Climate Change Impacts on Commodity Price Stability through Changing ENSO Patterns

Gilles Dufrénot* William Ginn† Marc Pourroy‡

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.

---

*Aix-Marseille Univ, CNRS, AMSE, Marseille, France. Gilles.Dufrenot@univ-amu.fr

†Labcorp, Sr. Economist / Data Scientist, USA and Coburg University of Applied Sciences, Germany. William.Ginn.OBA@said.oxford.edu

‡Correspondence author, University of Poitiers, France. Marc.Pourroy@univ-poitiers.fr. This work was supported by the French National Research Agency Grant ANR-17-EURE-0020, and by the Excellence Initiative of Aix-Marseille University - A*MIDEX. The authors would like to especially thank Jamel Saadaoui and participants of the CEMA Chicago, IMAC Rennes, GDRE, AFSE and FAERE Paris conferences, LEMNA and LéP Seminars, for their valuable comments and insightful suggestions.

Highlights

- We propose a novel GFALP model to isolate the global transmission of ENSO shocks on commodity markets, accounting for macroeconomic conditions.
- Unanticipated ENSO movements asymmetrically impact commodity price volatility, with distinct effects during El Niño and La Niña periods.
- Climate change may alter ENSO frequency and intensity, exacerbating commodity price instability through non-linear effects.
- We introduce an index quantifying commodity price exposure to ENSO-related climate disruptions, revealing heterogeneous vulnerabilities.
- Commodity price volatility that could result from climate change is found to be amplified by financialization, production concentration, and limited global market participation.

1 Introduction

Over the past decade, the literature on the impact of environmental shocks on commodity prices has expanded significantly. For instance, Su et al., 2025 examine how natural disasters, such as typhoons, affect food markets, while other studies have focused on the broader social consequences of commodity price fluctuations, including rising inequalities (Mohtadi and Castells-Quintana, 2021), increased malnutrition (Mekasha et al., 2022), and adverse effects on land distribution in developing countries (Albertus, 2019). This topic is also highly relevant to macroeconomists, as commodity price fluctuations serve as leading indicators of business and financial cycles (De Winne and Peersman, 2018, Romero, 2025).

In this paper, we examine the impact of climate change on commodity price movements. While rising global temperatures, more frequent extreme weather events, and rising sea levels are well-documented consequences of climate change, its influence extends beyond these factors. Climate change is also expected to alter large-scale climate phenomena, including the El Niño-Southern Oscillation (ENSO). ENSO is a major meteorological system driven by shifts in central and eastern Pacific wind patterns, which in turn influence ocean surface temperatures and global climate conditions. This phenomenon leads to abnormal temperature fluctuations across different regions, disrupting weather patterns, ecosystems, and economic activity. ENSO cycles alternate between El Niño, characterized by warmer-than-average sea surface temperatures, and La Niña, marked by cooler-than-average temperatures in the central and eastern Pacific. These fluctuations, occurring every two to seven years, cause significant climate anomalies, including shifts in rainfall patterns, temperature extremes, and increased storm activity. Such disruptions have profound consequences for agriculture, natural ecosystems, and economic stability worldwide.

Recent studies have increasingly emphasized the economic consequences of climatic conditions (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 shape economic outcomes and how policymakers can adapt institutions to mitigate adverse effects. Unlike studies that examine the effects of localized climate shocks, our research explores how global climate phenomena—specifically ENSO—affect commodity markets. More specifically, we investigate how long-term changes in ENSO patterns due to climate change alter the short-term effects of ENSO shocks. To address this question, we examine the short-term reaction of commodity prices to weather shocks while controlling for long-term ENSO parameters.

Existing literature has identified numerous ways ENSO conditions influence economic activity. The most obvious is the impact of ENSO 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, Callahan and Mankin, 2023, Dufrénot et al., 2024).

