Climate Change Impacts on Commodity Price Stability through Changing ENSO Patterns

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Outline

Introduction

Data

Empirical strategy
- Identification strategy
- Baseline Model
- Extreme events
- Faster Transition

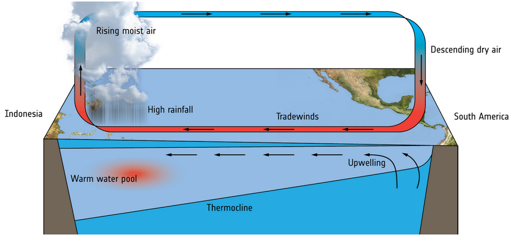
Results
- Baseline
- Stress

Research agenda

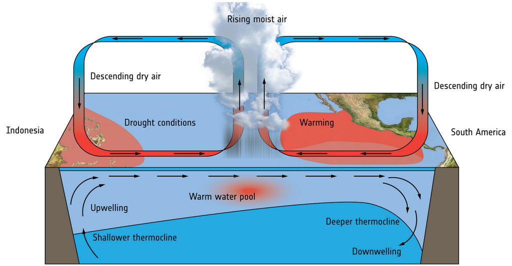
How climate change will impact our economies ?

- Chanel : impact of climate change on commodiites and therefore on relative prices
- This paper : Focus on El Niño-Southern Oscillation (ENSO)
  - How climate affects prices through ENSO conditions ?
  - How this relation may evolve due to climate change ?

El Niño-Southern Oscillation



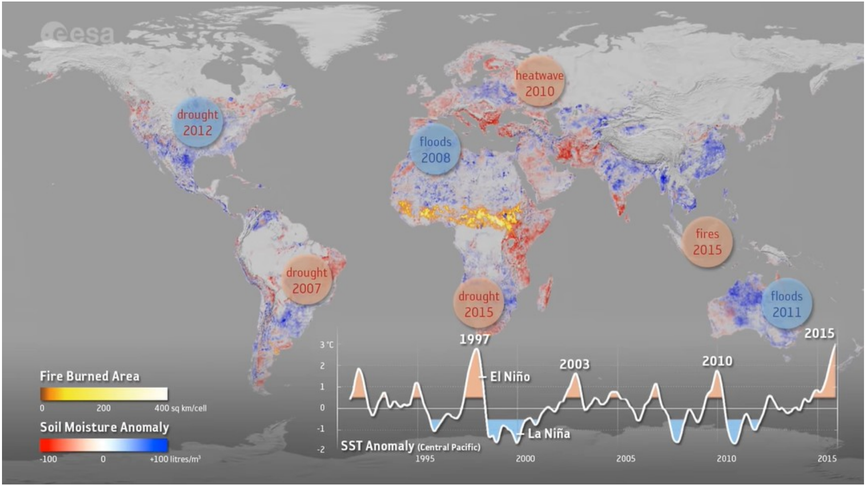
Normal conditions



El Niño conditions

Source : European Spatial Agency

ENSO is a global phenomenom



Source : European Spatial Agency

ENSO has large impacts on the economy

- Many channels from ENSO conditions to econ activity
  - e.g. weather anomalies $\Rightarrow$ agricultural commodities supply
  - e.g. no upwelling of colder water, nutrients $\downarrow$ phytoplankton population $\downarrow$ fish catch $\downarrow$
  - e.g. excessive precipitation, mines flooded, metals and minerals production $\downarrow$

- Many complexities
  - Commodities are not impacted all the same way
    - e.g. El Niño impact on coffee prices : $\uparrow$ Robustas, $\downarrow$ Arabicas
  - El Niño and La Niña are not symmetric
  - Large events have different effects : non-linearity

This paper

Our contributions :

- controlling for global factors
- introducing a method to measure changing ENSO paterns impact on commodities
- an index to express commodities exposure to climate change

  a metrix from *improved stability* to *greater instability*

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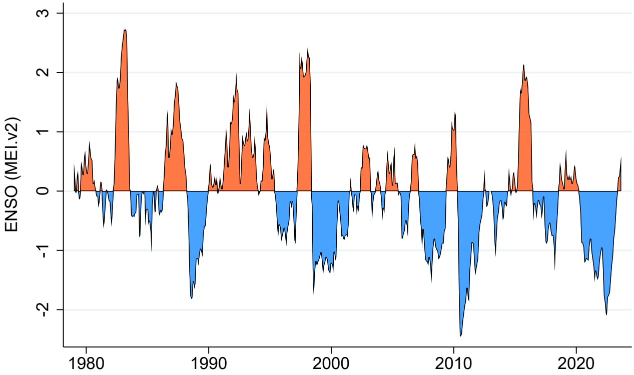
Our dataset

