G-7 Inflation, GDP, and SST Anomalies

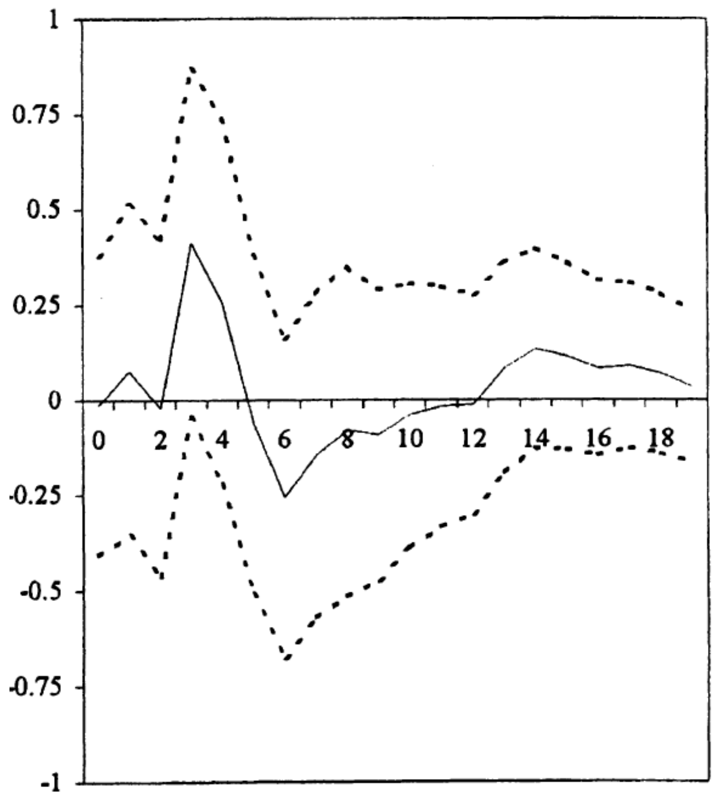


The Effects of SST

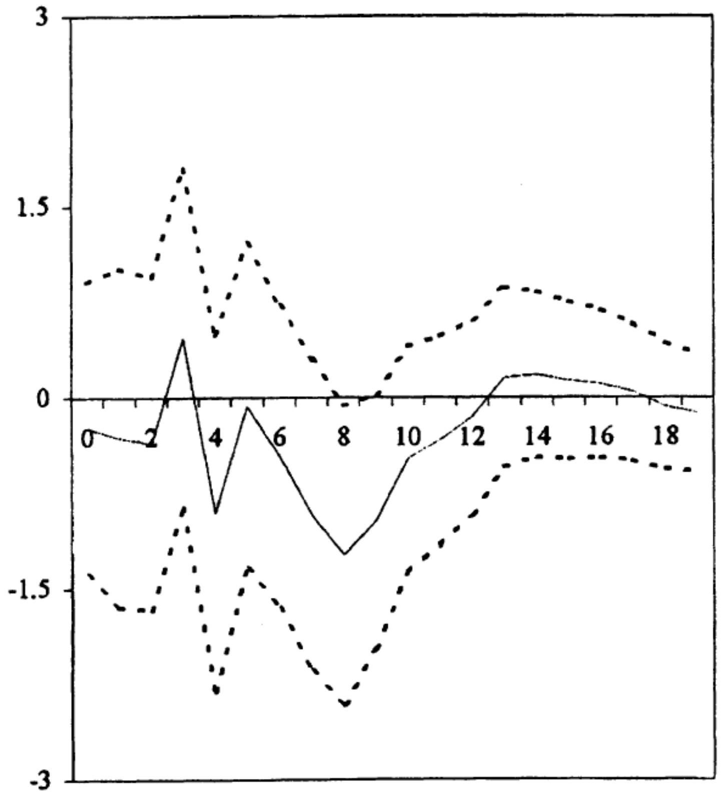
Effects on Real Commodity Price Inflation



Effects on GDP Growth



Effects on CPI Inflation



Main Results

- Not surprisingly, prices for food commodities are affected the most by ENSO, although prices of beverages, agricultural raw materials, and metals are also pushed up and then

- The hypothesis of no long-run effect on commodity price levels cannot be rejected.

- There might be a measurable increase in investment spending (especially residential construction)→ SST↑→ GDP↑

- Primary commodities account for only a fraction of overall finished products in the USA→ the effects on the inflations isn’t considerable.

