Climate Change Impacts on Commodity Price Stability through Changing ENSO Patterns

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Abstract

Climate change is a global phenomenon that has a significant impact on commodity prices. This paper analyzes the impact of El Niño–Southern Oscillation (ENSO) on global commodity prices, using a Global Factor Local Projections (GFALP) model. Firstly, we demonstrate that unanticipated ENSO movements contribute to commodity price volatility asymmetrically during El Niño and La Niña periods. Secondly, climate change might disrupt ENSO patterns. We compare the current situation with potential climate change outcomes to evaluate its impact on commodity price stability. We compute an index measuring commodity price exposure to these disruptions. We demonstrate that in most cases, these shifts exacerbate commodity price volatility. Finally, we explore several avenues to explain the observed heterogeneity in the exposure of commodity prices to the evolution of ENSO that could result from climate change, and we highlight the crucial role of international commodity markets in adapting to climate change.

JEL Classification: C32, G13, Q54, C50.

Keywords: ENSO, Commodity Price, Climate Change, Agriculture, Energy.

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1 Introduction

Numerous recent studies have highlighted the impact of weather conditions on economic activity. These studies help us to better understand how economic activity depends on climatic conditions and how weather shocks can impact the economy (e.g. Carleton and Hsiang, 2016, Henseler and Schumacher, 2019, Acevedo et al., 2020, De Winne and Peersman, 2021, Tol, 2024). A central question in this literature is how ongoing climate change will affect economies, so that society can adapt institutions and policymakers to make informed decisions that lead to sound economic policies. In this paper, we focus on a specific channel that links weather conditions to economic activity: commodity prices.

El Niño–Southern Oscillation (ENSO) is a climate phenomenon characterized by periodic fluctuations in sea surface temperatures and atmospheric pressure in the equatorial Pacific Ocean. It involves interactions between the ocean and the atmosphere and has significant impacts on weather patterns around the world. ENSO is characterized by the periodic alternation between El Niño conditions (warmer than average sea surface temperatures) and La Niña conditions (cooler than average sea surface temperatures in the central and eastern Pacific Ocean). ENSO events typically occur every two to seven years and can lead to various climate anomalies, including changes in rainfall patterns, temperatures, and storm activity, affecting ecosystems, agriculture, and economies globally.

Existing literature has identified numerous ways ENSO conditions influence economic activity. The most obvious is the impact of weather anomalies on the supply of agricultural commodities (Legler et al., 1999). However, the effects of ENSO extend far beyond agriculture. For instance, during the El Niño phase, the lack of upwelling of colder, nutrient-rich water near the South American Pacific coast leads to a decline in phytoplankton populations, resulting in reduced fish catches (Bertrand et al., 2020). Additionally, metals and minerals can be affected, particularly due to excessive rainfall causing flooding in mines (Vink and Robbins, 2012). This illustrates how all commodities are impacted by the ENSO phenomenon. Beyond commodities, it should be noted that this wide range of ENSO conditions' sectoral effects logically manifests at the macroeconomic level (Berry and Okulicz-Kozaryn, 2008 , Cashin et al., 2017, Liu et al., 2023).

The examples provided above are just a few of the numerous transmission channels between ENSO conditions and economic activities explored in the literature. These channels can sometimes appear contradictory. For instance, the impact of El Niño on coffee varies between arabica and robusta varieties (Ubilava, 2012). Another complexity arises from the asymmetry between El Niño and La Niña phenomena: meteorologically, La Niña is not simply the opposite of El Niño, but rather an intensification of "normal" conditions. A brief La Niña period is not necessarily followed by a similarly brief El Niño period, as there is no predictable cyclic pattern (An et al., 2005, An et al., 2005, Guo et al., 2017). The duration and scale of El Niño events influence their effects on economic activity, introducing numerous non-linearities (see Smith and Ubilava, 2017 and Generoso et al., 2020 on regime-dependent nonlinearity in the growth response to ENSO shocks). Furthermore, many researchers believe that climate change will alter the rate at which El Niño and

La Niña phases reverse and increase their intensity, although these projections are highly uncertain (Cai et al., 2014, Yeh et al., 2018, Hu et al., 2021, Cai et al., 2021). Ultimately, the significance of this phenomenon—both meteorologically and economically—combined with the complexity of its analysis, makes it a critical subject of study.

In this paper, we address two questions: How does climate affect commodity prices through ENSO conditions? And how might this relationship evolve due to climate change?

First, we introduce a method to measure ENSO unanticipated changes impact on commodities, while controlling for global factors. As the impact of El Niño or La Niña cannot be reduced to one country, but rather has global dimensions, this paper employs a global factor augmented local projections model (GFALP) framework to assess the transmission of weather shocks on commodities, while controlling for global output and financial condition, using monthly data over the period 1986 01 to 2023 06. Using monthly data has the potential benefit of capturing the short-term temporal effect that weather has on the economy (e.g., Barnston, 2015), as opposed to using quarterly data as in previous studies (Brunner, 2002, Cashin et al., 2017). To capture the non-linearities described above and following Auerbach and Gorodnichenk (2012) and Ventosa-Santaulària et al. (2024), we estimate a non-linear local projection model (NLLP, as opposed to Berry and Okulicz-Kozaryn (2008) or Anttila-Hughes et al., 2021 for example of linear framework). Our analysis demonstrates that aggregating commodities into broad categories (agriculture, energy, metals) significantly reduces the observed impact of ENSO on prices compared to examining individual commodities. This difference is due to the diverse reactions of individual commodities. Additionally, we show that the impact of shocks varies greatly between El Niño and La Niña periods, supporting the use of a non-linear model.

Second, we propose an original method to capture the effect of climate change through two parameters: the frequency and intensity of El Niño and La Niña events. We estimate these two parameters using historical data and then simulate the effects of shocks by calibrating values to reflect the assumed impacts of climate change. A key contribution of our paper is to propose three original statistical criteria to estimate these parameters. This approach allows us to observe how climate change influences the volatility of commodities through its effects on ENSO. From these simulations, we develop an index that measures each commodity's price exposure to changes in ENSO. This index helps us determine whether climate change will increase the vulnerability of each of the 67 commodities studied to ENSO events or leave it unaffected.

Our findings reveal considerable variation among commodities in their responses to climate change. Some commodities show minimal or no impact, with a few expected to have even more stable prices in the future. In contrast, others are projected to face significantly increased volatility, as indicated by our index. To explain this disparity, we conducted several tests and found that factors such as financialization, production concentration, and the limited proportion of a commodity sold on the global market tend to amplify volatility.

This research overlaps with two broad strands of literature. The first strand relates to a voluminous body of literature analyzing the effects of ENSO on activity, and particularly on commodities.

Previous studies generally focus on one commodity, such as Tack and Ubilava (2015) about cotton, or a given country, such as Ubilava (2012) and Melo-Velandia et al. (2022) about Colombia, Mueller and Osgood (2009) about Brazil, Mainardi (2011) about Burkina Faso and Niger or Li et al. (2019) about China. We add to the literature by showing that the effects of ENSO operate also at the global level. Also, our work is close to Ubilava (2018) who finds an effect of ENSO on a large number of commodities, particularly agricultural commodities. However Ubilava (2018) does not address the issue of climate change. Conversely, Liu et al. (2023) find a damaging impact from an El Niño on global production and they show how climate warming will exacerbated economic damage from changing ENSO. In a close work, Callahan and Mankin (2023) use a cross-country model with two separated measures to capture El Niño and La Niña (and without controlling for the global economy). They show that El Niño persistently reduces country-level economic growth. Hence, Liu et al. (2023) and Callahan and Mankin (2023) take into account the effect of climate change, but looks at GDP and not commodities. Therefore, our position in the literature is clear: to our knowledge, this paper is the first to propose a method for projecting the effect of climate change on the impact of ENSO on a large number of commodities.[1]

The second strand relates to a growing literature analyzing the impact of climate shocks on financial stability (see Buhr et al., 2018, Giuzio et al., 2019, Fabris, 2020, Stan et al., 2021, Strabel and Wurgler, 2021) such as Flori et al. (2021) who concludes that "climate conditions affect financial stability by impacting commoditiy comovements". Among all these papers, our work is connected to a small body of literature that highlights the financial impact of ENSO. In particular, Damette et al. (2024) find a significant positive impact of ENSO on sovereign risk in Latin America, and De Marco et al. (2023) investigate show that ENSO affects the banking system in the US through lower house prices and mortgage lending during El Niño phase. We focus on the impact of ENSO on the commodities market, and show in particular that the financialization of this market exacerbates volatility after ENSO shocks. Because of the importance of climate shocks for financial stability, there is increased interest from government and central banks to incorporate climatic risk into adaptation and resilience management (see Pointner and Ritzberger-Grünwald, 2019, Battiston et al., 2021, Svartzman et al., 2021). In addition, a few papers have pointed out that central banks mandate for price stability is also threatened by weather regimes and climate change (Mukherjee and Ouattara, 2021, Kabundi et al., 2022, Boneva et al., 2022, Cevik and Jalles, 2023, Ventosa-Santaulària et al., 2024). By showing that climate change weighs on commodity prices stability, we contribute to this literature, which defines the channels through which climate change can

[1] In contrast to studies such as Liu et al. (2023) and Callahan and Mankin (2023), but in line with Mourtzinis et al. (2016) and others, our work does not rely on Shared Socioeconomic Pathways (SSP) projections. The reason we do not use SSP projections is that our ENSO measurement (MEI.V2, see Section 2.1) incorporates multiple dimensions, such as sea level pressure and surface zonal winds, which are not included in SSP projections. Moreover, we do not compare different CO2 emission scenarios and their effects on commodity volatility. Instead, our focus is on identifying which commodities exhibit increased volatility in response to changes in the intensity and frequency of the ENSO phenomenon, and on understanding why certain commodities are more impacted than others.

jeopardize price stability.[2]

The rest of the paper is structured as follows: in Section 2 describes the data and discusses the global dimensions of the business cycle considered in the paper. The empirical strategy is developed in Section 3. Empirical results are summarized in Sections 4 and 5. Section 6 concludes the paper.

2 Data

Three types of global variables are considered: a weather index (MEI.v2); global factors (output and interest rate); and 67 commodity prices. Each are discussed in turn.

2.1 Global Weather Patterns

ENSO is one of the most important climate indicators, which has a major influence of global weather conditions (e.g., Ropelewski and Halpert, 1987, Rosenzweig et al., 2001, McPhaden et al., 2006, Dai, 2013 and Brönnimann et al., 2007).[3] When a major El Niño (La Niña) occurs, there is an anomalous loss (increase) of heat from the ocean to atmosphere so that global mean temperatures rise (fall) (McPhaden et al., 2020). The anomalous atmospheric patterns are known as the Southern Oscillation, as ENSO relates to cyclical, environmental conditions that occur across the equatorial Pacific Ocean. Changes to ENSO are due to natural interactions between sea surface temperature, rainfall, air pressure, atmospheric and oceanic circulation. The effects of ENSO, commonly called "teleconnections", emphasize that changing conditions can have a profound effect on global climate, which can in turn directly affect people's livelihoods (e.g., Barlow et al., 2001, Diaz et al., 2001, and Alexander et al., 2002).

Various series have been used in the literature to capture ENSO phenomena.