- ENSO : El Niño-Southern Oscillation
  - MEI V2 : multi-variate index (uses SST, winds, SLP, etc.)
  - Sources : National Oceanic and Atmospheric Administration (NOAA)



Our dataset

- ENSO
- Commodities
  - World Bank Pinksheet
  - 3 subgroups : agriculture + energy + metal and minerals
  - 67 International Commodity Prices :
    - Rice Wheat Maize Barley Soybeans Soybean Oil Soybean Meal Palm Oil Coconut Oil Groundnut Oil Sugar Bananas Meat, beef Meat, chicken Oranges Coffee Cocoa Tea Timber Cotton Natural Rubber Tobacco Aluminum Copper Iron Ore Lead Nickel Tin Zinc Natural Phosphate Rock Phosphate Potassium Nitogenous Gold Silver Platinum Coal Crude Oil Natural Gas...

Graph : Composition of the commodities data set

Our dataset

- ENSO
- Commodities
- Control
  - 9 economies (2/3 of global output)
    - Output Growth (Industrial Production, OECD, FRED)
    - Short-term interest rate (OECD, FRED, CEIC)
  - global factor = principal component
- monthly data set from 2002 :04 to 2019 :12

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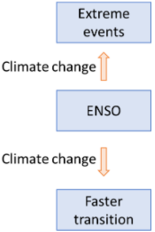
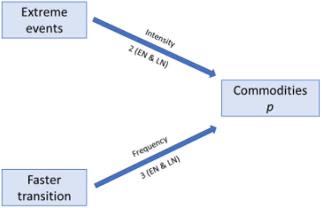
Identification strategy

Assumption :



Step 1 : benchmark

Step 2 : Counterfactual



Step 3 : Comparison

Commodity *i*

For each commodity i and **ENSO scenario** $s \in \{s_1, s_2, s_3, s_4\}$

- **Intensity (extreme events)**
  - s_1 more intense EN
  - s_2 more intense LN
- **Frequency**
  - s_3 faster transitions during EN
  - s_4 faster transitions during LN

Define scenario-specific **volatility response** ($V_{i,s}$):

- $Index_i = \begin{cases} +1 & \text{if volatility significantly increases} \\ 0 & \text{if no statistically significant change} \\ -1 & \text{if volatility significantly decreases} \end{cases}$
- $Index_i = \sum_{s=1}^{4} V_{i,s}$
- $Index_i \in [-4, +4]$

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Baseline Model

Local projections with transition function *à la* Jorda (2005)

$$\pi_{t+h} = F(\zeta_{t-1})(\alpha_{h,EN} + \phi_{h,EN}(L)x_{t-1} + \beta_{h,EN} shock_t) \\ + (1 - F(\zeta_{t-1}))(\alpha_{h,LN} + \phi_{h,LN}(L)x_{t-1} + \beta_{h,LN} shock_t) \\ + \epsilon_{t+h}$$

with

- π_t commodity price change (1 among 67 indices)
- x_t control variables (global Y_t, global i_t, π_{t-1})
- $shock_t$ surprise components of MEI.V2 : $\zeta_t = \alpha + \sum_{n=1}^{h} \beta_i \zeta_{t-h} + u_t$
- $\beta_{h,EN}$ impact of the weather shock in a El Niño state
- $\beta_{h,LN}$ same for La Niña state
- $F(\zeta_t)$ $= \frac{\exp(-\gamma \zeta_t)}{1+\exp(-\gamma \zeta_t)}$
  - Transition function representing climate state
  - During La Niña $F(\zeta_t) \rightarrow 0$; During El Niño $F(\zeta_t) \rightarrow 1$

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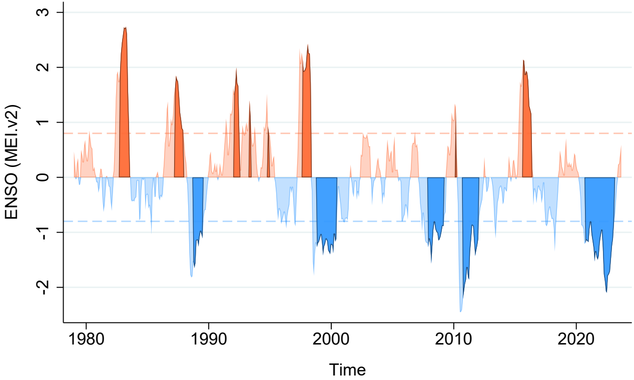
Extreme events : El Niño Anomalous Weather Conditions

two join criteria to define anomalies :