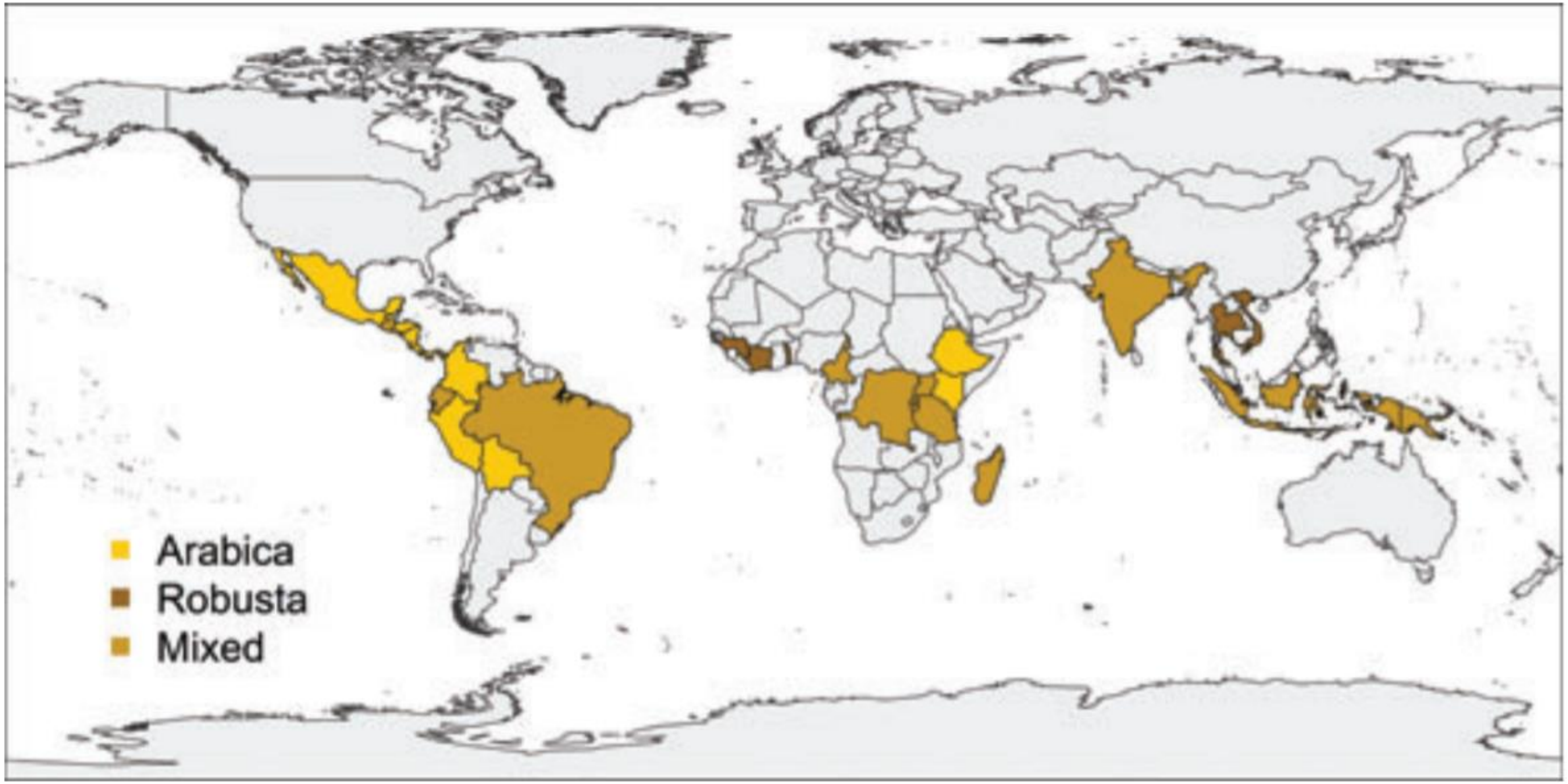
Case Study: El Niño, La Niña and Coffee Price

- David Ubilava, 2011, **El Niño, La Niña, and world coffee price dynamics, Agricultural Economics.**

- Studying the role of large-scale medium-frequency weather anomalies in the performance of various economic variables.
- Coffee producing regions are also most affected by the El Nino Southern Oscillation (ENSO)—a climatic phenomenon that causes extreme droughts or excess precipitation in these parts of the world.

- Econometric framework: The smooth transition autoregressive (STAR) type model, Vector Error Correction (VEC).

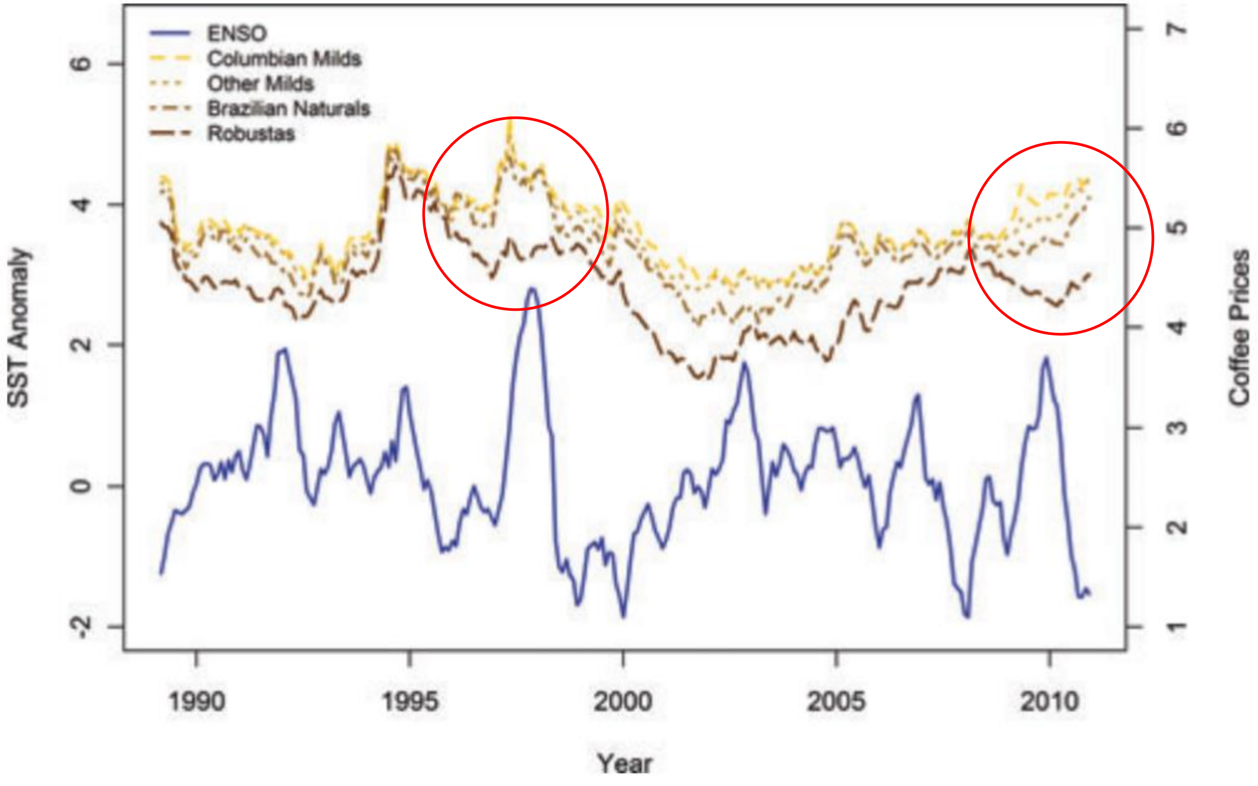
Case Study: El Niño, La Niña and Coffee Price



Geography of world coffee production by variety

Data and Proxy

- El Nino Southern Oscillation, or ENSO/ Sea Surface Temperatures (SST).