A first one is the Sea Surface Temperature (SST) anomalies (Hansen et al., 1998, Brunner, 2002, Ubilava, 2018, Atems and Sardar, 2021). SST indices are measures based on the average sea-surface temperature over a fixed area in the tropical Pacific. They look particularly relevant for annual data analysis.

Another measure is the Oceanic Niño Index (ONI) (Sarachik and Cane, 2010, Hsiang et al., 2011, Generoso et al., 2020). ONI is a 3 month rolling index tracking the ocean part of ENSO.

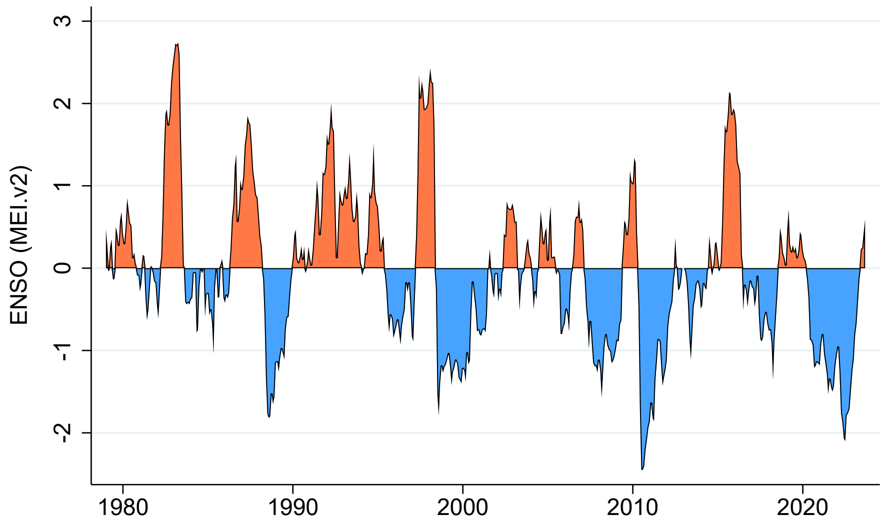
Finally, some indices have been created to integer many dimension of ENSO: SST, winds, etc. One of the most used in the literature is MEI.v2, published by the National Oceanic and Atmospheric Administration (NOAA) and available from 1979. MEI.v2 uses 5 variables: sea level pressure (SLP), sea surface temperature (SST), surface zonal winds (U), surface meridional winds

[2] Note that some papers find that temperature shocks lead to inflationary pressures, such as Mukherjee and Ouattara (2021) for developing countries, while other papers seems to indicates the opposite, such as Cevik and Jalles (2023) who find that following a temperature shock, headline inflation falls. See Kranz et al. (2024) for a literature review.

[3] The NOAA considers ENSO as "one of the most important climatic phenomena on Earth", see `https://www.weather.gov/mhx/ensowhat`.

(V), and Outgoing Longwave Radiation (OLR). [4] It is a bi-monthly index that is calculated for 12 overlapping bi-monthly “seasons” (Jan-Feb, Feb-Mar,...). Therefore, it takes into account ENSO seasonality and reduce effects of higher frequency intra-seasonal variability (see De Marco et al., 2023).

Composite positive MEI events can be read as warm periods, which correspond to El Niño events. [5] Negative MEI events have opposite characteristics and can therefore be seen as La Niña events. NOAA generally applies a $+/-0.5$ threshold to define non-overlapping hot and cold periods, the in-between been neither El Niño nor La Nina. Figure 1 displays the evolution of MEI.v2 since 1979. Top warm El Niño events can be seen in 1983, 1987, 1992, 1998 and 2016. Similarly, top cold La Niña events can be seen in 1989, 1996, 1999, 2008 and 2011.



Areas shaded blue indicate negative values of the MEI.v2 that represent the cold ENSO phase, a.k.a. La Niña, while areas shaded red indicate positive MEI.v2 that values represent the warm ENSO phase, a.k.a. El Niño.

Figure 1: MEI.v2 Evolution over Time

2.2 Commodities

A total of 67 international commodities are analyzed in this study, taken from the World Bank “pinksheet” monthly data. The sample period covers 1986:01 to 2023:06. Figure 2 presents the composition of the data set according to the type of commodities. Apart from a large group of

[4]See `https://psl.noaa.gov/enso/mei/`

[5]As defined by NOAA : ”Key features of composite positive MEI events (warm, El Niño) include (1) anomalously warm SSTs across the east-central equatorial Pacific, (2) anomalously high SLP over Indonesia and the western tropical Pacific and low SLP over the eastern tropical Pacific, (3) reduction or reversal of tropical Pacific easterly winds (trade winds), (4) suppressed tropical convection (positive OLR) over Indonesia and Western Pacific and enhanced convection (negative OLR) over the central Pacific.”

food and beverage commodities, the data set is balanced over the 6 dimensions: energy, fertilizers, metals end minerals, precious metals. To make the results easier to read, we sometimes reason at an aggregate level, using the World Bank's 3 categories: agriculture, energy and metals/minerals prices. All prices are converted to logarithm. The commodity price data, denominated in U.S. dollars, is deflated by dividing by Producer Prices Index (OECD Total Area).

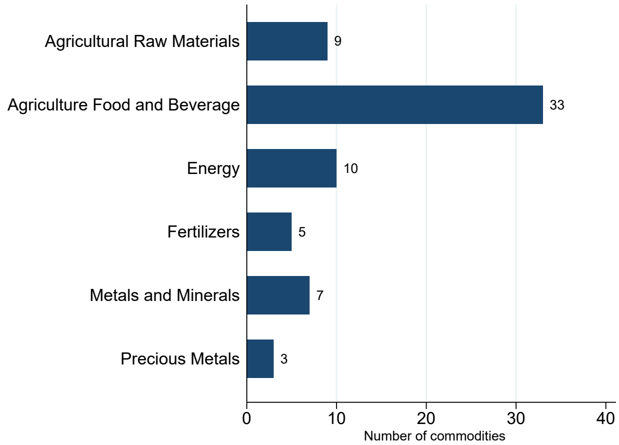


Figure 2: Composition of the commodities data set

2.3 Control variables

The global dimension of our macro variables is obtained by considering the first principal component of nine economies covering output and the interest rate. Following the approach by Ratti and Vespignani (2016), we construct a global factor using the principal component indices for output and interest rate using normalized loadings.[6] The benefit of this approach is that by taking the first principal component establishes a dimension reduction techniques that can replicate the main features of a global environment. The global factors represent nine economies which approximate two-thirds of global output.[7]

[6] Output is proxied by OECD and Fred industrial production data. For India, manufacturing production index (FRED mnemonic INDPRMNTO01IXOBM) is used as opposed to total production index (FRED mnemonic INDPROINDMISMEI), considering data availability (the correlation between the production indices is 0.9918 for Jan 2000 to Dec 2018). For China, we use total production excluding construction (FRED mnemonic CHNPRINTO01IXPYM). As the production index for China includes missing values, the Kalman smoother using an ARIMA state space representation is used to impute missing values. For India, the interest rate is based on the 90 day Treasury Bill interest rate (e.g., Patnaik et al., 2011, Gabriel et al., 2012, Saxegaard et al., 2010, Anand et al., 2014 and Ginn and Pourroy, 2022).

[7] The nine economies include: Canada ("CAN"), China ("CHN"), Euro zone (19 countries; "EUR"), United Kingdom ("GBR"), India ("IND"), Japan ("JPN"), South Korea ("KOR"), Russia ("RUS") and the United States ("USA"). Based on IMF data in purchasing power parity terms, the nine economies considered in this paper represent 66.1% of global output, see `https://www.imf.org/external/datamapper/PPPSH@WEO/OEMDC/ADVEC/WEOWORLD/EU`. The Euro zone values are based on the 19 member countries (i.e., Austria, Belgium, Cyprus, Estonia, Finland,

$$Y_t^G = [Y_t^{CAN}, Y_t^{CHN}, Y_t^{EUR}, Y_t^{GBR}, Y_t^{IND}, Y_t^{JPN}, Y_t^{KOR}, Y_t^{RUS}, Y_t^{USA}] \quad (1)$$

$$R_t^G = [R_t^{CAN}, R_t^{CHN}, R_t^{EUR}, R_t^{GBR}, R_t^{IND}, R_t^{JPN}, R_t^{KOR}, R_t^{RUS}, R_t^{USA}] \quad (2)$$

We use one factor (the principal component) for the global variables (Ratti and Vespignani, 2016). The results are provided in Table 1, which shows the top three principal components of each global variable for the nine economies. The first principle component captures significant share of the variance relating to output (54.9%) and the interest rate (54.1%).[8]

Figure 3 plots the global factors along with the economy data. The top-pane shows a sizable decline in output which occured during the global financial crisis.[9]

	Global Output	Global Interest Rate
First Principal Component	54.9%	54.1%
Second Principal Component	33.5%	18.3%
Third Principal Component	6.4%	12.3%

Table 1: Variation Explained by First Three Principal Components

The correlation between global variables (output and interest rate) is provided in Table 2. The correlation between global factor and country output is quite high for CAN, RUS and USA; and somewhat moderate for EUR and IND. There is lower correlation between the China and global output. The negative correlation between the UK and global output may be due to higher uncertainty in the UK related with Brexit. While it remains unclear to the extent that Brexit has had an impact on the domestic economy, a common thread is uncertainty, which has been linked with reduced investment, employment and productivity growth (Bloom et al., 2018).

Country	GLO	CAN	CHN	EUR	GBR	IND	JPN	KOR	RUS	USA
Global Output	1.00	0.63	-0.81	0.51	-0.46	0.92	-0.1	0.91	0.98	0.81
Global Interest Rate	1.00	0.92	0.56	0.95	0.94	0.01	0.61	0.91	-0.25	0.81

Table 2: Correlation by Country and Global Variable

France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain).

[8]The higher dimensions of the principal components are provided in the Appendix, see the Scree plot in Figure 20. These values are similar to Ratti and Vespignani (2016), where the first principle component in their paper captures for global output and interest rate represents 60.0% and 44.5% of the total variance, respectively.

[9]According to the NBER, the recession dates for the U.S. is between 2007:DEC to 2009:JUN.