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, 2012a). 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 cyclical 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 the unanticipated impact of ENSO-related changes on commodity prices, explicitly accounting for global factors. As the effects of El Niño or La Niña cannot be confined to a single country but rather have global dimensions, this paper employs a global factor-augmented local projections (GFALP) model, utilizing principal component analysis (PCA) based on output and interest rates from 9 economies using monthly data over the period 1986:01 to 2023:06. This approach allows us to assess the transmission of ENSO shocks across commodities while controlling for global economic conditions, rather than focusing on country-specific shocks. Using monthly data has the potential benefit of capturing the short-term temporal effect that ENSO 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, in contrast with the linear frameworks used in Berry and Okulicz-Kozaryn (2008) and Anttila-Hughes et al., 2021). 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 impulse 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 three 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 (2012a) 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 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 exacerbate economic damage from changing ENSO. In a related study, 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

---

[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.

and Wurgler, 2021) such as Flori et al. (2021) who concludes that "climate conditions affect financial stability by impacting commodity comovements". Among all these papers, our work is related 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, Kashif et al., 2022, Ray Biswas and Rahman, 2023). In addition, a few papers have pointed out that central banks mandate for price stability is also threatened by climate change (Mukherjee and Ouattara, 2021, Kabundi et al., 2022, Boneva et al., 2022, Cevik and Jalles, 2024, 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 jeopardize price stability.[2]

The third strand is related to the literature on the non-linearities inherent in the dynamics of commodity prices. For example, Baffes and Kabundi (2023) show that the permanent component of certain commodities (energy, metals, tree crops) is non-linear, which they relate to irreversible investments and intervention policies to coordinate supply mechanisms at the international level. The nonlinearity of ENSO effects is also a phenomenon documented to study the effects on commodity prices (e.g., Ubilava, 2013, Ubilava, 2017, Cashin et al., 2017, Ubilava, 2018, Nam, 2021, Dufrénot et al., 2024, Dufrénot et al., 2024). In this paper, we propose a new model in which the non-linear causal relationships between the different ENSO regimes and commodity prices are captured by a local non-linear projection model where the reaction of ENSO shocks is measured using a sigmoid regime-switching function.

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 Multivariate ENSO Index (MEI.v2); global factors (output and interest rate); and 67 global commodity prices. Each are discussed in turn.

---

[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 (2024) who find that following a temperature shock, headline inflation falls. See Kranz et al. (2024) for a literature review.

2.1 Global ENSO 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 integrate numerous dimensions 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 (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).

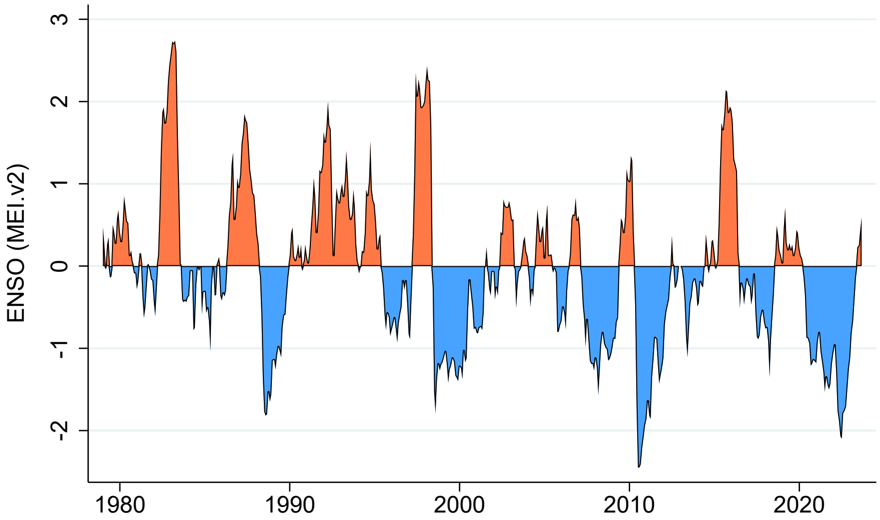
Composite positive MEI events can be read as warm periods, which correspond to El Niño events.[5] Negative MEI events have opposite characteristics and can therefore be seen as La Niña events. NOOA generally applies a $+/-0.5$ threshold to define non-overlapping hot and cold periods, the in-between been 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.

---

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

[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."



Note: Areas shaded blue indicate negative values of the MEI.v2 that represent the cold ENSO phase (i.e., La Niña), while areas shaded red indicate positive MEI.v2 that values represent the warm ENSO phase (i.e., El Niño).