Method

$$X_t = (P_t^{CM}, P_t^{OM}, P_t^{BN}, P_t^{RB})'$$

- Dependent variables: vector of time series including prices of Columbian Milds, other Milds, Brazilian Naturals, and Robustas, respectively.

$$\Delta X_t = \mu_0 \hat{e}_{t-1} + \sum_{i=1}^{p-1} \Gamma_{0,i} \Delta X_{t-1} + \Psi_0 z_t$$
$$+ \left(\mu_1 \hat{e}_{t-1} + \sum_{i=1}^{p-1} \Gamma_{1,i} \Delta X_{t-1} + \Psi_1 z_t \right) \tilde{G}(s_t; y.c) + v_t$$

- Transition variable: $\Delta y_t = \theta_0' x_t + \theta_1' x_t G(s_t; y.c) + \varepsilon_t,$

a moving average functional form of the dependent variable

Method

- In order to account for seasonal effects we include monthly dummy variables in the equation.

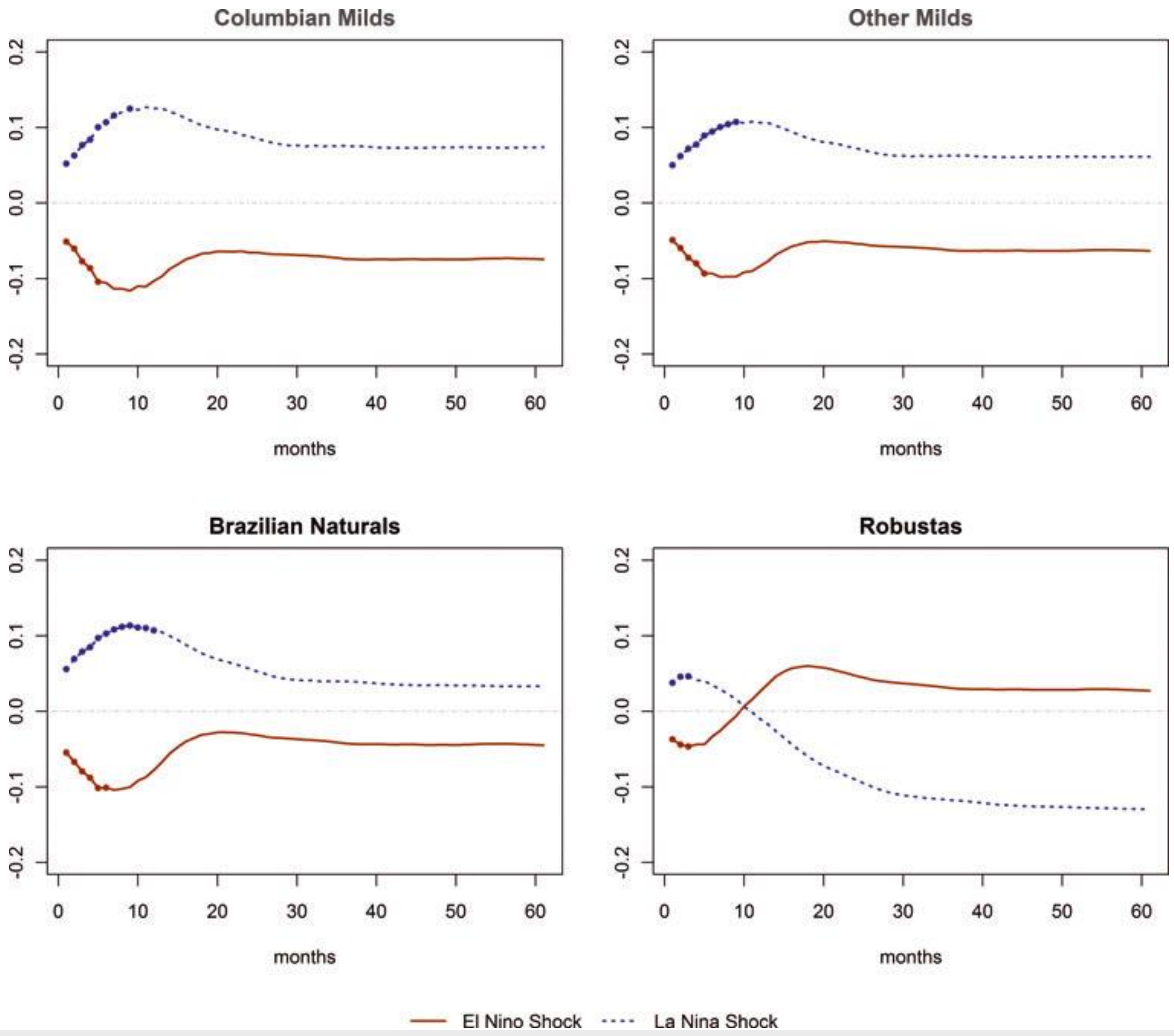
$$
\begin{aligned}
\Delta ENSO_t = {} & \alpha_0 + \beta_0 ENSO_{t-1} + \sum_{j=1} \phi_{0,j} \Delta ENSO_{t-j} + \Psi_0' D_t \\
& + \left(\alpha_1 + \beta_1 ENSO_{t-1} + \sum_{j=1}^{5} \phi_{1,j} \Delta ENSO_{t-j} \right. \\
& \left. + \Psi_1' D_t \right) G_1(s_{1,t}; \gamma_1, c_1) + \varepsilon_t
\end{aligned}
$$

$$
\begin{aligned}
\Delta X_t = {} & \mu_0 \hat{e}_{t-1} + \Gamma_0 \Delta X_{t-1} + \sum_{q=0}^{1} \Phi_{0,q} ENSO_{t-q} + \Psi_0 D_t \\
& + \left(\mu_1 \hat{e}_{t-1} + \Gamma_1 \Delta X_{t-1} + \sum_{q=0}^{1} \Phi_{1,q} ENSO_{t-q} \right) \\
& \times G_2(s_{2,t}; \gamma_2, c_2) + v_t
\end{aligned}
$$

The ENSO equation

The price equation

Results



Columbian Milds
Other Milds
Brazilian Naturals
Robustas
0.2
0.1
0.0
-0.1
-0.2
0
10
20
30
40
50
60
months
El Nino Shock
La Nina Shock

Results

- ENSO does impact coffee prices, and the effect is statistically significant for a period of up one year! Short run!?

- ENSO-related asymmetries are observed in coffee prices, due to regime-specific asymmetries associated with ENSO and coffee prices.