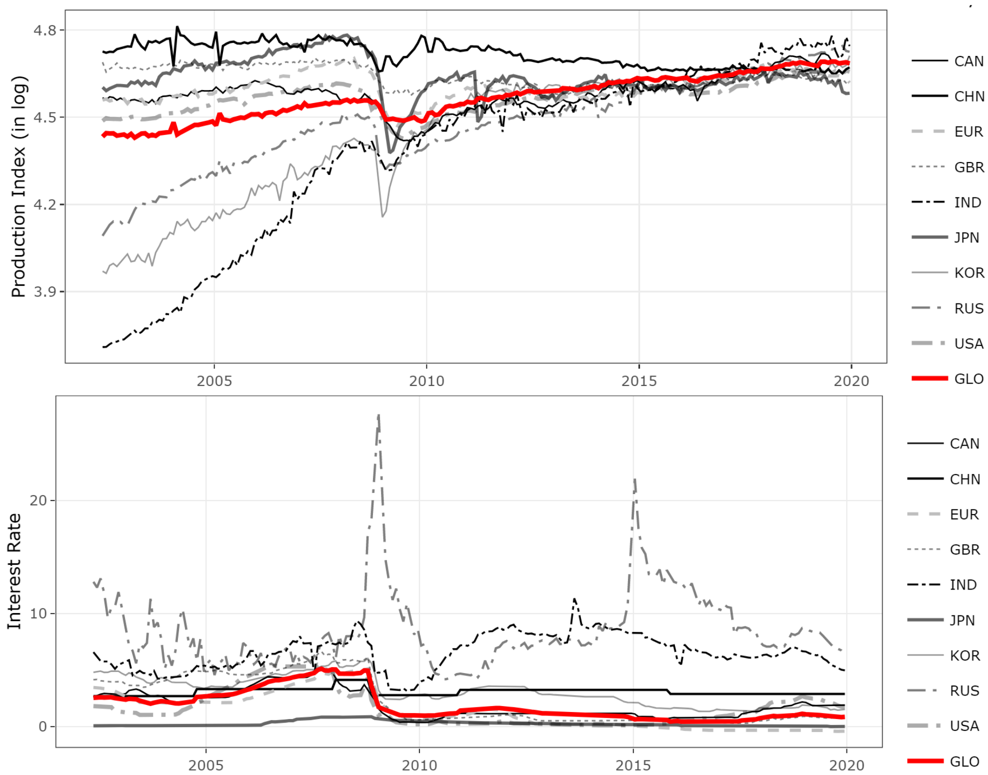


Figure 3: Global Factors

3 Empirical strategy

3.1 Baseline Model

The linear local projections model with transition function, developed by Jordà (2005), is employed to estimate the dynamic responses that changing ENSO patterns have on commodity prices.[10] In the benchmark specification, we estimate commodity price change in real terms (π_t) as follows:

$$\begin{aligned}\pi_{t+h} =& (1-F(\zeta_{t-1}))(\alpha_{h,EN} + \phi_{h,EN}(L)x_{t-1} + \beta_{h,EN}u_t) \\ &+ F(\zeta_{t-1})(\alpha_{h,LN} + \phi_{h,LN}(L)x_{t-1} + \beta_{h,LN}u_t) \\ &+ \epsilon_{t+h}\end{aligned} \tag{3}$$

which accounts for an asymmetry, defined as an El Niño (EN) and La Niña (LN) climate state, with $\pi_{t+h} = p_{t+h} - p_{t-1}$ where p_{t+h} is 1 commodity price (in log form) among 67 indices which is projected on the space generated by a set of control variables (x_{t-1}). The vector of control variables includes lags of the respective commodity price change (π_t), global output growth, global interest rate and control variables for the global financial crisis and the Covid-19 lock-down period. In this specification, we allow the prediction of π_{t+h} to differ according to the state of the climate (i.e., in an El Niño and La Niña state) when a weather shock (u_t) occurs. The coefficient $\beta_{h,EN}$ ($\beta_{h,LN}$) corresponds with the estimated impact of the weather shock in a El Niño (La Niña) state.

The variable u_t is the surprise components of MEI.V2 obtained as follows:

$$\zeta_t = \alpha + \sum_{n=1}^{h} \beta_i \zeta_{t-h} + \gamma T_t + u_t$$

with ζ_t our ENSO measure (MEI.v2), considered with $h = 1, ..., 6$ lags, T_t is a monthly control variable that captures seasonality, and u_t is the residual.

$F(\zeta_t)$ is a smooth transition function that represents the state of the climate:

$$F(\zeta_t) = \frac{\exp(-\gamma\zeta_t)}{1+\exp(-\gamma\zeta_t)} \tag{4}$$

where $\gamma > 0$ controls the degree of smoothness of the transition between states and $|\zeta_t| < \infty$ is a standardized transition variable.

As opposed to Gorodnichenko and Auerbach (2013) and Ramey and Zubairy (2018), the transition variable is not standardized by taking the cyclical component using the Hodrick and Prescott filter, as MEI.v2 is already centered and cyclical. Consistent with Auerbach and Gorodnichenk (2012), the transition function is dated $t-1$ in Equation (3) to avoid contemporaneous feedback from policy actions with regard to the state of the economy (i.e., $F(\zeta_{t-1})$).

In equation (4), the parameter γ denotes the degree of smoothness of the transition between the two state, the larger γ the faster the regime change from El Niño to La Niña and vice-versa.

[10] Following Auerbach and Gorodnichenk, 2012, we develop here a non-linear version of the local projection model, sometimes refereed as NLLP (Ventosa-Santaulària et al., 2024).

In Appendix 8.2 we illustrate how does this function work: we simulate different values for ζ, and then observe the values taken by $F(\zeta)$ assuming alternative values for γ.

We propose a methodology to estimate γ value in order to obtain a transition function the closest to the "true" transition process, which can be proxied by MEI.v2 cumulative distribution function (CDF) function.[11]

Assuming a random evaluation grid: $X = -1, ..., x, ...1$, the CDF of ζ is given by $\mathtt{F}_\zeta(x) = P(\zeta \leq x)$ which is the *probability* that ζ takes on a value less than or equal to x. Empirically, we compute for any x the *proportion*:

$$\mathcal{F}_\zeta(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{[\zeta_i < x]} \tag{5}$$

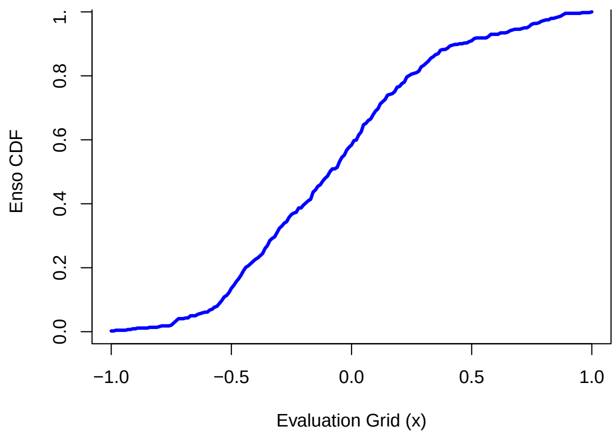


Figure 4: MEI.v2 Empirical CDF

The Empirical CDF, $\mathcal{F}_\zeta(x)$ for MEI.v2, is represented on Figure 4. The calibration of γ must ensure that the transition function $F(x|\gamma)$, given in Equation 4, is as close as possible to the empirical CDF, given in equation 5. We suggest three alternative criteria to obtain such an optimal estimated $\hat{\gamma}$, based on Total Sum of Squares, the Kolmogorov–Smirnov statistic and the Dvoretzky–Kiefer–Wolfowitz Confidence Interval .

(1) Our first criterion to estimate γ is based on the Sum of Squares and consist in minimizing the mean distance between the Empirical CDF and the transition function. We minimize the mean square deviation between the Empirical CDF and the transition function. The result is the transition function that is, on average, closest to the empiric CDF, for all x considered. The criterion is :

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

[11] In the literature, this parameter is generally calibrated (see Auerbach and Gorodnichenk (2012) among other).

(2) Our second criterion consist in minimizing the Kolmogorov–Smirnov statistic applied to $F()$ and $\mathcal{F}$, where *sup* is the supremum function. The focus not on the average deviation but on largest one (as we concentrate on the x_i that gives the biggest gap between the Empirical CDF and the transition function). The criterion is :

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

(3) Our last criteria is based on Dvoretzky–Kiefer–Wolfowitz Confidence Interval with $\epsilon = \sqrt{\frac{ln\frac{2}{\alpha}}{2n}}$ and $\alpha \in [0,1]$ a parameter such that the larger α, the tighter the confidence interval that contains F & $\mathcal{F}$. In other words, we look for γ value that gives the tightest confidence interval around $\mathcal{F}_{\zeta}(x)$ that contains $F(\zeta_t|\gamma)$. The criterion is defined as

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

Figure 5 displays γ estimation outputs. On the left column, we observe the value taken by the TSS, KS and DKW criteria as a function of γ. The three estimation crieterion give very similar results: the value of γ that minimizes the Total Sum of Squares is 4.328; similarly the Kolmogorov–Smirnov statistic is minimal for $\hat{\gamma} = 4.224$; and the Dvoretzky Kiefer Wolfowitz Inequality's alpha is maximized for $\hat{\gamma} = 4.276$. Figure 5 right column displays MEI.v2 empical CDF and the transition function obtained with the optimal γ. Whatever the criteria used to estimate γ, the shape of the transition functions is fairly closed to the empirical CDF.

3.2 Changing ENSO patterns: extreme conditions

Climate change is expected to influence the ENSO. While the precise details are still an area of ongoing research, there is evidence suggesting that climate change could alter the frequency and intensity of El Niño and La Niña events (Cai et al., 2014, Yeh et al., 2018, Hu et al., 2021, Cai et al., 2021). Some models suggest an increase in the frequency of extreme El Niño events, which could have significant implications for global weather patterns (e.g., Timmermann et al., 1999, Chen et al., 2001, An and Wang, 2000). Accordingly, we investigate anomalous ENSO conditions.

Following NOAA among other, we use two join criteria to define anomalies: amplitude and duration of the variation. Therefore, we define anomalies as periods where MEI.V2 absolute value is above .8 and when this threshold is met for a minimum of 5 consecutive overlapping seasons. Anomalies periods are shown in dark on Figure 6.

To estimate whether an anomalous weather conditions matter in an El Niño state, Equation 3 is extended to include a latent variable and interaction terms:

$$\begin{aligned}\pi_{t+h} =& (1 - I^{ENA}F(\zeta_{t-1}))(\alpha_{h,ENA} + \phi_{h,ENA}(L)x_{t-1} + \beta_{h,ENA}u_t) \\ &+ I^{ENA}F(\zeta_{t-1})(\alpha_h + \phi_h(L)x_{t-1} + \beta_h u_t) \\ &+ \epsilon_{t+h}\end{aligned} \tag{6}$$