- amplitude
  - MEI.V2 absolute value is above .8
- duration of the variation.
  - a minimum of 5 consecutive overlapping seasons

Figure – MEI.v2 Anomalies



El Niño Anomalous Weather Conditions

$$\pi_{t+h} = (1 - I^{ENA} F(\zeta_{t-1}))(\alpha_{h,ENA} + \phi_{h,ENA}(L)x_{t-1} + \beta_{h,ENA}u_t) + I^{ENA} F(\zeta_{t-1})(\alpha_h + \phi_h(L)x_{t-1} + \beta_h u_t) + \epsilon_{t+h}$$

π_t commodity price change (1 among 67 indices)

x_t control variables (global Y_t, global i_t, π_{t-1})

$shock_t$ MEI.V2 surprise : $\zeta_t = \alpha + \sum_{n=1}^{h} \beta_i \zeta_{t-h} + \gamma T_t + u_t$

$\beta_{h,ENA}$ impact of the weather shock in an extrem El Niño state

$F(\zeta_t) = \frac{\exp(-\gamma\zeta_t)}{1+\exp(-\gamma\zeta_t)}$

I^{ENA} = anomalous weather dummy :

- $I_t^{EN} = 1$ if MEI.v2 $< .8$ for at least 5 months
- $I_t^{EN} = 0$ otherwise

$\Rightarrow$ similar approach for La Niña

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Transition function illustration

π_t 1 commodity price change

$$\pi_{t+h} = F(\zeta_{t-1})(\alpha_{h,EN} + \phi_{h,EN}(L)x_{t-1} + \beta_{h,EN}shock_t) \\ + (1 - F(\zeta_{t-1}))(\alpha_{h,LN} + \phi_{h,LN}(L)x_{t-1} + \beta_{h,LN}shock_t) + \epsilon_{t+h}$$

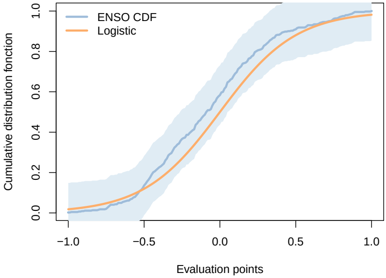
$$F(\zeta_t) = \frac{\exp(\gamma\zeta_t)}{1 + \exp(\gamma\zeta_t)}$$

γ = degree of smoothness of the transition between states

$\rightarrow$ the larger γ the faster the regime change

Transition function : γ estimation results

- Transition function : $F(x|\gamma) = \frac{\exp(\gamma x)}{1+\exp(\gamma x)}$
- Empirical CDF : $\mathcal{F}_\zeta(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{[\zeta_i < x]}$

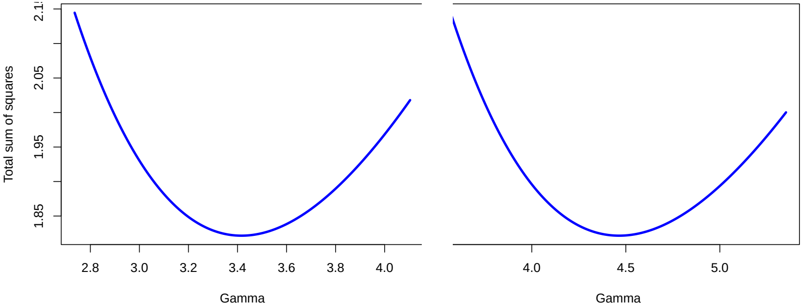


We suggest three alternative criteria to estime γ : Estim

- Total Sum of Squares : $\hat{\gamma} = 4.328$ Details TSS
- Kolmogorov–Smirnov statistic : $\hat{\gamma} = 4.224$ Details KS
- Dvoretzky–Kiefer–Wolfowitz Inequality : $\hat{\gamma} = 4.276$ Details DKW

γ is already changing over time

Figure – Shortening transition times : historical $\hat{\gamma}$



$\hat{\gamma}$ estimated over 1970-1990 $\hat{\gamma}$ estimated over 1990-2010

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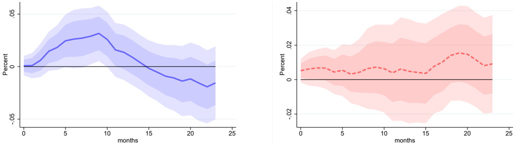
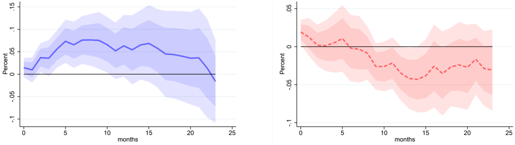
Figure – Impact of MEI.v2 on commodities