- A positive ENSO shock -El Nino- has a positive effect on prices of Robustas, but a negative effect on prices of Arabicas. The opposite is true for a La Nina shock.

Case Study: El Niño, La Niña and Commodity Price

- David Ubilava, 2018, The Role of El Niño Southern Oscillation in Commodity Price Movement and Predictability**, American Journal of Agricultural Economics.**

- Econometric framework: The smooth transition autoregressive (STAR) type model. Niño 3.4 region.

- Proxy: sea surface temperature (SST), persistent positive (negative) SST deviations from their historical mean are associated with El Niño (La Niña) events.

Method

i. an autoregressive distributed lag model;
ii. a time–varying autoregressive distributed lag model;
iii. an autoregressive smooth transition distributed lag model;
iv. a time–varying autoregressive smooth transition distributed lag model

$$\Delta y_t = \boldsymbol{\alpha}_{y0}(t) + \boldsymbol{\beta}_0' \boldsymbol{y}_{t-1} + \left[\boldsymbol{\alpha}_{y1}(t) + \boldsymbol{\beta}_1' \boldsymbol{y}_{t-1}\right] G(t^*; \gamma_\tau, \tau) + \boldsymbol{\theta}' \boldsymbol{z}_t + \varepsilon_t$$

$$\Delta y_t = \boldsymbol{\alpha}_{y0}(t) + \boldsymbol{\beta}_0' \boldsymbol{y}_{t-1} + \boldsymbol{\theta}_0' \boldsymbol{z}_t + \boldsymbol{\theta}_1' \boldsymbol{z}_t G(s_t; \gamma_c, c) + \varepsilon_t$$

$$\Delta y_t = \boldsymbol{\alpha}_{y0}(t) + \boldsymbol{\beta}_0' \boldsymbol{y}_{t-1} + \left[\boldsymbol{\alpha}_{y1}(t) + \boldsymbol{\beta}_1' \boldsymbol{y}_{t-1}\right] G(t^*; \gamma_\tau, \tau) + \boldsymbol{\theta}_0' \boldsymbol{z}_t + \boldsymbol{\theta}_1' \boldsymbol{z}_t G(s_t; \gamma_c, c) + \varepsilon_t,$$

Method

$$G^{(l)}\left(s_t;\gamma,c\right)=\left\{1+\exp\left[\gamma\left(\frac{s_t-c}{\sigma_s}\right)\right]\right\}^{-1}$$

$$G^{(e)}\left(s_t;\gamma,c\right)=\left\{1-\exp\left[\gamma\left(\frac{s_t-c}{\sigma_s}\right)^2\right]\right\}$$

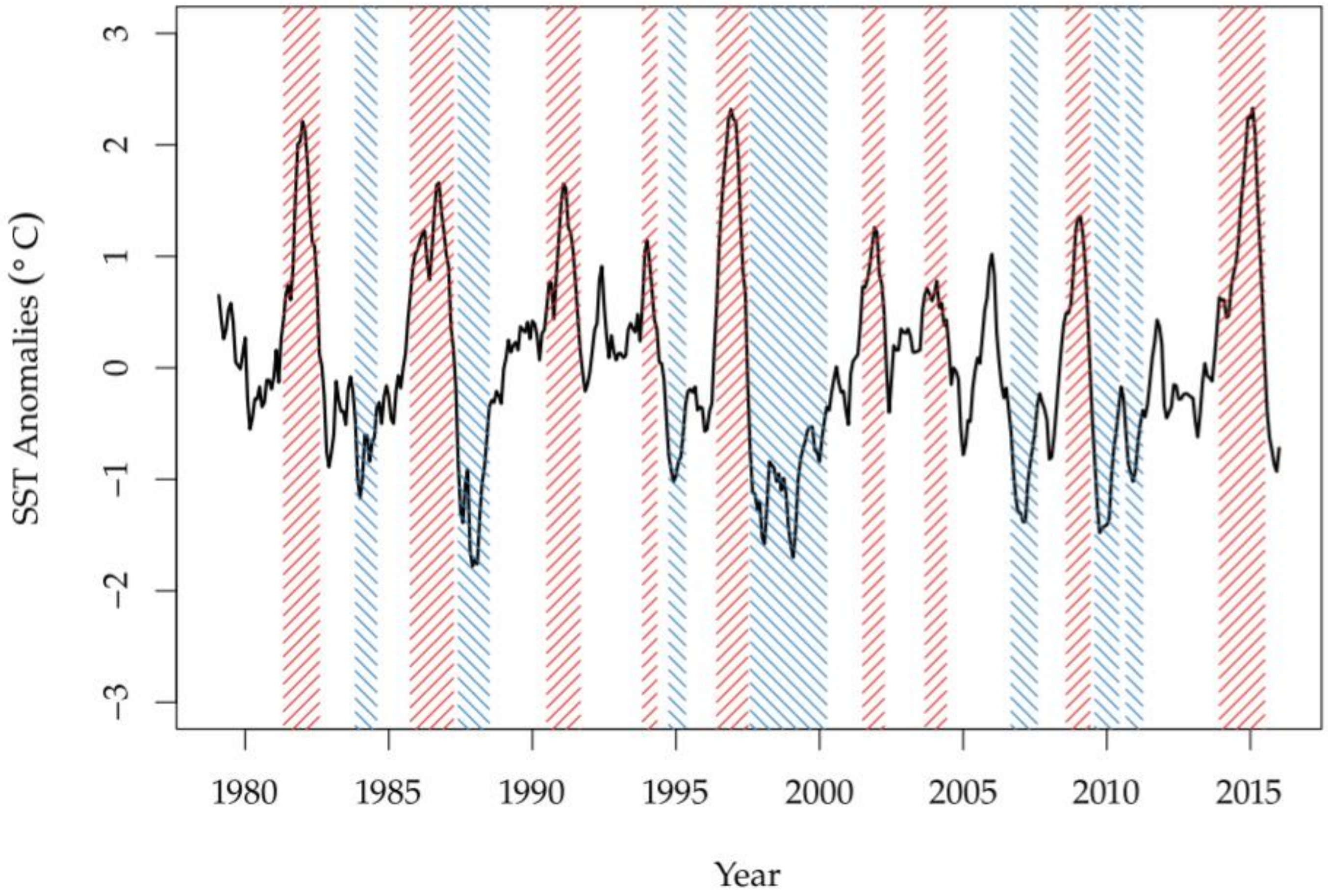
Transition function:

$\mathrm{G}(s_t;\gamma_c,c)$, $\mathrm{G}(t^*;\gamma_\tau,\tau)$

$s_t = y_{t-d}$: lagged dependent variables,

$t^* = t/T$: time,

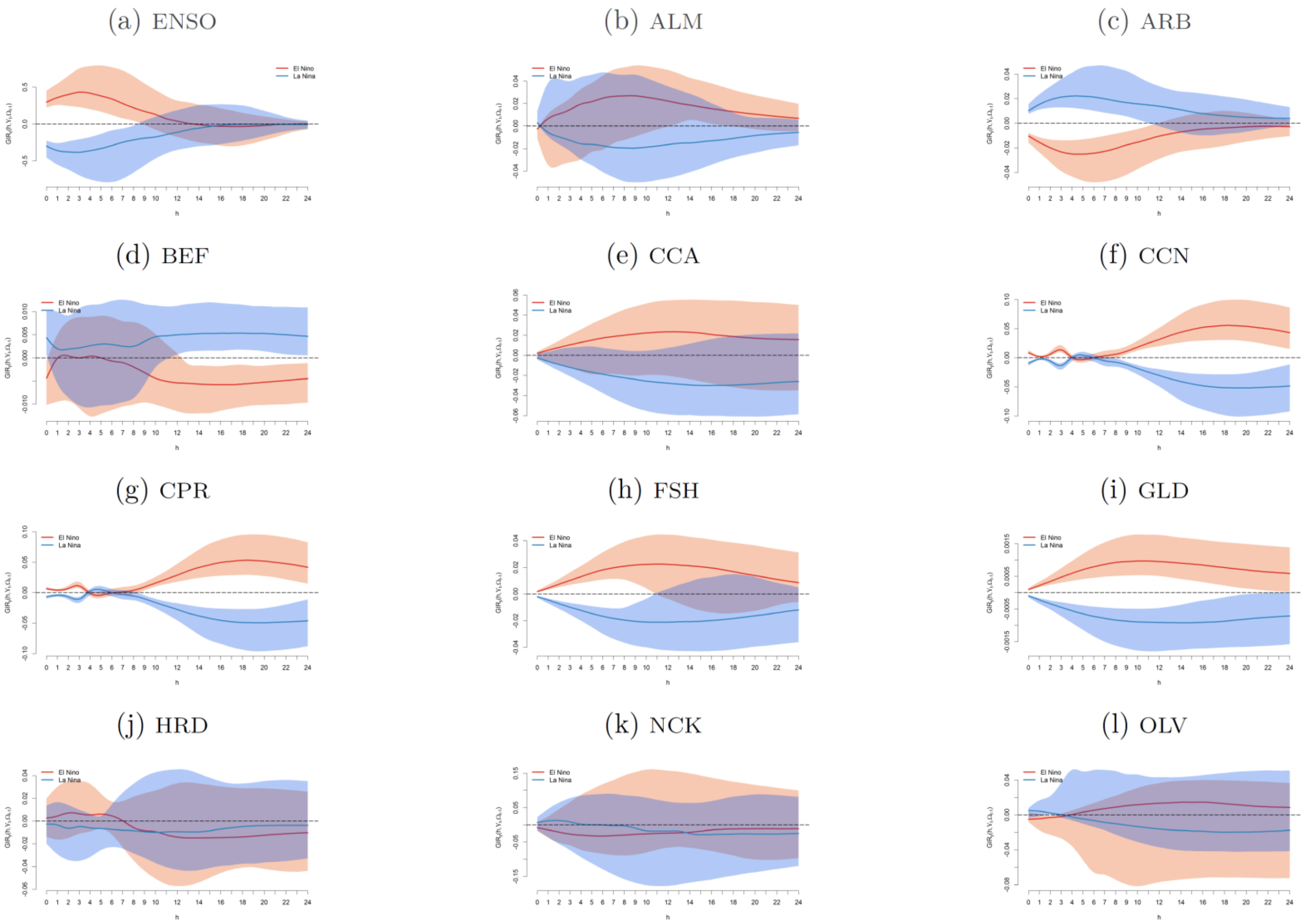
Data and Proxy



Results

Commodity	Model	p	q	ℓ	d	k	$\hat{\gamma}_c$	$\hat{c}$	$\hat{\gamma}_\tau$	$\hat{\tau}$	p_{t^*}	p_{AC}	p_{ARCH}
Aluminum	ARDL	2	1		0	16					0.253	0.226	<0.000
Barley	AR	2			0	14					0.117	0.506	<0.000
Beef	AR	3			1	14					0.507	0.532	0.592
Chicken	LTVARDL	2	2		0	36			2.00	0.15	0.017	0.363	<0.000
									(1.16)	(0.21)			
Cocoa	ARDL	3	0		1	15					0.541	0.570	0.016
Coconut Oil	ARDL	2	5		1	19					0.610	0.967	0.422
Coffee (Arabica)	ARDL	3	1		0	17					0.944	0.690	<0.000
Coffee (Robusta)	ARDL	2	1		1	15					0.732	0.477	0.024
Copper	AR	2			1	13					0.945	0.059	0.003
Copra	ARDL	2	5		1	19					0.194	0.537	0.923
Cotton	AR	2			0	14					0.859	0.255	<0.000
Fishmeal	ARDL	2	0		1	14					0.126	0.144	0.072
Gold	AR	2			1	13					0.013	0.163	0.055
Groundnut Oil	AR	2			0	14					0.065	0.838	0.138
Hides	LSTARDL	2	8	6	1	46	33.0	−0.48			0.508	0.073	0.001
							(33.5)	(0.03)					
Lamb	LTVAR	3			1	30			2.00	0.15	0.073	0.729	0.101
									(1.28)	(0.21)			
Lead	AR	2			1	13					0.583	0.960	<0.000
Logs (Hard)	LTVAR	2			0	30			100	0.22	0.116	0.066	<0.000
									(271)	(0.01)			
Logs (Soft)	AR	2			1	13					0.204	0.553	0.003
Maize	AR	2			0	14					0.936	0.790	0.827
Nickel	AR	2			1	13					0.932	0.305	0.980
Olive Oil	LTVAR	2			1	28			13.6	0.85	0.622	0.053	0.001
									(10.6)	(0.02)			
Palm Oil	ARDL	5	6		0	24					0.383	0.975	0.551
Platinum	AR	2			1	13					0.204	0.765	0.002
Pork	LTVAR	1			0	28			3.66	0.27	0.775	0.221	<0.000
									(1.66)	(0.05)			