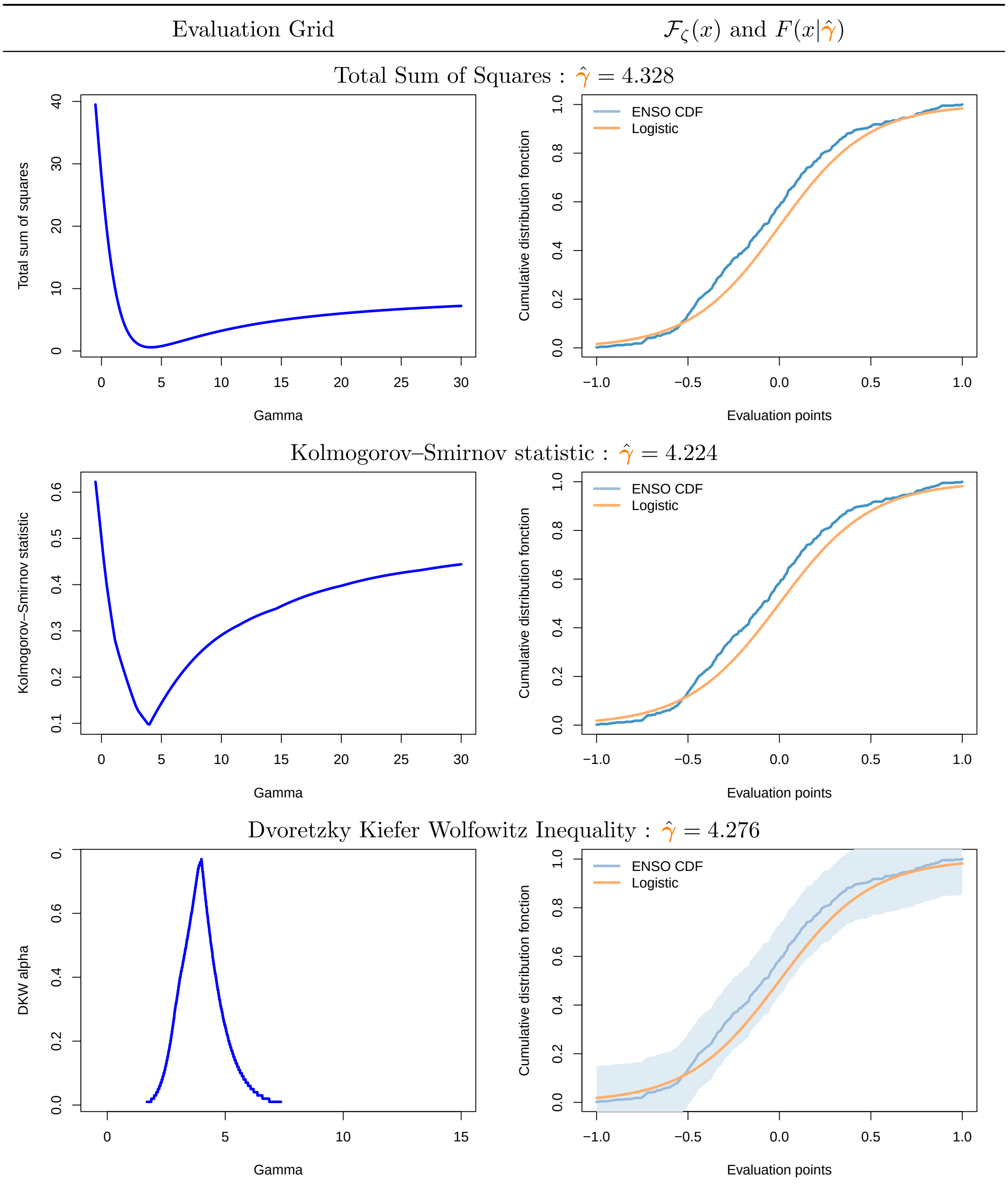
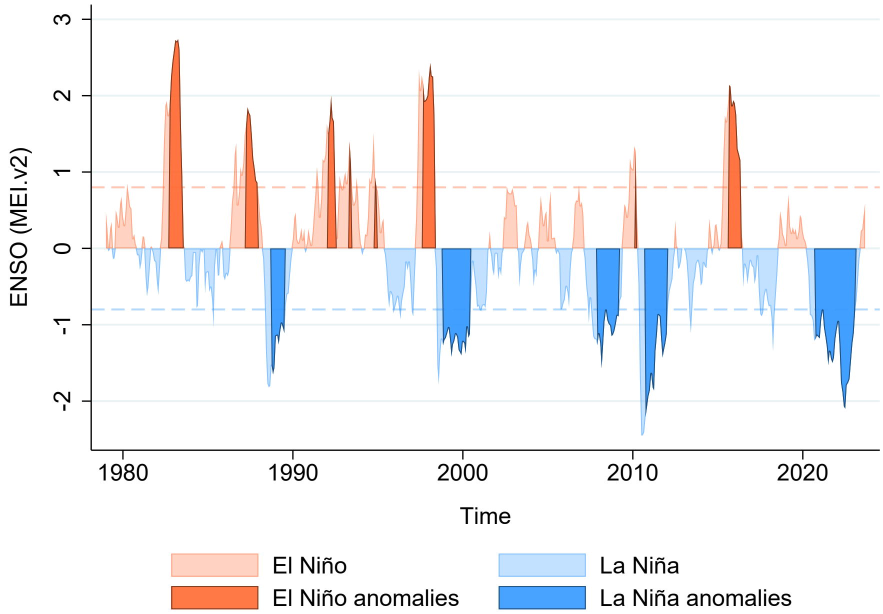


Figure 5: γ estimation

where I^{ENA} equals 1 if MEI.v2 < .8 for at least 5 months in a row, 0 otherwise.



Areas shaded dark blue indicate negative values of MEI.v2 below -.8 for more than 5 periods that represent La Niña anomalies, while areas shaded dark red indicate MEI.v2 values above .8 that represent El Niño anomalies.

Figure 6: MEI.v2 Anomalies

Similarly we estimate the same equation for La Niña anomalies :

$$\begin{aligned}\pi_{t+h} =& I^{LNA} F(\zeta_{t-1})(\alpha_{h,LNA} + \phi_{h,LNA}(L)x_{t-1} + \beta_{h,LNA}u_t) \\ &+ (1 - I^{LNA} F(\zeta_{t-1}))(\alpha_h + \phi_h(L)x_{t-1} + \beta_h u_t) \\ &+ \epsilon_{t+h}\end{aligned} \tag{7}$$

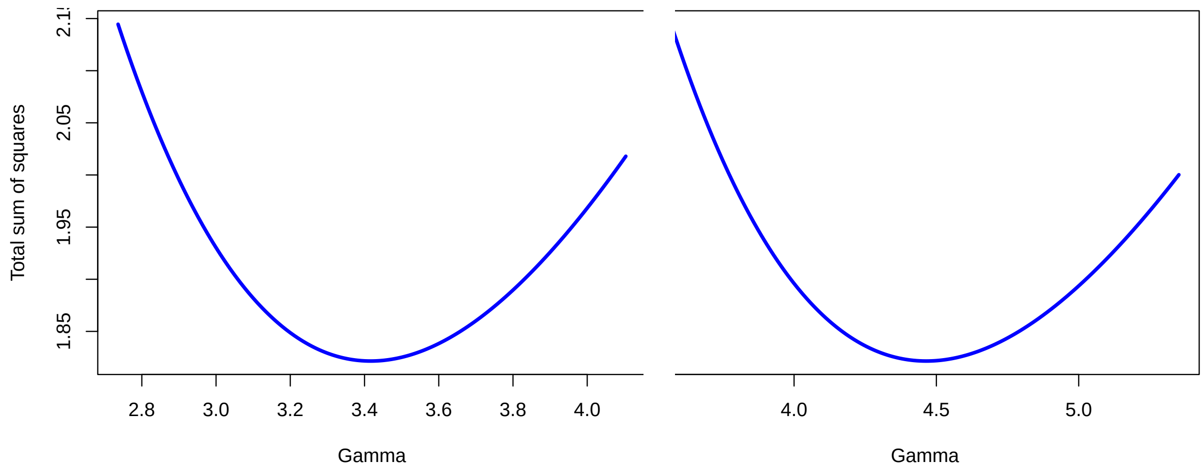
where I^{LNA} equals 1 if MEI.v2 $< -.8$ for at least 5 months in a row, 0 otherwise.[12]

3.3 Changing ENSO patterns: faster transition speeds

Climate change could impact ENSO cycle by shortening transition times from one phase to another (transitions from El Niño to La Niña, and vice versa). How can we account for this change in our set-up? Faster transitions between El Niño and La Niña, and vice versa, should lead to an increase in parameter γ. [13] To test this hypothesis, we estimate the value of γ by splitting the MEI.v2 series into two sub-samples: 1979-1999 and 2000-2022. Results are displayed on Figure 7. It appears that γ is already changing over time.

[12]Note that $I^{LNA} = 0$ during large EN events, and not the other way around, because $F(\zeta)$ tends to 0 for large EN events.

[13]Faster transitions means a steeper CDF, that corresponds to larger γ, as illustrated in Appendix 8.2.



$\hat{\gamma}$ estimated over 1970-1990 $\hat{\gamma}$ estimated over 1990-2000

Figure 7: Shortening transition times: historical $\hat{\gamma}$

In order to identify whether this evolution of γ parameter will have an impact on the influence of ENSO shocks on commodities, we estimate Equation 3 taking into account higher value of γ. The baseline value is $\gamma = 4$. For the robustness section, we use a calibrated parameter, denoted by $\bar{\gamma}$, that takes a value ten times larger than the baseline estimated γ.

$$\begin{aligned}\pi_{t+h} =& trend_t \\ &+ (1 - F(\zeta_{t-1|\bar{\gamma}}))(\alpha_{h,EN|\bar{\gamma}} + \phi_{h,EN|\bar{\gamma}}(L)x_{t-1} + \beta_{h,EN|\bar{\gamma}}u_t) \\ &+ F(\zeta_{t-1})(\alpha_{h,LN|\bar{\gamma}} + \phi_{h,LN|\bar{\gamma}}(L)x_{t-1} + \beta_{h,LN|\bar{\gamma}}u_t) \\ &+ \epsilon_{t+h}\end{aligned} \tag{8}$$

3.4 Changing ENSO patterns: an index to identify commodities under stress

To summarize the information obtained using the estimates presented above, we construct an index that captures the exposure of each commodity price to changing ENSO pattern.

To do this, we compare the results of the baseline estimate (equation 3 in section 3.1) with estimates obtained by considering stressed values, i.e. extreme values (equation 6 and 7 in section 3.2) or a faster transition speed (equation 8 in section 3.1).

Each commodity is therefore evaluated under four stress exercises: during El Niño periods $\beta_{h,EN}$ is compared with $\beta_{h,ENA}$ and $\beta_{h,EN|\bar{\gamma}}$ and during La Niña periods $\beta_{h,LN}$ is compared with $\beta_{h,LNA}$ and $\beta_{h,LN|\bar{\gamma}}$.

We classify the result of each stress exercise into three categories: "less volatility" (e.g $|\beta_{h,EN}| > |\beta_{h,ENA}|$), "no change" (e.g $\beta_{h,EN} \sim \beta_{h,ENA}$) and "more volatility" (e.g $|\beta_{h,EN}| < |\beta_{h,ENA}|$) .

Comparisons are made at a significance level of 5%.[14]

Finally, to give an overview of the four stress scenarios in a single measure, we calculate an index centered on 0, which increases by one unit for any scenario concluding to higher volatility and decreases for any scenario concluding to lower volatility.

The lowest possible value is therefore -4 (all scenarios lead to more volatility) and the maximum is +4 (all scenarios lead to more volatility). The central value, 0, corresponds to the case where there are no more scenarios leading to more volatility than scenarios leading to greater stability (or simply ENSO shocks are never found to impact significantly the commodity price).

[14]Note that the value of h is set to pick the period with the strongest effect. So we typically compare the strongest effect of ENSO shocks on the price of cotton in the baseline scheme with the strongest effect of ENSO shocks on the price of cotton in the case of anomalies, and this effect may arrive after 7 periods in one case and 8 periods in the other, it doesn't matter, we just want to measure the capacity of the shock to vary the price of cotton.

4 Baseline results

4.1 ENSO impact on aggregated prices

The IRFs are obtained by scaling the estimated coefficient (β_h) to a 1 standard deviation shock. As MEI.V2 is positive (negative) on average during an El Niño (La Niña) phase, we assume a positive (negative) shock. By doing so, we make sure that a shock can always be interpreted as strengthening the ENSO phenomenon.[15] The impulse response functions (IRF) are presented in Figure 8. The IRF plots include the 68 and 90% confidence bands using the Newey-West standard errors.