Figure 1: MEI.v2 Evolution over Time

2.2 Global Commodities

The dataset is based on World Bank *Pinksheet* monthly data and covers the period from January 1986 to June 2023 for 67 international commodities. Figure 2 presents the composition of the dataset by commodity type. In addition to a large group of food and beverage commodities, the dataset is well-balanced across six categories: energy, fertilizers, metals and minerals, and precious metals. For ease of interpretation, we occasionally aggregate commodities into three broader categories following the World Bank classification: agriculture, energy, and metals/minerals. All prices are expressed in logarithmic form. Commodity prices, originally denominated in U.S. dollars, are deflated using the Producer Price Index (PPI) for the OECD total area.

2.3 Control variables

The global dimension of our macroeconomic variables is derived from the first principal component of five economies, covering both output and interest rates.[6] Following the approach of Ratti and Vespignani (2016), we construct the global factor using principal component indices, applying normalized loadings (see Equations 1 and 2). The advantage of this approach is that the first principal component serves as a dimension-reduction technique, effectively capturing the key features of the global economic environment. In our baseline model, which spans the longer time sample (1986:01–2023:06), the global factor represents five economies accounting for 38.5% of global out-

---

[6] Output is proxied by OECD and Fred industrial production data.

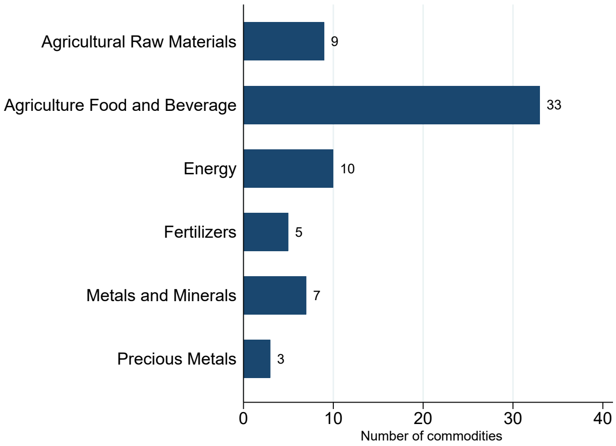


Figure 2: Composition of the commodities data set

put.[7] For robustness, we also consider an alternative dataset covering a broader set of twenty-one economies over a shorter time period (1999:01–2023:06), which accounts for 78.5% of global output (see Section 4.4 for details).

$$\ln Y_t^G = [\ln Y_t^{CAN}, \ln Y_t^{EUR}, \ln Y_t^{GBR}, \ln Y_t^{JPN}, \ln Y_t^{USA}] \tag{1}$$

$$R_t^G = [R_t^{CAN}, R_t^{EUR}, R_t^{GBR}, R_t^{JPN}, R_t^{USA}] \tag{2}$$

The results, presented in Table 2, display the top three principal components for the two variables. The first principal component, which we use to construct the global variables, explains a substantial share of the variance in output (79.2%) and interest rates (86.2%).[8] Figure 18 plots the global factors alongside the corresponding economic data. The top panel highlights the sharp decline in output observed during the global financial crisis and the pandemic era. Table 3 presents the correlation between global and national variables. Consistent with studies documenting the presence of a global business cycle, the relationship between the global factor and country-specific output is positive across all countries.[9]

---

[7] The five economies include: Canada (”CAN”), Euro zone (19 countries; ”EUR”), United Kingdom (”GBR”), Japan (”JPN”) and the United States (”USA”). Based on IMF data in purchasing power parity terms, these economies represent 36.8% of global output. The Euro zone values are based on the 19 member countries (i.e., Austria, Belgium, Cyprus, Estonia, Finland, 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 14. These values are similar to Ratti and Vespignani (2016), where the first principal component in their paper captures global output and interest rate representing 60.0% and 44.5% of the total variance, respectively.

[9] For discussions on the global business cycle, see Kose et al., 2003, Monfort et al., 2003, Ciccarelli and Mojon, 2010, Ginn, 2023a, and Ginn, 2023b among others.