Results: IRF

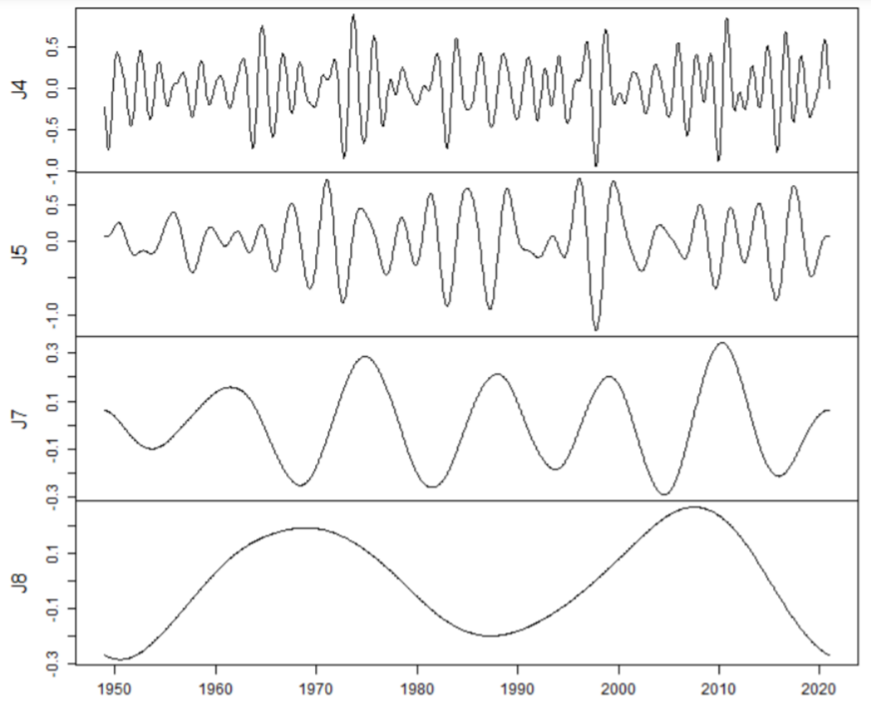

(a) ENSO
(b) ALM
(c) ARB
(d) BEF
(e) CCA
(f) CCN
(g) CPR
(h) FSH
(i) GLD
(j) HRD
(k) NCK
(l) OLV
El Nino
La Nina
h

Results

- SST anomalies facilitate price movements in selected primary commodities, particularly those in the agricultural sector.
- Vegetable oils and protein meals—particularly those produced in the western region of the Pacific Ocean—represent a key group of commodities that respond most robustly to ENSO shocks.
- No evidence of any price effect of SST anomalies for cereal grains. This may be the result of the limited exposure of temperate regions to ENSO shocks
- The ENSO–price linkage can be seen as an important channel through which climate shocks can affect the well-being of citizens in these lower-income countries.

Case Study: ENSO Shocks and Commodity Price

- Dufrénot, Ginn, Pourroy, 2021. The Effect of ENSO Shocks on Commodity Prices: A Multi-Time Scale Approach**.**
- Econometric framework: ARMA model using frequency domain analysis.



Background

- Agricultural commodities are more impacted by shocks on long cycles than on short cycles→ agricultural production choices are long memory processes. Example: potatoes have been grown for thousands of years, farmers will continue to grow them even if climate changes drastically.

- On the other hand, energy, metal and mineral commodities are more impacted by shocks on short cycles→ the ability of capital markets to shift investment in the medium run and therefore to avert from long run cycles shocks.

Data and Proxy

- Brown and Kshirsagarb, 2015, Weather and international price shocks on food prices in the developing world**,** Global Environmental Change**.**

- Proxy: the vegetation index measure derived from remote sensing observations as a proxy for yield changes. Vegetation data provides information on the amount of photosynthetic activity of chlorophyll molecules.

- The normalized difference vegetation index (NDVI): a ratio of the light reflected in the red portion (RED) of the electromagnetic spectrum versus the light reflected in the near-infrared (NIR),

$$NDVI = (NIR - RED)/(NIR + RED)$$

Method

Estimation model: state space model using a Kalman Filter.

- Model I: a (generalized) seasonal random walk
- Model II: weather disturbances influence local prices
- Model III: international prices influence local prices
- Model IV: world prices and weather disturbances influence local prices

The effects of NDVI is mainly in the short run.

Results

Table 2
Summary of results by commodity and influence.

	Driver of local food prices				
	Weather	International	Both	Neither	Total
Maize	36	10	11	103	160
Wheat	13	8	8	39	68
Rice	17	19	1	77	114
Millet	13	1	0	53	67
Sorghum	17	2	1	48	68
Other	12	8	0	57	77
Total	108	48	21	377	554

- Due to market power, prices may not reflect demand and supply shocks.
- Short run effects

Weather-induced Risk

- Why weather volatilities matter?

  - Biological process of production
  - Production decision
  - Temperature stress
  - Transportation and temperature volatilities over region

- The mechanism of weather volatilities in agri-food sector?

Time-varying Volatility

Volatility is a statistical measure of the dispersion (risk). Volatility can either be measured by using the standard deviation or variance

Risk: the outcome is unknown, but the probability distribution governing that outcome is known.

Uncertainty: characterized by both an unknown outcome and an unknown probability distribution (Knight 1921).

How to measure volatility!?