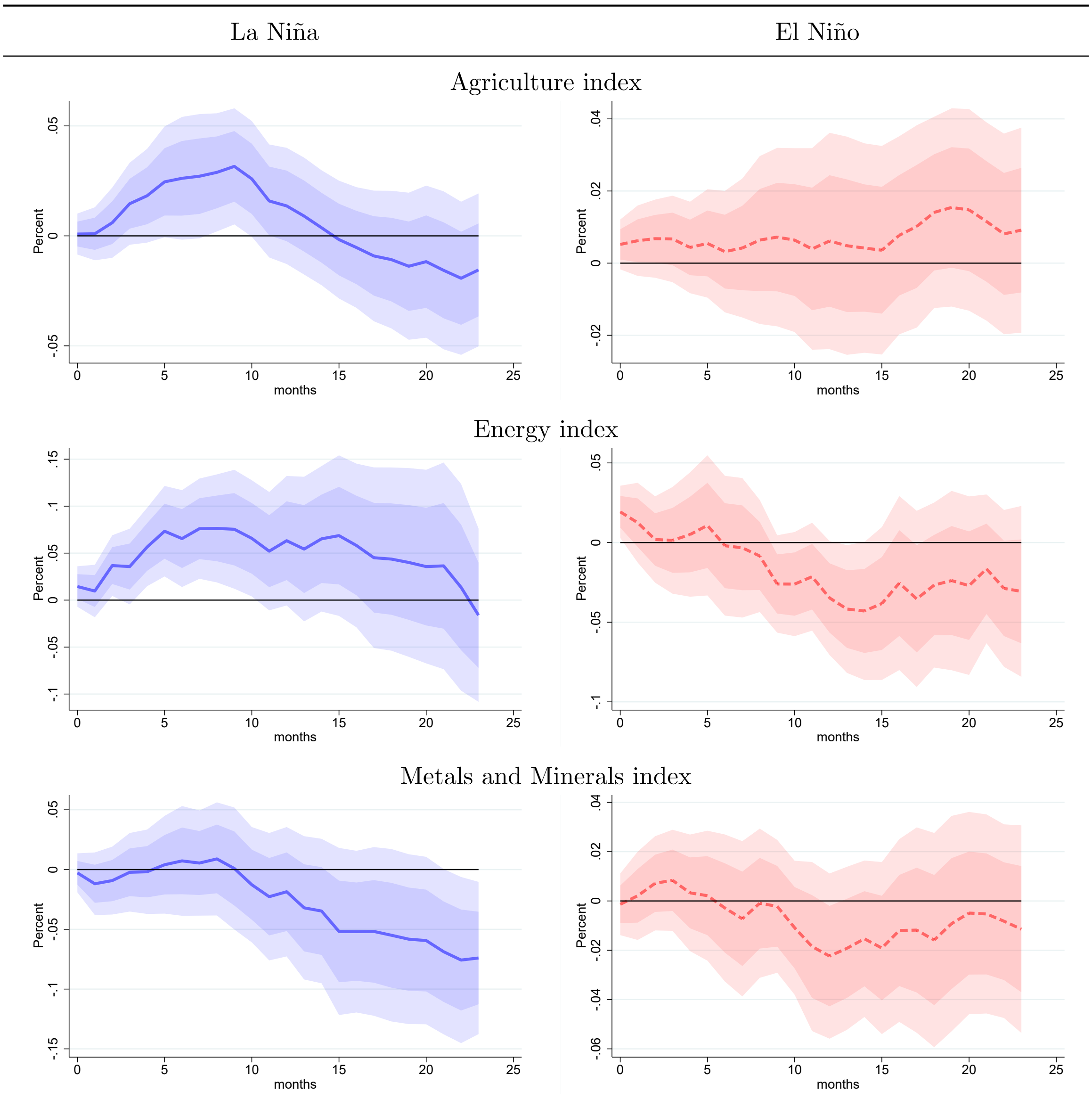
IRFs provide interesting information. A shock during a La Niña phase tends to raise prices for all three indices (agriculture, energy, minerals). Conversely, a shock during an El Niño phase tends to push the Energy and Met/Min price indices down. As the two shocks are opposite in nature, the asymmetry between El Niño and La Niña seems limited for Energy prices. However, the magnitude of the results is not the same during El Niño and LN. The three indices have a more marked reaction during LN. The reaction of the agricultural index is significantly different from 0 during LN, but not during EN. The same behavior is observed for Energy. Finally, all 3 indices show low reactivity. IRF values are generally not different from 0. This may be due to the heterogeneity of the prices making up these indices.

4.2 ENSO impact on individual commodities

An important limitation of the results presented above is that they are based on aggregated variables. These three price indices group together very different commodities, produced in different places and under different climates. They are therefore average results, which may conceal very different realities. We therefore carried out the same exercise for each of the 67 commodities, one by one. A quick overview is provided by Figure 9, considering significance at 10%. The effect of an ENSO shock pushes some prices upwards, but also pushes other prices downwards. This result explains why the IRF on aggregated indices in the figure above appears limited.

Finally, we plot the reactions, grouped by commodity type on Figure 10. Each point has the price reaction during El Niño as its ordinate and the reaction during La Niña as its abscissa. For any group, linear reactions can be found in the upper left-hand box (ENSO shock is positive during El Niño and negative during LN) or in the lower right-hand box (ENSO shock is positive during La Niña and negative during EN), along the -45 degree line. Only a very few commodities are precisely on the line. For example, among the Agricultural Raw Materials, two commodities, namely Cotton and Log, are on the line, therefore displaying a linear reaction to MEIV2 shocks, whatever the state (EN or LN). Other commodities' reaction to ENSO shocks appears to be dependent on ENSO state (EN or LN). These non-linearities confirm our empirical strategy.

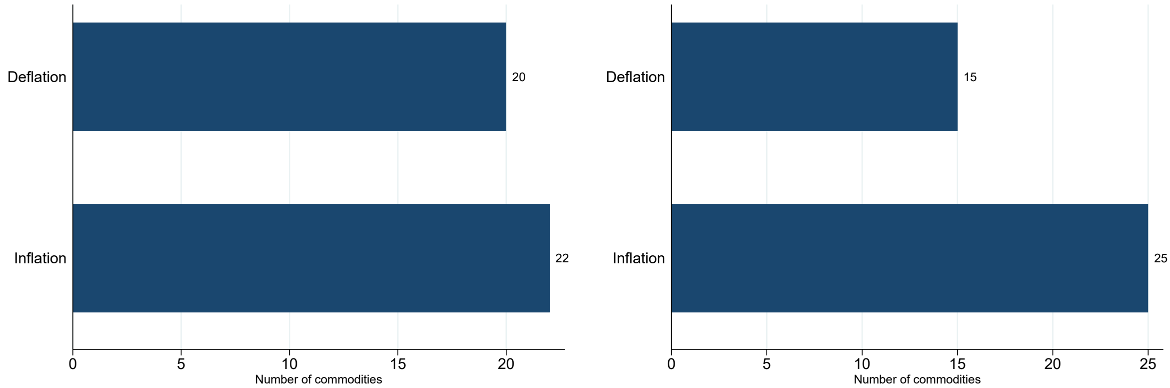
[15] If the response function equals 0.02 at time t+3, it basically means that prices were 2% larger than their mean value at time t+3, in reaction to a 1 standard deviation increase of MEI.V2 that happened in t0.



Notes: responses of price indices to 1 sd MEIV2 negative shock during La Niña phase (solid blue) and positive shock during El Niño phase (dash red), percent, with 68 and 90 percent confidence bands

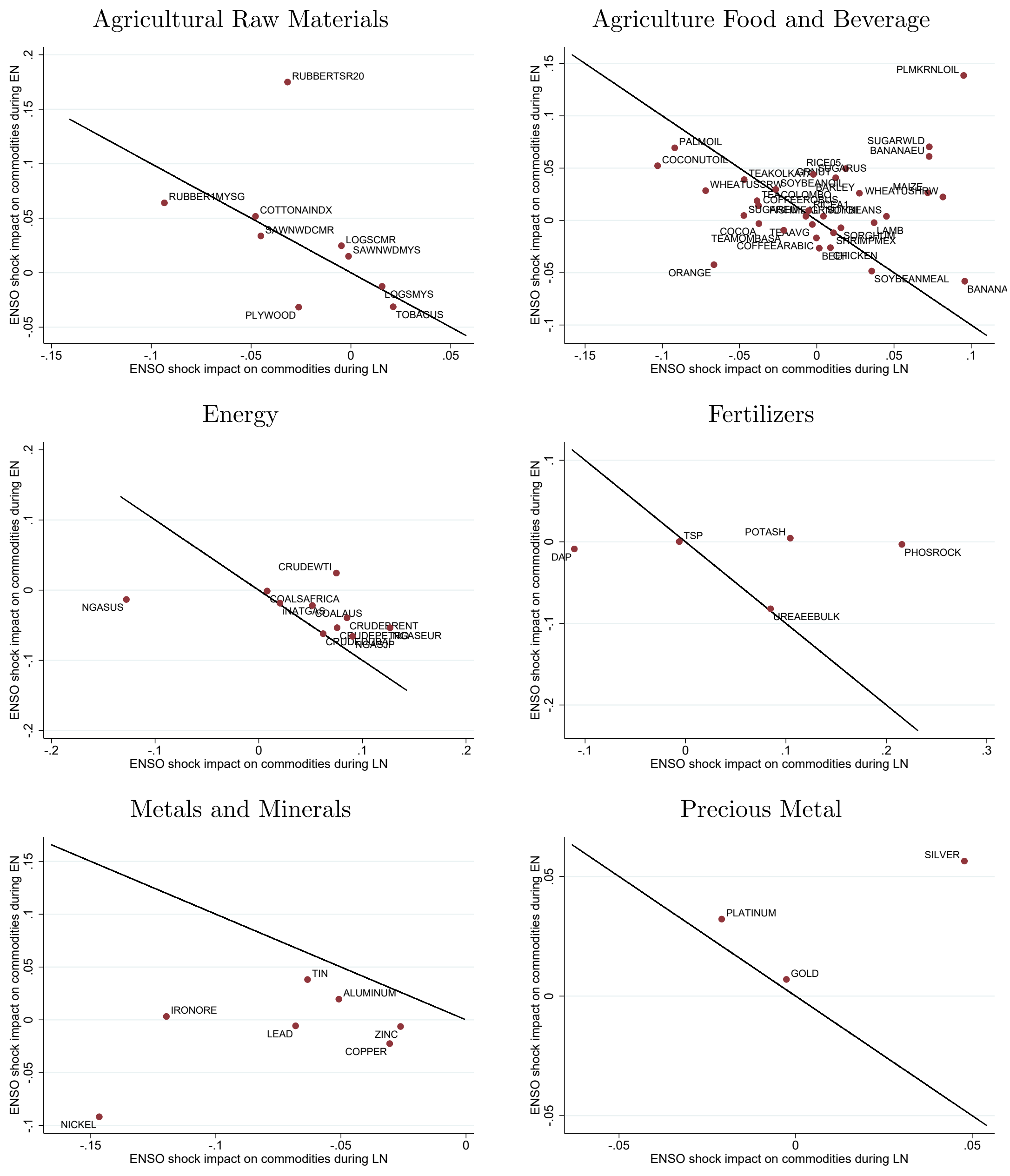
Figure 8: Impact of MEI.v2 on commodities

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

Figure 9: Inflationary or deflationary impact of MEI.v2 on commodities



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.