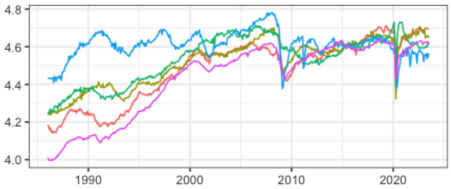
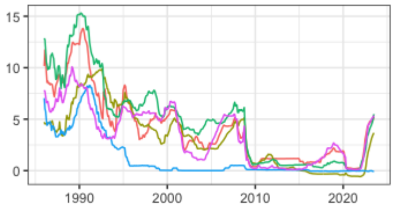
Coverage	Output	Interest Rate
CAN EA1 GBR JPN USA		
	Country-Level (observed)	
World (PCA)		
	Global-Level (principal component)	

Table 1: Economic Data: From Country-Level to Global-Level

	Global Output	Global Interest Rate
First Principal Component	79.2%	86.2%
Second Principal Component	16.0%	7.6%
Third Principal Component	2.6%	4.7%

Table 2: Variation Explained by First Three Principal Components

Country	CAN	EUR	GBR	JPN	USA
Global Output	0.9661	0.9802	0.9483	0.4650	0.9756
Global Interest Rate	0.9777	0.9007	0.9829	0.8755	0.9014

Table 3: Correlation between Country and Global Variables

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 impulse 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 defined as the 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 ENSO shock (u_t) occurs. The coefficient $\beta_{h,EN}$ ($\beta_{h,LN}$) corresponds with the estimated impact of the ENSO shock in a El Niño (La Niña) state.

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

$$\zeta_t = \alpha + \sum_{n=1}^{h} \beta_i \zeta_{t-h} + \gamma T_t + u_t \tag{4}$$

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:

$$F(\zeta_t) = \frac{\exp(-\gamma\zeta_t)}{1 + \exp(-\gamma\zeta_t)} \tag{5}$$

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., $F(\zeta_{t-1})$).

---

[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 equation (5), 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. 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*:

$$\mathcal{F}_\zeta(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{[\zeta_i < x]} \tag{6}$$

The calibration of γ must ensure that the transition function $F(x|\gamma)$, given in Equation 5, is as close as possible to the empirical CDF, given in equation 6. 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:

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

(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 3 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 criterion give very similar results: the value of γ that minimizes the Total Sum of Squares is 4.328; similarly the

---

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

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 3 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 4.

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

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

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

Similarly we estimate the same equation for La Niña anomalies:

$$\begin{aligned}\pi_{t+h} =&I^{LNA} F(\zeta_{t-1})(\alpha_{h,LNA} + \phi_{h,LNA}(L)x_{t-1} + \beta_{h,LNA}u_t)\\ &+ (1 - I^{LNA} F(\zeta_{t-1}))(\alpha_h + \phi_h(L)x_{t-1} + \beta_h u_t)\\ &+ \epsilon_{t+h}\end{aligned} \tag{8}$$

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

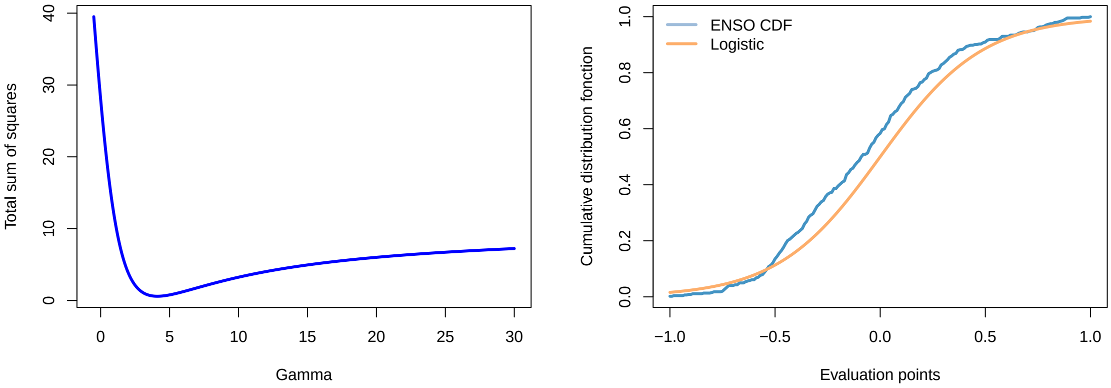
Climate change could impact ENSO cycle by shortening transition times from one phase to another (transitions from El Niño to La Niña, and vice versa). How can we account for this change in our