Volatility Measures

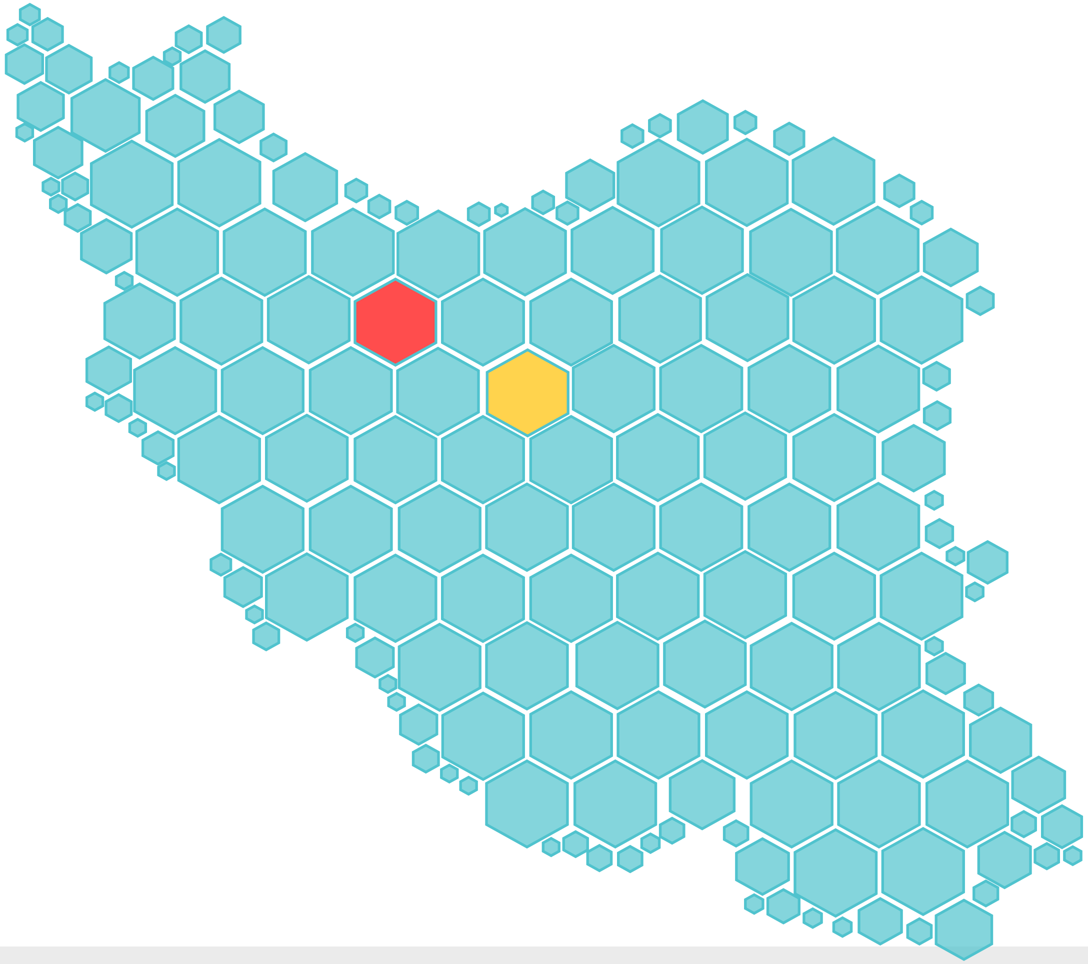
1) Temperature volatilities:

– Standard deviation (and variance):

Within and between regions volatilities,

Within deviations:

$$S_t = \sqrt{\sum_{i=1}^{N} (Temp_{it} - \overline{Temp_t})^2 / N}$$



Volatility Measures

2) Seasonal standard deviations:

Calculating standard deviation over seasons (according to solar calendar).

The volatility is constant over seasons!

$$S_s = \sqrt{\sum_{i=1}^{N} (Temp_{is} - \overline{Temp_s})^2 / N}$$

3) The variance of the temperature around its predicted trend as,

$$Temp_{it} = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + e_{it}$$

Squared Error term,

Volatility Measures

4) Absolut percentage change (error term):