Figure 10: Reactions to ENSO shocks grouped by commodity categories

5 ENSO under stress: an exposure index

5.1 Index overview

For the 67 commodities, we calculate the price response to an ENSO shock in the baseline framework, and then repeat the process according to our two scenarios for the evolution of ENSO: assuming extreme conditions and a faster transition speed (see Figure 13). Then, we compute, for the 67 commodities, our index of commodity price exposure to the evolution of ENSO. The index, represented on Figure 11, is centered on 0, in which case the evolution of ENSO patterns does not, on average, change the effect of ENSO shocks on the price of these commodities. This is the case for 31% of the commodities. The index takes a negative value for 13% of the commodities (9+1+3). For these commodities, the effect of ENSO shocks on commodity prices should be less significant in the future, due to the evolution of ENSO patterns. More specifically, for 3% of the commodities, we observe a highly stabilizing effect from the evolution of ENSO patterns. However, this stabilizing effect remains rare. A majority of commodities are expected to be more exposed to ENSO shocks in the future, due to the evolution of ENSO patterns. Indeed, in 63% of cases (31+28+3+1), our index takes a positive value. In 4% of cases (3+1), we even find a highly destabilizing effect, with our index taking values greater than or equal to three.

Thus, we can draw two conclusions from our index of commodity exposure to the evolution of ENSO. Firstly, the evolution of exposure is highly heterogeneous across commodities, with some becoming less exposed while others are much more exposed. Secondly, the dominant effect clearly points towards an accentuation of commodity price volatility due to ENSO shocks, as the index takes a positive value in a majority of cases.

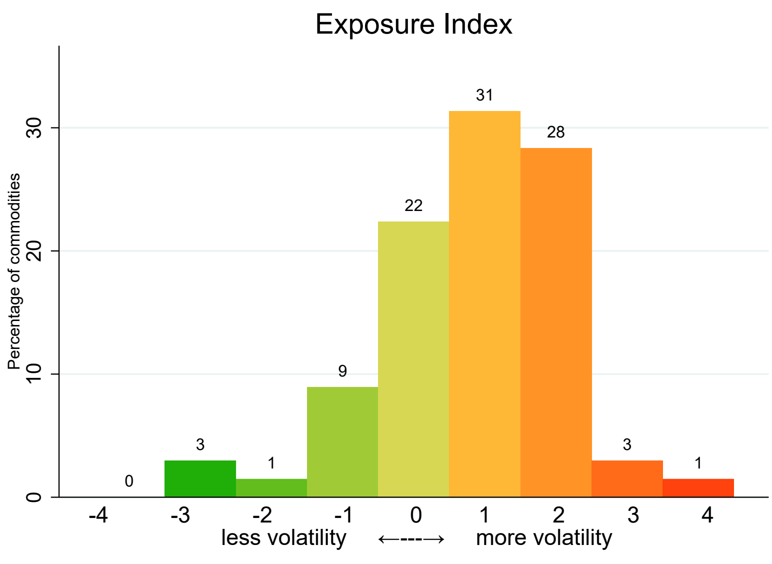


Figure 11: Commodity price exposure to the evolution of ENSO: index overview

Figure 12: Commodities under stress

Figure 13: Commodities under stress (cont.)

5.2 Index construction

Before we address the question of which commodities are most exposed and why, it is important to revisit the values taken by the index. The index reflects, for a given commodity, whether, in the event of a change in ENSO patterns, the effect of a shock is stronger or weaker than currently observed (identified in the baseline). However, as shown in the Figure 14, the two scenarios have vastly different implications. In the case of a faster transition speed (represented by an increase in the value of parameter γ), the effect of an ENSO shock on the commodity price remains unchanged for a majority of commodities. There is no significant difference. Conversely, in the scenario with stronger ENSO events, anomalies increase volatility for approximately one commodity out of two. This is an important finding: an increase in the transition speed of ENSO cycles is less concerning than an increase in the intensity of ENSO phases.

5.3 Index by commodity categories

In order to identify which commodities are most exposed to the evolution of ENSO patterns, we represent the value of the index for each commodity and group commodities by categories (Agriculture, Energy, etc.). The result is depicted in Figure 15.

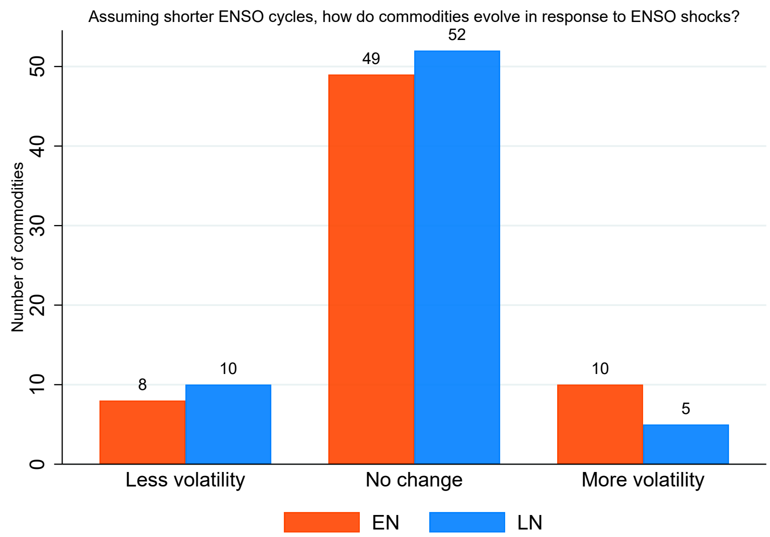
No category stands out from the others. In all cases, significant heterogeneity is observed. One exception to note is that for oil prices, the index systematically takes the value of 0. There are two possible explanations. Firstly, climatic conditions only have a minimal impact on oil prices. Secondly, oil prices appear to be linearly related to MEI.V2, meaning that positive shocks (El Niño) are offset by negative shocks (La Niña), and thus these prices do not particularly stand out when one looks at the overall trend.

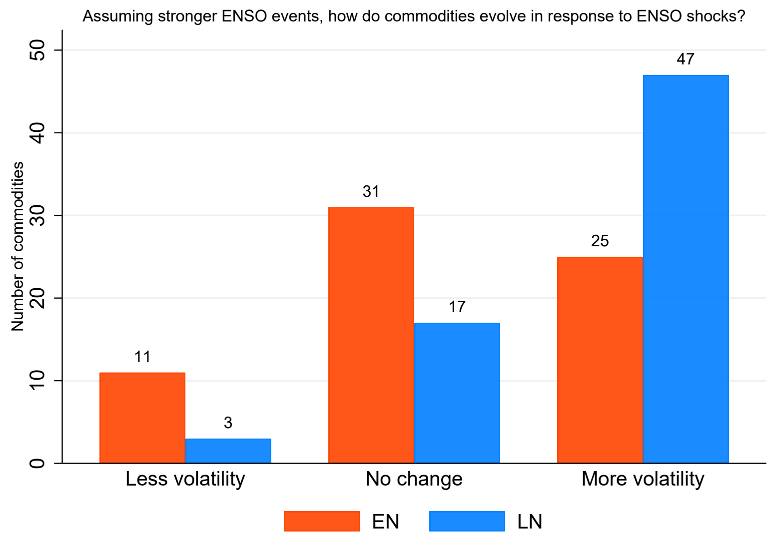
5.4 Determining factors

Our index reveals a significant heterogeneity in commodity price exposure to changing ENSO patterns. Several explanations can be put forward to account for this heterogeneity. We consider three possibilities. Firstly, volatility may be higher for commodities produced in geographic regions most influenced by ENSO. Secondly, volatility may be higher for commodities whose production is concentrated in a small number of areas. Finally, price volatility may be influenced by the financialization of certain commodities, which tends to correlate prices.

5.4.1 Financialization

As pointed by Tang and Xiong (2012), index investment in commodity markets increases the correlation between non-energy and energy commodity prices. For these authors, the financialization of the commodity markets explains part of the price volatility of non-energy commodities around 2008. More recently, Kang et al. (2023) update this result and confirm that financialization increase pairwise return correlation within commodity futures markets. Figure 16 display our Exposure Index for commodities exposed to financialization (top panel) and for commodities not





Notes : Based on the maximum response over 24 months, for each individual commodities, to 1 sd MEIV2 negative shock during La Niña phase and positiv shock during El Niño phase, considering on a 90 percent confidence bands, comparing local projection with $\gamma = 4$ and $\gamma = 40$ on the upper graph and comparing local projection with baseline EN/LN definition and anomalies on the lower graph.

Figure 14: Changing ENSO patterns impact on commodities

exposed (bottom panel). We assume commodities to be exposed to financialization if they appear in the Bloomberg Commodity Index (BCOM Index) or the Thomson Reuters CoreCommodity (TR CRB) Index . As the Exposure Index is more right skew on the top panel, financialization seems to contribute to volatility.

Indeed, financialization involves greater participation of financial investors, such as hedge funds