---

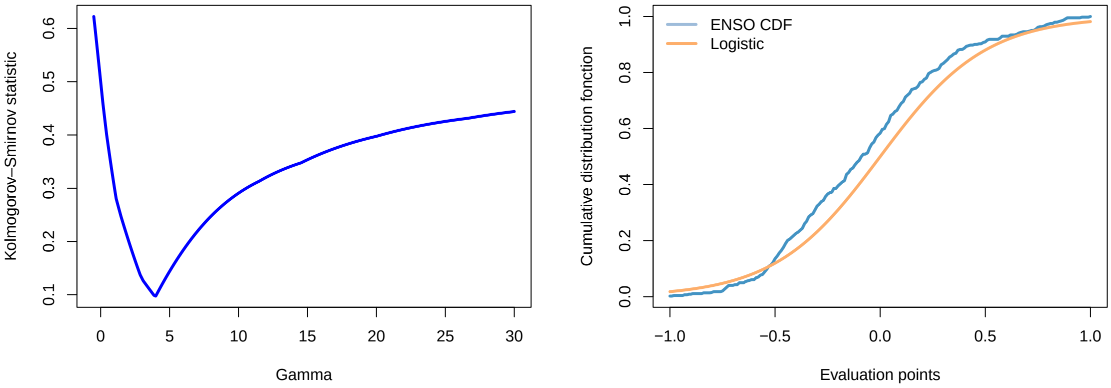
[12] Note that $I^{LNA} = 0$ during large EN events, and not the other way around, because $F(\zeta)$ tends to 0 for large EN events.

Evaluation Grid	$\mathcal{F}_{\zeta}(x)$ and $F(x\|\hat{\gamma})$

Total Sum of Squares: $\hat{\gamma} = 4.328$



Kolmogorov–Smirnov statistic: $\hat{\gamma} = 4.224$



Dvoretzky Kiefer Wolfowitz Inequality: $\hat{\gamma} = 4.276$

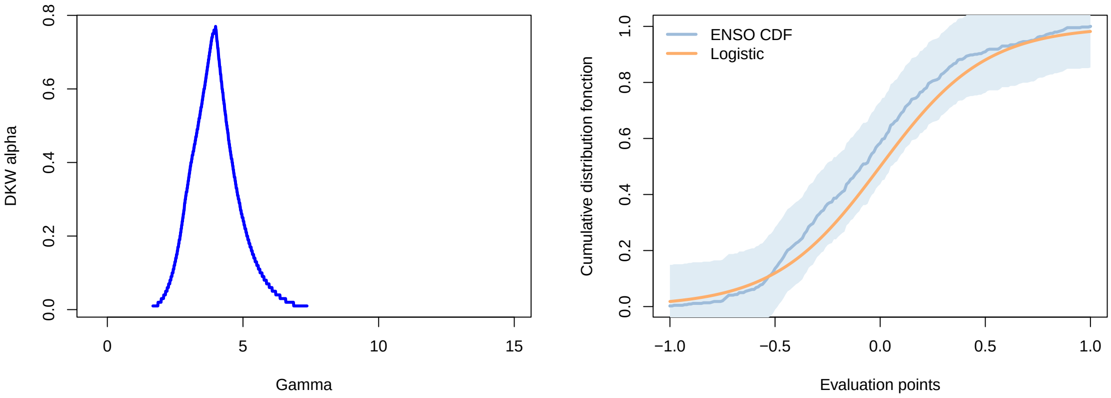
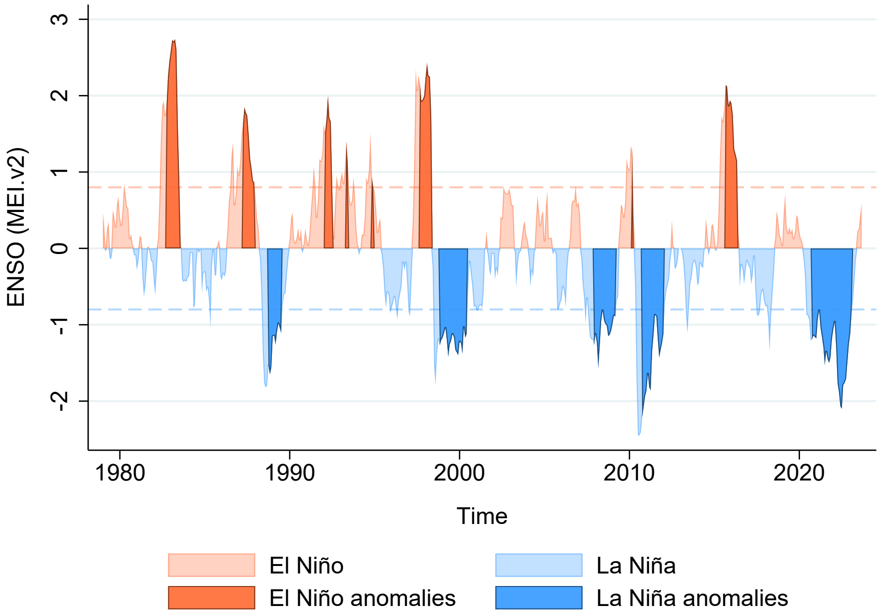