La Niña	El Niño

Agriculture index



Energy index



Metals and Minerals index

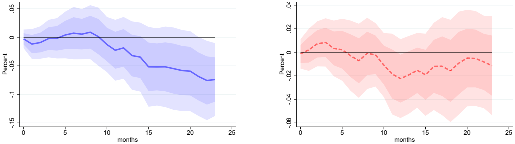
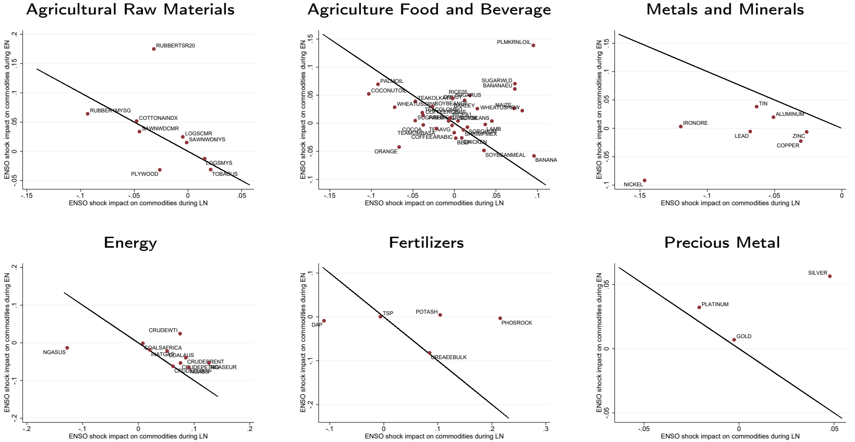


Figure – Reactions to ENSO shocks grouped by commodity categories



Notes : Maximum response over 24 months, of each individual commodities to 1 sd MEIV2 negative shock during La Niña phase and positive shock during El Niño phase.

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Index construction

Fore each commodity, compared with the benchmark, is the result under stress : less volatile / statistically not different / more volatile ?

Values :

	Extreme events	Faster Transition
El Niño	{-1 ;0 ;1}	{-1 ;0 ;1}
La Niña	{-1 ;0 ;1}	{-1 ;0 ;1}

Figure – Commodity price exposure to the evolution of ENSO : index overview

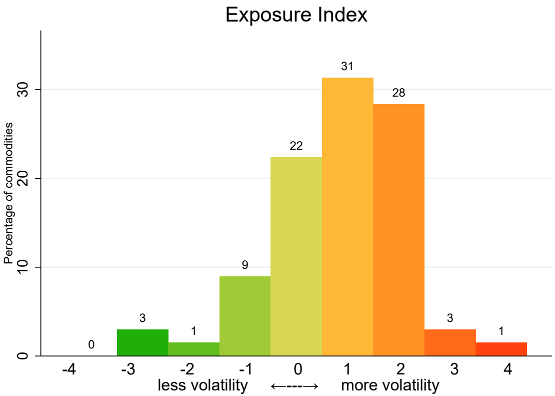
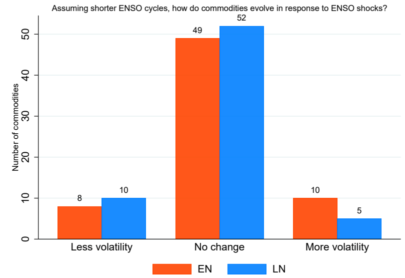