$$V_{i,t-1} = \left| \frac{e_{it} - e_{it-1}}{e_{it-1}} \right|$$

5) Moving average standard deviation

$$V_{i,t-1} = \sqrt{\sum_{i=1}^{N} (e_{i,t} - e_{i,t-1})^2 / N}$$

6) Autoregressive Conditional Heteroskedasticity

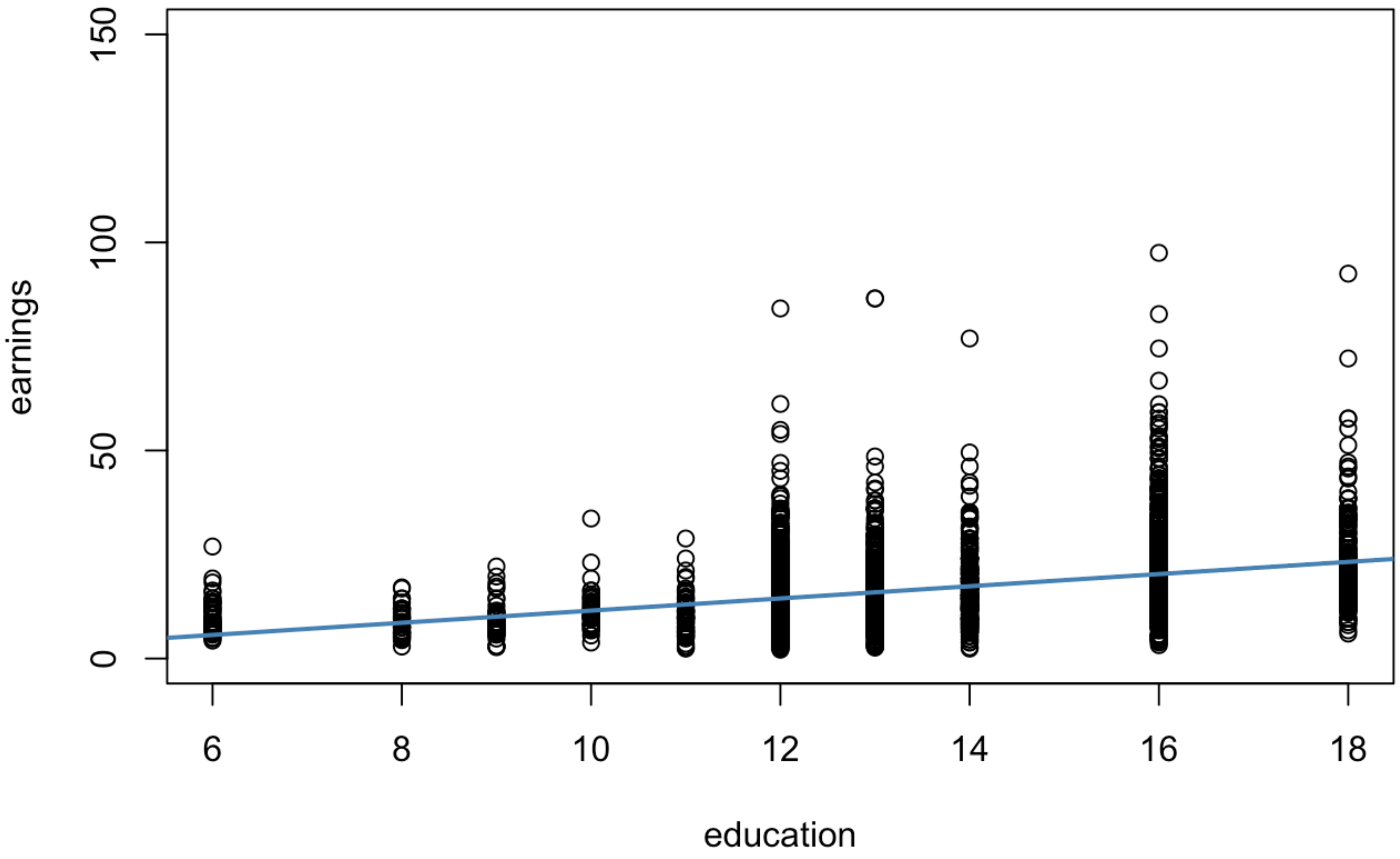
Heteroskedasticity and Volatility

- Heteroskedasticity and Homoskedasticity

- The error term of our regression model is homoskedastic if the variance of the conditional distribution of u_i given X_i, $Var(u_i|X_i)$ is constant for all observations in our sample: $Var(u_i|X_i) = \sigma^2$

- If instead there is dependence of the conditional variance of u_i on X_i, the error term is said to be heteroskedastic. We then write $Var(u_i|X_i) = \sigma_i^2$.

Heteroskedasticity



https://www.econometrics-with-r.org/5-4-hah.html

Autoregressive Conditional Heteroskedasticity

- Auto
- Regressive
- Conditional
- Heteroskedasticity

$$y_t = C + \varepsilon_t \rightarrow \varepsilon_t = w_t \sigma_t = w_t \sqrt{\alpha_0 + \alpha_1 \varepsilon_{t-1}^2}$$

w_t: white noise, σ_t: the conditional standard deviation (volatility).

"The ARCH process introduced by Engle (1982) explicitly recognizes the difference between the unconditional and the conditional variance allowing the latter to change over time as a function of past errors." Bollerselv, 1986.

Autoregressive Conditional Heteroskedasticity

- The ARCH model was originally introduced for modeling inflationary uncertainty.
- The basic ARCH models consist of two equations:

The mean equation: describes the behavior of the mean of the time series; it is a linear regression function that contains a constant and possibly some explanatory variables,

Auto-Regressive Integrated Moving Average: estimate/forecast the mean of variable.

For example: $ARIMA(1,0,1)$

$$p_t = \alpha_0 + \alpha_1 p_{t-1} + \alpha_3 u_{t-1} + u_t$$

Autoregressive Conditional Heteroskedasticity

– We use ARCH model for the **conditional variance**

– ARCH process: conditional variance is specified as a linear function of pas sample variance only.

$$\varepsilon_t = w_t \sigma_t = w_t \sqrt{\alpha_0 + \alpha_1 \varepsilon_{t-1}^2}$$

ARCH(q): $\mathrm{var}(\varepsilon_t | \mathrm{I}_{t-1}) = h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2$

- When modeling volatility using ARCH, there might be a need for a large value of the lag q, hence a large number of parameters to be estimated. This may result the difficulties to estimate parameters.

GARCH

- The GARCH estimates the variance (volatility) of the error term:

For example: $\mathrm{GARHG}(1,1)$

$$var(\varepsilon_t|\mathrm{I}_{t-1}) = h_t = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \upsilon_t$$

where *p* is the order of the GARCH terms h_{t-1} and *q* is the order of the ARCH terms ε_{t-1}^2.

ARCH Model in Stata

arch depvar [indepvars] [if] [in] [weight] [, options]

ARCH(1)

arch r, arch(1)

ARCH family regression

Sample: **1 - 500**
Distribution: **Gaussian**
Log likelihood = **-740.7932**

Mean

Variance Parameters

Number of obs = 500
Wald chi2(.) = .
Prob > chi2 = .

r	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
r						
_cons	1.063941	.0394424	26.97	0.000	.9866353	1.141247
ARCH						
arch L1.	.569351	.1028432	5.54	0.000	.3677821	.77092
_cons	.6421377	.0632134	10.16	0.000	.5182418	.7660337

GARCH models in Stata

Mean equations:
arima [varlist], arima(1,0,1)

Predict error term
Predict [name], resid
How many lags of mean equation, arch term, and autoregressive.
Arch [var], ar(p) ma(q) arch(p) garch(q)

Predict var, variance

Summary

- So far, we capture the reaction of prices to the extreme weather shocks.
- There might be long-run effects of weather variation, but the short run effect is dominated.
- Extreme weather shock may lead to extreme volatilities in the food markets.
- Policy implications: Buffer stock scheme! Improving the public interventions, seasonal trade policies.
- It is important for the policymakers to know, how long it takes that a cost changes (due to a policy) at farm level to be passed through to the final consumers.
- Perishability may aggravate the short run effects of weather variations.

Summary

Some potential topics for future studies:

- The effects of weather shocks on (grocery) shopping behavior, e.g. panic buying, hoarding effects and so on. Low food elasticity.
- Linkages between extreme weather events, commodity prices, and measures of inflation and GDP growth.
- Extreme weather shocks and financial markets!
- Spatial correlations.
- Frequency domain analysis of weather variations.

Summary

Limitation and Challenges

- Unclear cause and drivers.

The results should be in line with the market structure.

- Proxies: which proxy can reflect climate variabilities (change).
- Data: dimensions, scanner data.

Feedback and question!