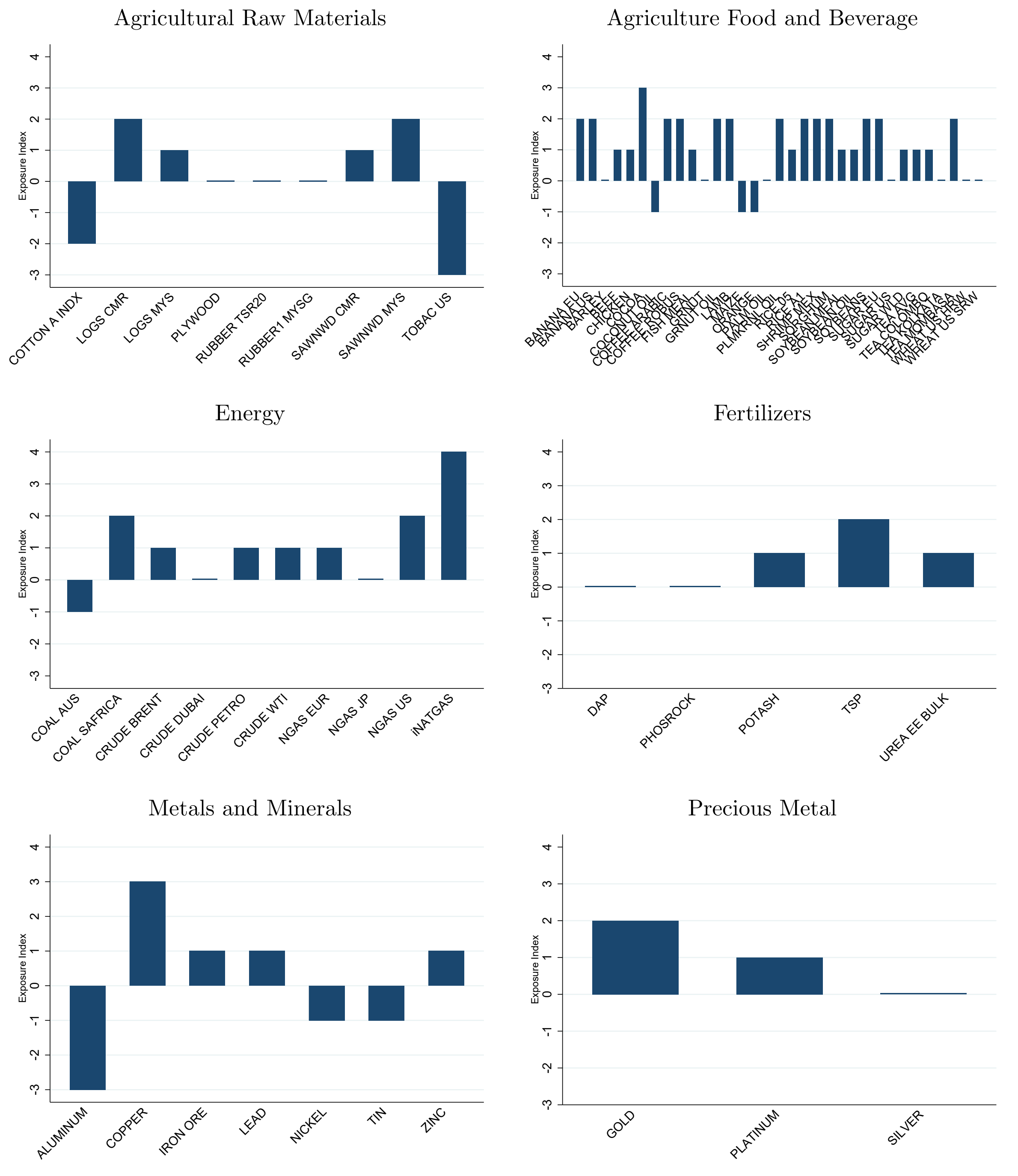


Figure 15: Index value by categories

or institutional investors in commodity markets. These investors often engage in trading aiming to profit from short-term price movements rather than physical delivery or consumption of commodities. Their trading activities can amplify price fluctuations and contribute to increased market volatility. Financialization can also lead to herding behavior among investors, where large numbers of market participants follow similar investment strategies based on trends or market sentiment. While the liquidity induced by financialization can enhance market efficiency and price discovery, it can also lead to rapid price changes as large volumes of capital flow in and out of markets, particularly during periods of market stress or uncertainty.

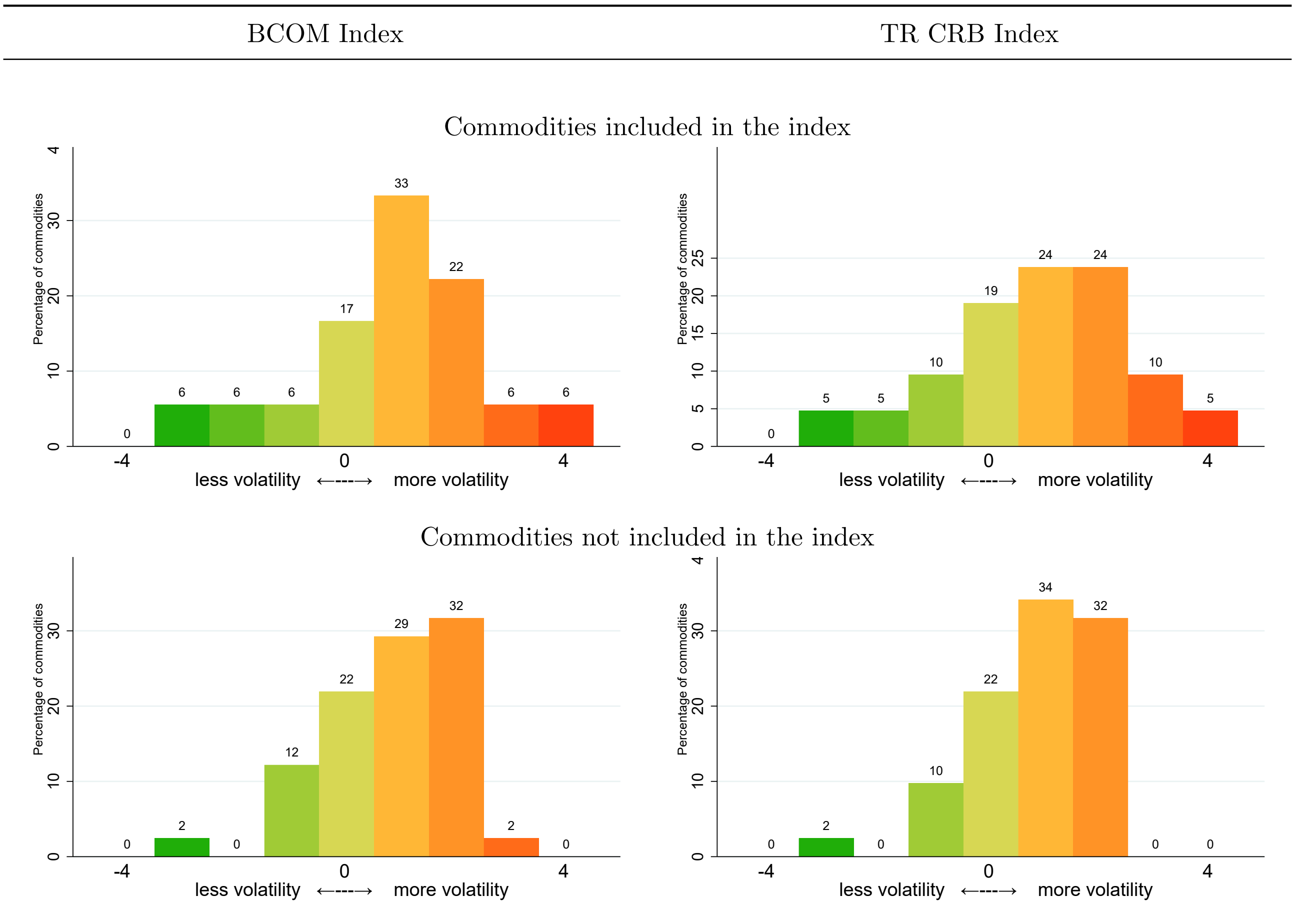


Figure 16: Commodity price exposure and financialization

5.4.2 Production concentration

Commodity production frequently exhibits high levels of concentration due to natural resource distributions or natural endowments. Consequently commodities elasticity of supply may be low: the responsiveness of quantity supplied to changes in price is limited, commodities are difficult to substitute in the short term, leading to more pronounced price movements. When commodity production is concentrated in a few countries, any disruptions to production in these areas can have a significant impact on overall supply. We therefore expect our Exposure Index to be positively correlated with concentration.

Figure 17 display our Exposure Index for commodities whose production is concentrated on a limited number of countries (top panel) and for commodities produced more broadly (bottom panel). We capture this feature using IMF (2023) data about the share of countries that import a given commodity from three suppliers only (left column) and data about the share of top three countries in total commodity world production (right column). We assume production to be concentrated if the two variables take values larger than 8% and 15% respectively. As the Exposure Index take greater values (+3, +4) on the top panel, production concentration seems to contribute to volatility. This is less clear-cut when considering the share of top three producers (right column).

5.4.3 Trade

As a result of commodity production concentration (mentioned earlier) access to global commodity markets is essential for many countries. If the global market for a commodity is large, it promotes market liquidity, facilitates access to diversified sources, facilitates arbitrage activities, improves the flow of information and supports risk management strategies - all of which help to reduce price volatility. In the opposite, according to Campos et al. (2023) and IMF (2023), market fragmentation (typically due to geopolitical events) can lead to more volatility on commodity markets. Figure 18 display our Exposure Index for commodities whose world production is largely available on the market (top plot), considering commodities whose share of traded world production is above 1/3, based on IMF (2023) data. The lower plot represent commodities with limited share of traded world production. Our Exposure Index is clearly lower for largely traded commodities. This is consistent with Gouel and Laborde (2021) among other, who shows the crucial role of international markets for agricultural products in adapting to climate change.

5.4.4 South America

Finally, as its name suggests, ENSO could affect South American countries more than others. However, this is a misconception, as ENSO is a global phenomenon. For example, El Niño brings drier conditions to southern Africa and parts of the Sahel, while eastern equatorial Africa experiences wetter conditions during the short rainy season, and rainfall in South and Southeast Asia is decreasing. To illustrate this point, we plot on Figure 19 our Exposure Index for commodities with a least one of the top three countries in total commodity production located in South America (top panel, based on IMF (2023) data). Our exposure index is no higher than for commodities whose main producer is in any other region (bottom panel), confirming that ENSO is a global phenomenon and that all regions are affected by its evolution.

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

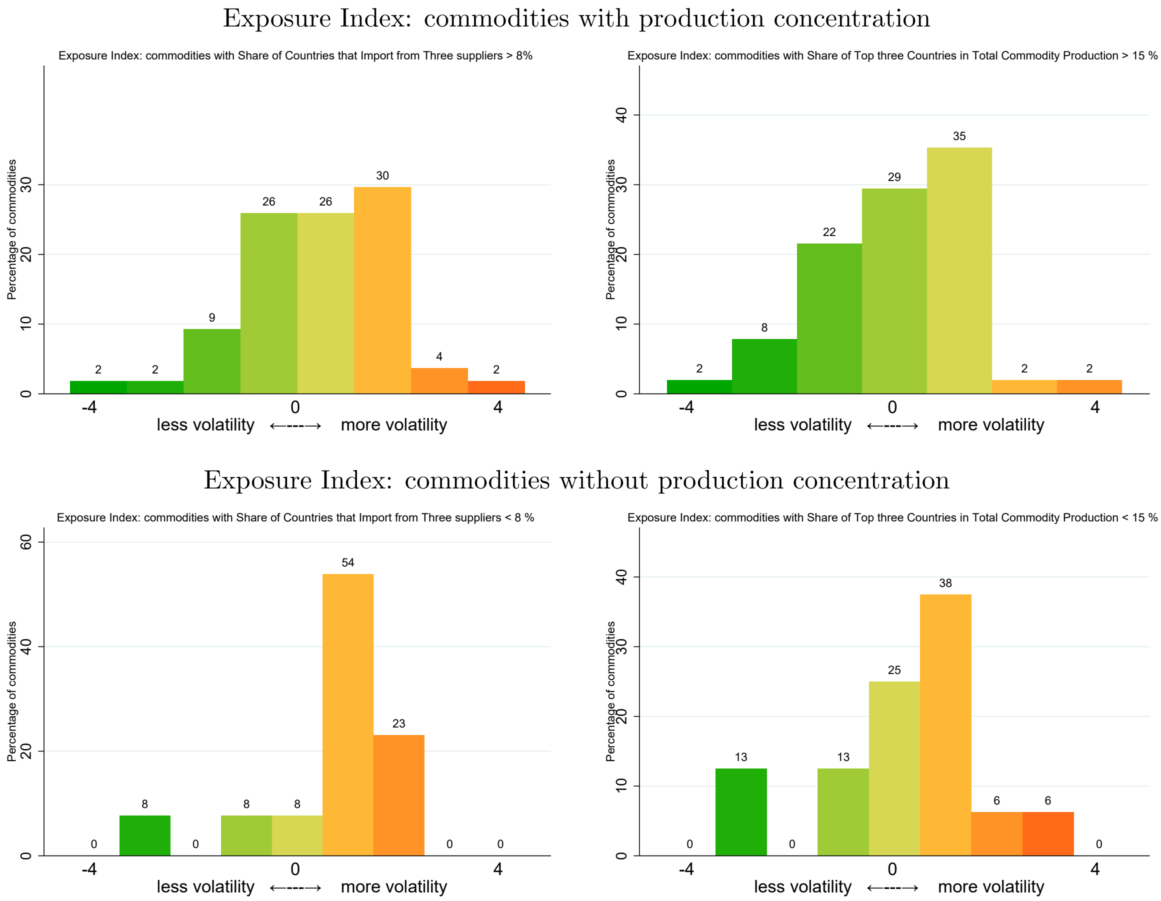
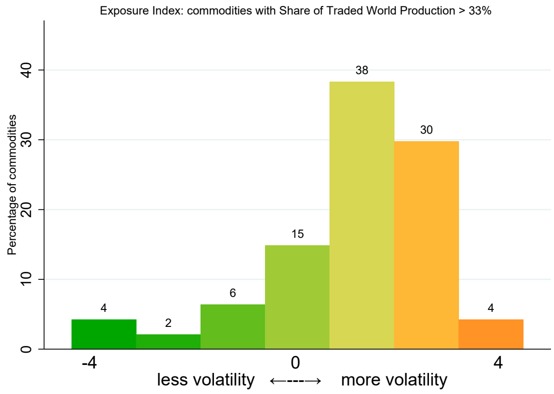