Figure – Changing ENSO paterns impact on commodities



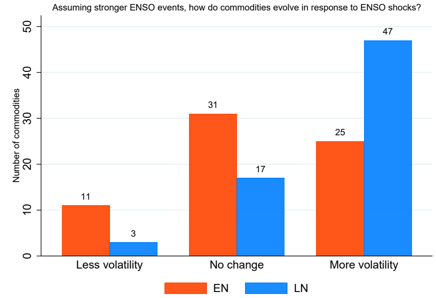


Figure – Index value by categories

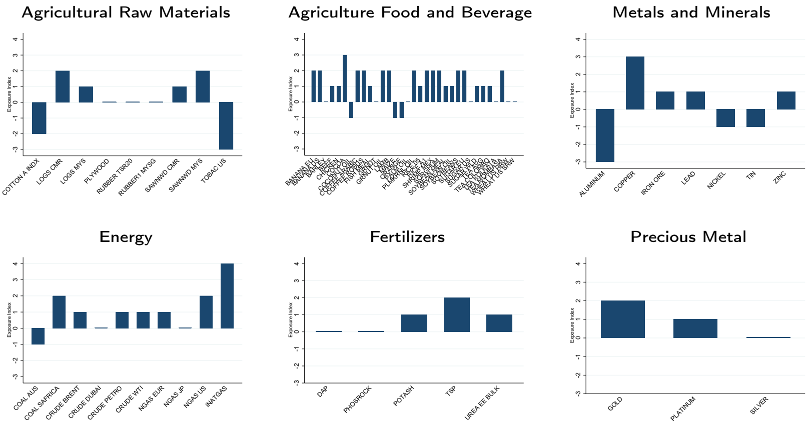
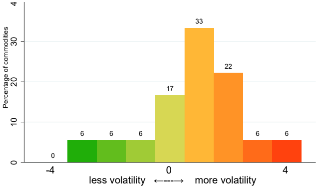
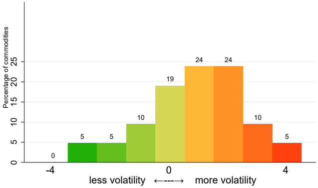


Figure – Commodity price exposure and financialization

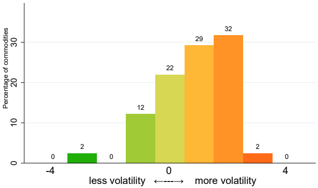
BCOM Index	TR CRB Index

Commodities included in the index





Commodities not included in the index



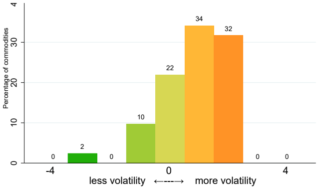
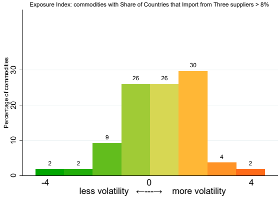
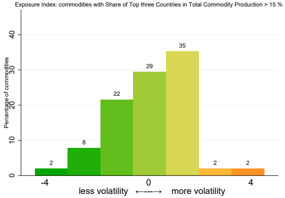


Figure – Commodity price exposure and production concentration

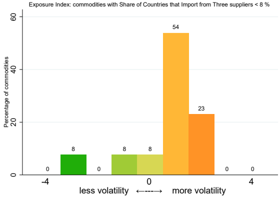
Share of Countries that Import from Three suppliers	Share of Top three Countries in Total Commodity Production

Exposure Index : commodities with production concentration





Exposure Index : commodities without production concentration



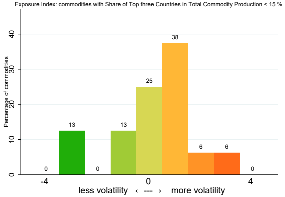
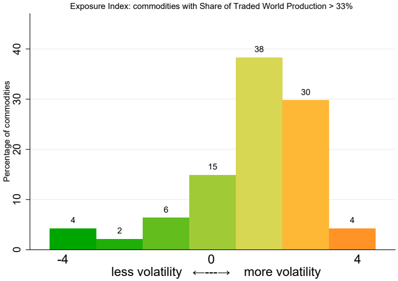


Figure – Commodity price exposure and trade

Share of Traded World Production

Large

Share of Traded



Limited

Share of Traded

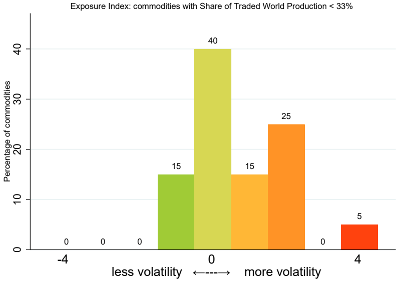
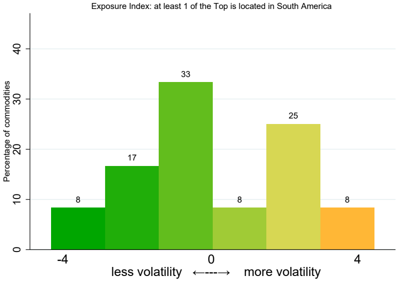
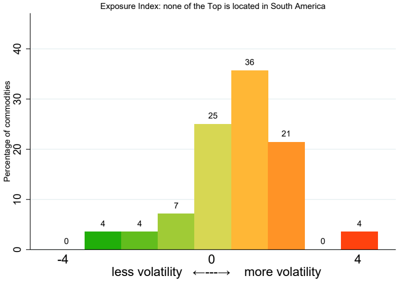


Figure – Commodity price exposure and production concentration in South America

Are Top Three Countries in Total Commodity Production is located in South America ?