Figure 3: γ estimation

set-up? Faster transitions between El Niño and La Niña, and vice versa, should lead to an in-



Note: 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 4: MEI.v2 Anomalies

crease in parameter γ. To test this hypothesis, we estimate the value of γ by splitting the MEI.v2 series into two sub-samples: 1980-2000 and 2000-2020. Results are displayed on Figure 15 in Appendix. It appears that γ is already changing over time: according to our estimate, during the first period (1980-2000), $\hat{\gamma}$ was about 3.4, while it was about 4.5 during thee second period (2000-2020).

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.

$$\begin{aligned}\pi_{t+h} =& trend_t \\ &+ (1 - F(\zeta_{t-1|\bar{\gamma}}))(\alpha_{h,EN|\bar{\gamma}} + \phi_{h,EN|\bar{\gamma}}(L)x_{t-1} + \beta_{h,EN|\bar{\gamma}}u_t) \\ &+ F(\zeta_{t-1})(\alpha_{h,LN|\bar{\gamma}} + \phi_{h,LN|\bar{\gamma}}(L)x_{t-1} + \beta_{h,LN|\bar{\gamma}}u_t) \\ &+ \epsilon_{t+h}\end{aligned} \tag{9}$$

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

To summarize the insights from the estimates presented above, we construct an index that measures each commodity price's exposure to changes in ENSO patterns.

This index is derived by comparing the results from the baseline estimation (equation 3 in Section 3.1) with those obtained under stressed conditions, specifically, extreme ENSO values (equations 7 and 8 in Section 3.2) or a faster transition speed (equation 9 in Section 3.1).

Each commodity is assessed under four stress scenarios: during El Niño periods $\beta_{h,EN}$ is compared with $\beta_{h,ENA}$ and $\beta_{h,EN|\bar{\gamma}}$ while 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%.[13]

Finally, to summarize the four stress scenarios in a single measure, we construct an index centered at 0. The index increases by one unit for each scenario indicating higher volatility and decreases by one unit for each scenario indicating lower volatility. The index ranges from -4 (indicating that all scenarios lead to reduced volatility) to +4 (indicating that all scenarios lead to increased volatility). A central value of 0 corresponds to cases where the number of scenarios indicating higher volatility equals those indicating greater stability, or where ENSO shocks are never found to have a significant impact on commodity prices.

---

[13] Note that the value of hh is selected to capture the period with the most significant impact. For example, we compare the peak effect of ENSO shocks on cotton prices in the baseline scenario with the peak effect under anomaly conditions. While the strongest impact may occur at $h = 7$ periods in one case and $h = 8$ periods in another, the exact timing is not critical. Our primary focus is on assessing the magnitude of the shock's influence on cotton prices.