Figure 17: Commodity price exposure and production concentration

Share of Traded World Production

Commodities with large Share of Traded World Production



Commodities with limited Share of Traded World Production

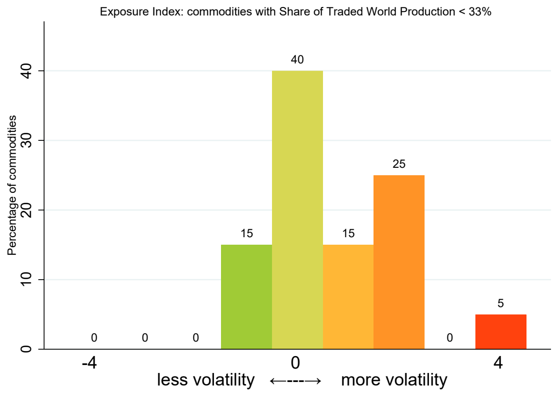
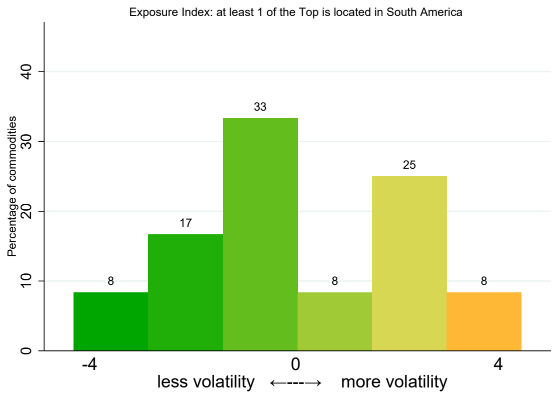


Figure 18: Commodity price exposure and trade

Top Three Countries in Total Commodity Production

At least 1 of the Top Three Countries in Total Commodity Production is located in South America



None of the Top Three Countries in Total Commodity Production is located in South America

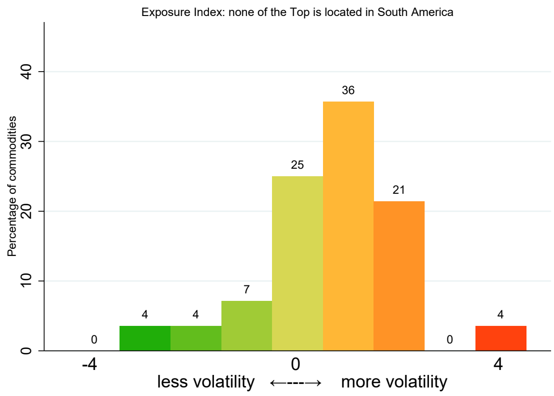


Figure 19: Commodity price exposure and production concentration in South America

6 Conclusion

This paper analyzes the global transmission of weather on commodity prices and proposes an assessment of the potential effects of climate change on price stability.

We estimate a global factor augmented non-linear local projections model using a rich and extensive monthly data set from 1986 01 to 2023 06 relating to circa two-thirds of global output and 67 international commodity price sets. We contribute to a growing literature on the ”new climate economy” (Dell et al., 2014) in two ways. First, this paper exploits the global factor structure to investigate the global dimensions of weather and commodity shocks. Second, we exploit the multivariate dimension of data using a nonlinear framework to account for possible changes in climate *regimes*.

We first demonstrate that El Niño and La Niña climatic events have an impact on commodity prices. At the aggregate level, a non-expected evolution of the ENSO cycle has a particularly significant impact during La Niña phases, especially pronounced for energy and agricultural goods. This effect is observed with a lag of 6 to 12 months for agricultural goods, which could reflect both the time lag between weather events and crop outcomes and the importance of futures markets in price determination.

These relatively modest results at the aggregate level contrast with much more significant impacts at the disaggregated level when estimating the effect of a non-expected evolution of the ENSO cycle on commodity prices individually. We show that about two third of commodity prices are impacted by a non-expected evolution of the ENSO cycle (or ENSO shock), generally with non-linearity associating climatic conditions with commodity prices.

We conduct two exercises to simulate the impact of climate change on the ENSO cycle and thereby measure the repercussions on commodity prices. One exercise focuses on intensity, and the other on the transition speed of the cycles. Thus, we obtain an index that captures commodity price exposure to the evolution of ENSO, due to climate change. We then show that in most cases, climate change is likely to result in greater commodity prices volatility. This result is particularly explained by the assumption of increased extreme events, which seem to have a greater impact on commodity prices than the evolution of the frequency of EN/LN cycles. Our results indicate significant heterogeneity among commodities, with some being minimally or not impacted by climate change (and a handful of commodity prices expected to me even more stable than now) while others are expected to experience significantly increased volatility, as represented by our index. We carry out several tests to explain this heterogeneity, and show that financialization, production concentration and the fact that only a small proportion of a commodity is sold on the world market tend to increase volatility. Conversely, the origin of production of the commodity plays little role: ENSO does not only affect South American countries; ENSO is a global phenomenon, therefore all part of the world may somehow be impacted.

The results from this research have both immediate and long-term policy implications regarding the adaptation to climate changes. A starting point for short-term policy is to establish sources of vulnerability that could create economic risks. The findings from this paper serve to do just that in a global factor environment by analyzing the propagation mechanisms through which weather shocks influence commodity price change. Our work highlights the ways in which climate change can create new challenges for financial and price stability, and underscores the importance of international trade. First, our work is important for policymaker with regards to financial stability: we show how climate change can create new challenges, particularly when commodities are integrated into many financial products (see Adams and Glück, 2015, Basak and Pavlova, 2016 on the spillovers between commodities and the stock market). Second, these insights are of paramount importance for for central banks whose mandate is to insure price stability. We show that climate change will contribute to commodity price volatility, which is a key determinant of headline inflation. Although the primary objective of central banks is generally core inflation, central banks need to monitor headline inflation to ensure that second-round effects are limited. In this respect, increased commodity volatility can complicate their mission of price stability. Finally, our research underscores the significance of integrated global commodity markets in managing supply shocks and mitigating rising price volatility. Consequently, international commodity markets should be harnessed to meet the challenges posed by climate change.

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8 Appendix

8.1 Scree Plots

The scree plots are provided for the global factor analysis of output and interest rate. The scree plot is a plot of the eigenvalues of principal components.

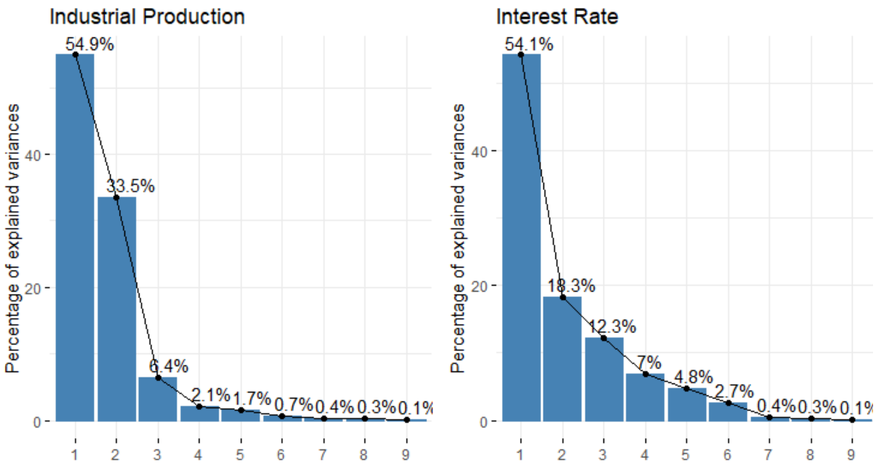

Figure 20: Scree Plots for Global Variables

ζ	$F(\zeta)$		
	$\gamma = 5$	$\gamma = 1$	$\gamma = 0.1$
-1	0.99	0.73	0.52
-0.1	0.62	0.52	0.50
0	0.50	0.50	0.50
0.1	0.38	0.48	0.50
0.2	0.27	0.45	0.50
0.3	0.18	0.43	0.49
1	0.01	0.27	0.48

Table 3: Simulation for illustration purposes

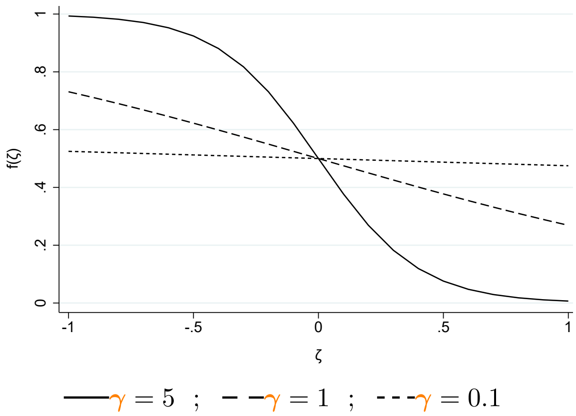

Figure 21: Representation of F(ζ) for alternative γ values

8.2 Exploring the transition function

To illustrate how does this function works, we simulate different values for ζ, and then observe the values taken by $F(\zeta)$ assuming alternative values for γ. Table 3 shows the numerical values, the first column contains simulated values for ζ while the second column shows the value taken by $F(\zeta)$, the transition function, for each of the proposed values of ζ, assuming $\gamma = 5$. Similarly, columns 3 and 4 show the values of $F(\zeta)$ for the same values of ζ, but assuming $\gamma = 1$ and $\gamma = 0.1$.

As it can be seen in Figure 21, for very small values of γ, the transition function $F(\zeta)$ varies only slightly. Conversely, the higher the γ, the more abrupt the transition from a high to a low value of $F(\zeta)$.