At least 1 of the Top Three	None of the Top Three
	

Conclusion

1 global transmission of weather on commodity prices

- Results

  El Niño and La Niña climatic events have an impact on commodity prices

  - more significant impacts at the disaggregated level
  - non-linearity

Conclusion

2. the potential effects of climate change on price stability

- in most cases, climate change is likely to result in greater commodity prices volatility

  particularly explained by increased extreme events
  (more than frequency of EN/LN cycles)

  heterogeneity among commodities
  volatility increases with :
  - financialization
  - production concentration
  - low market participation

Conclusion

$\rightarrow$ policy implications :

climate change $\rightarrow$ adaptation

- financial stability :
  commodities are integrated into financial products

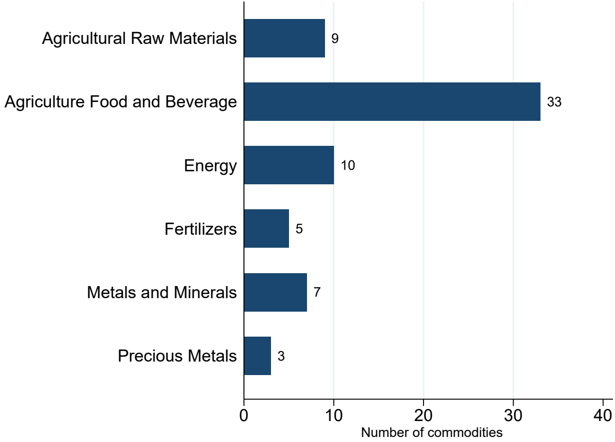
- price stability :
  CB's objective = core inflation, impacted through 2nd round effects

- marekt framentation :
  integrated global commodity markets helps managing shocks

Thanks !

Our dataset

Figure – Composition of the commodities data set



Source : World Bank

Transition function : γ estimation

We suggest three alternative criteria to estime γ :

(1) Total Sum of Squares :

$$\min_{\gamma} Sq = \sum_{1=1}^{n} [F(x_i|\gamma) - \mathcal{F}_{\zeta}(x_i)]^2$$

(2) Kolmogorov–Smirnov statistic :

$$\min_{\gamma} KS = \sup_x |F(\zeta_t|\gamma) - \mathcal{F}_{\zeta}(x)|$$

(3) Dvoretzky–Kiefer–Wolfowitz Confidence Interval :

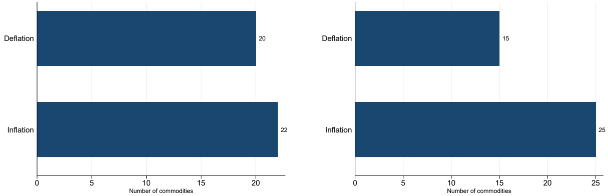
$$\max_{\gamma,\alpha} H(\alpha) = [1]\Big(\mathcal{F}_{\zeta}(x) - \epsilon(\alpha) \leq F(\zeta_t|\gamma) \leq \mathcal{F}_{\zeta}(x) + \epsilon(\alpha)\Big)$$

where $\epsilon = \sqrt{\frac{ln\frac{2}{\alpha}}{2n}}$ and $\alpha \in [0,1]$

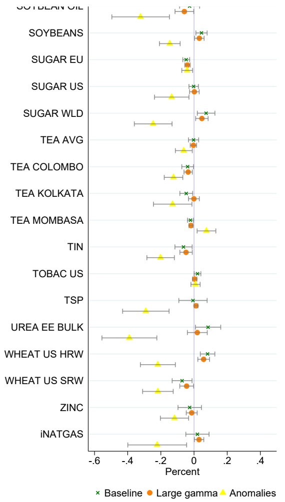
$\rightarrow$ the larger α = the tighter the confidence interval that contains F & $\mathcal{F}$

Figure – Inflationary or deflationary impact of MEI.v2 on commodities

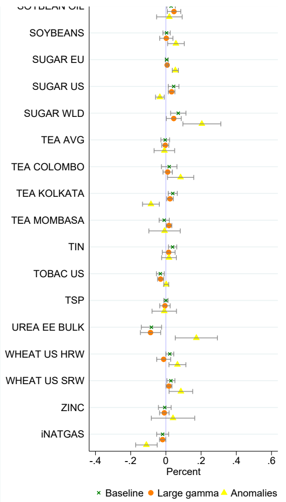
La Niña	El Niño



Notes : responses of price indices to 1 sd MEIV2 negative shock during La Niña phase and positive shock during El Niño phase percent, considering significance at 10%, over a total of 67 commodities



SOYBEAN OIL
SOYBEANS
SUGAR EU
SUGAR US
SUGAR WLD
TEA AVG
TEA COLOMBO
TEA KOLKATA
TEA MOMBASA
TIN
TOBAC US
TSP
UREA EE BULK
WHEAT US HRW
WHEAT US SRW
ZINC
iNATGAS
-.6 -.4 -.2 0 .2 .4
Percent
Baseline
Large gamma
Anomalies



SOYBEAN OIL
SOYBEANS
SUGAR EU
SUGAR US
SUGAR WLD
TEA AVG
TEA COLOMBO
TEA KOLKATA
TEA MOMBASA
TIN
TOBAC US
TSP
UREA EE BULK
WHEAT US HRW
WHEAT US SRW
ZINC
iNATGAS
-.4 -.2 0 .2 .4 .6
Percent
Baseline
Large gamma
Anomalies

Transition function : γ estimation

- Assuming : $X = -1, ..., x, ...1$
- Transition function : $F(x|\gamma) = \frac{\exp(-\gamma x)}{1+\exp(-\gamma x)}$
- Empirical CDF : $\mathcal{F}_\zeta(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{[\zeta_i < x]}$

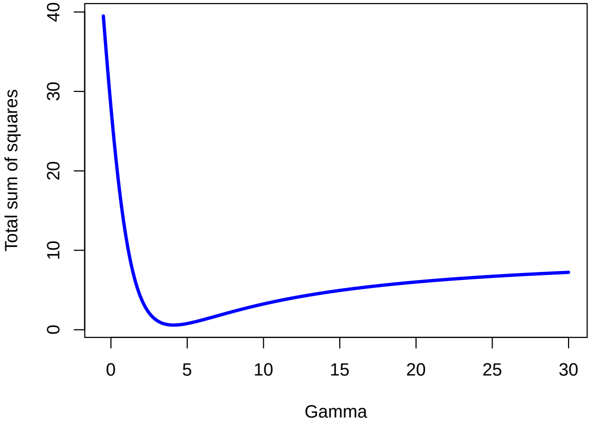
We suggest three alternative criteria to estime γ :

(1) Total Sum of Squares

$$\min_{\gamma} Sq = \sum_{1=1}^{n} [F(x_i|\gamma) - \mathcal{F}_\zeta(x_i)]^2$$

Transition function

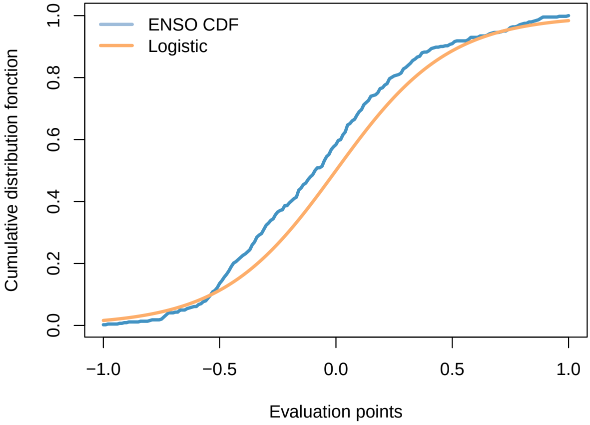
Results Total Sum of Squares



$\hat{\gamma} = 4.328$

Transition function

Results Total Sum of Squares



$\hat{\gamma} = 4.328$

Back to gammma results

Transition function : γ estimation

- Assuming : $X = -1, ..., x, ...1$
- Transition function : $F(x|\gamma) = \frac{\exp(-\gamma x)}{1+\exp(-\gamma x)}$
- Empirical CDF : $\mathcal{F}_\zeta(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{[\zeta_i < x]}$

We suggest three alternative criteria to estime γ :

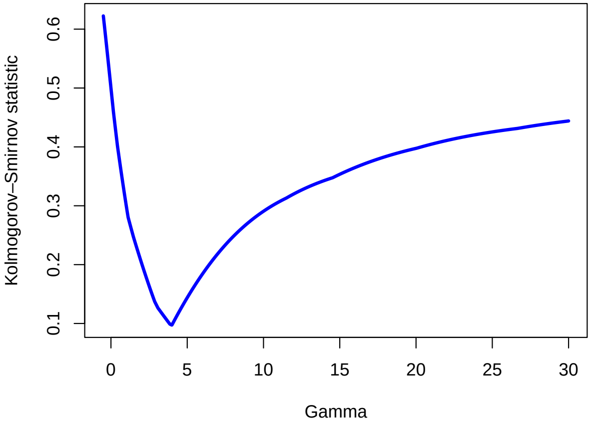
(2) Kolmogorov–Smirnov statistic

$$\min_{\gamma} KS = \sup_{x} |F(\zeta_t|\gamma) - \mathcal{F}_\zeta(x)|$$

sup is the supremum function $\rightarrow$ focus on the one x_i that gives the biggest gap

Transition function

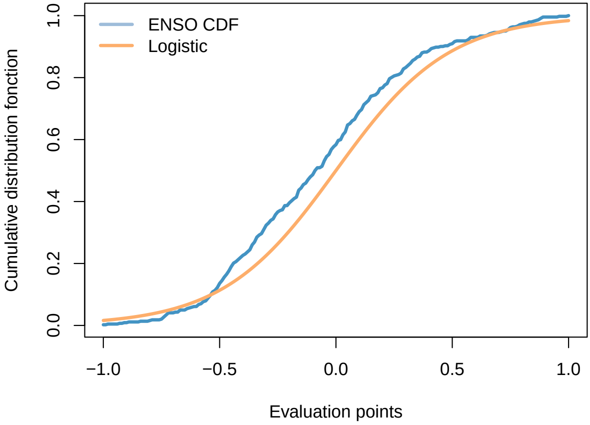
Results Kolmogorov–Smirnov



$\hat{\gamma} = 4.224$

Transition function

Results Kolmogorov–Smirnov



$\hat{\gamma} = 4.224$

Back to gammma results

Transition function : γ estimation

- Assuming : $X = -1, ..., x, ...1$
- Transition function : $F(x|\gamma) = \frac{\exp(-\gamma x)}{1+\exp(-\gamma x)}$
- Empirical CDF : $\mathcal{F}_\zeta(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{[\zeta_i < x]}$

We suggest four alternative criteria to estime γ :

(3) Dvoretzky–Kiefer–Wolfowitz Confidence Interval :

$$\max_{\gamma,\alpha} H(\alpha) = [1]\left(\mathcal{F}_\zeta(x) - \epsilon(\alpha) \leq F(\zeta_t|\gamma) \leq \mathcal{F}_\zeta(x) + \epsilon(\alpha)\right)$$

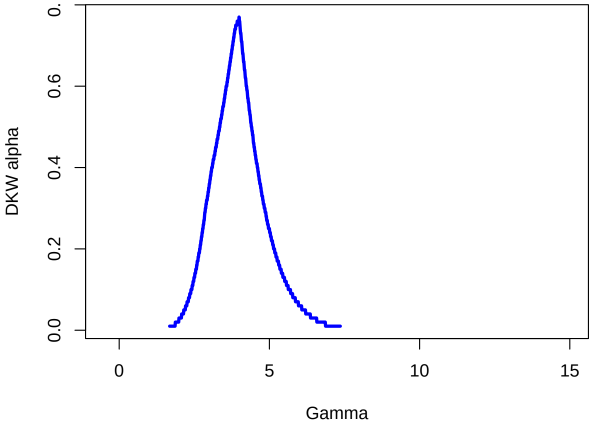
where $\epsilon = \sqrt{\frac{ln\frac{2}{\alpha}}{2n}}$ and $\alpha \in [0, 1]$

$\rightarrow$ identify γ value for which (F & $\mathcal{F}$) are in a given interval

$\rightarrow$ larger α = tighter confidence interval

Transition function

Results Dvoretzky–Kiefer–Wolfowitz Inequality

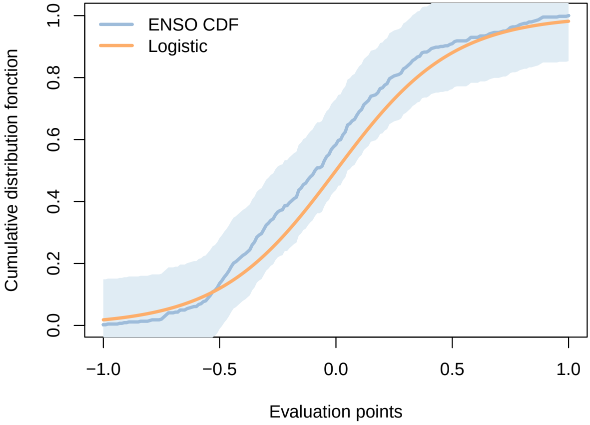


The tightest confidence interval around $\mathcal{F}_\zeta(x)$ that contains $F(\zeta_t|\gamma)$

- is defined by $\mathcal{F}_\zeta(x) \pm \sqrt{\frac{ln\frac{2}{.56}}{2n}}$
- is obtained with $\gamma = 4.276$

Transition function

Results Dvoretzky–Kiefer–Wolfowitz Inequality



$\hat{\gamma} = 4.276$

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