4 Baseline results

4.1 ENSO impact on aggregated prices

The impulse response functions (IRF) are presented in Figure 5 for the major commodity price sets (we provide additional IRFs in the Appendix, see Figure 17). The IRF plots include the 68% and 90% confidence bands using the Newey-West standard errors. 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.[14]

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.[15]

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. As a result, the findings represent averages that may mask significant differences across individual. We therefore carried out the same exercise for each of the 67 commodities, one by one. A quick overview is provided by Figure 6, considering significance

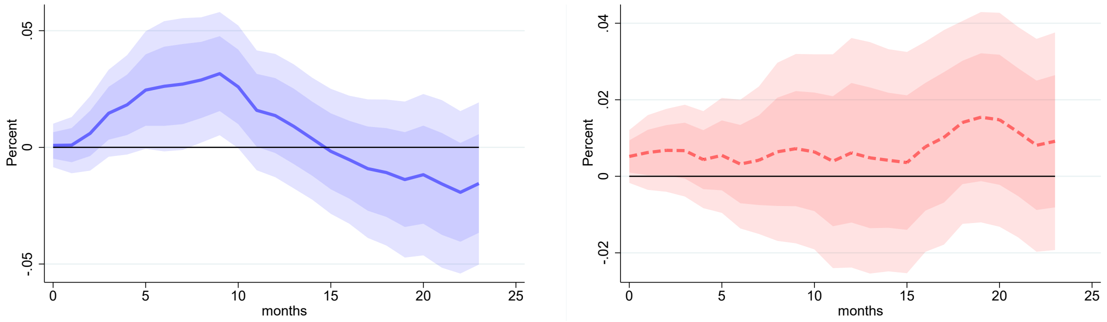
---

[14] 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.

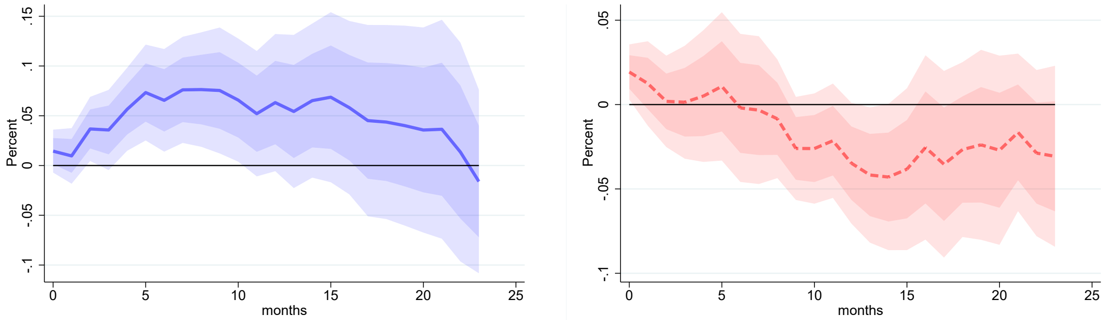
[15] While our approach relies on a large sample of commodities and does not focus on individual trajectories, other studies provide anecdotal evidence that illustrates the various channels through which ENSO affects different commodities in distinct ways. For example, Ubilava (2017) finds that global wheat prices tend to increase after La Niña events and decrease following El Niño events, a pattern consistent with the economics of storage. Iizumi et al. (2014) shows that yields of four major crops (soybean, maize, rice, and wheat) tend to be below normal during La Niña years. As Ubilava (2017) states, "[i]f the global weather conditions associated with a La Niña episode have a net negative global impact on wheat production, the international grain reserves will deteriorate. In such a low-inventory regime, any further ENSO-induced shocks (or ENSO-related news) will result in more amplified price responses". Similarly, Gutierrez (2017) finds that La Niña has a more pronounced negative impact on wheat yield anomalies, exports, and stock-to-use ratios than El Niño, and that wheat export prices are positively correlated with La Niña episodes. Regarding coffee markets, Ubilava (2012b) finds that El Niño shocks reduce the prices of three varieties of Arabica coffee, whereas La Niña events lead to price increases. Additionally, Ubilava (2012b) shows that while La Niña initially raises Robusta coffee prices, the effect diminishes over the course of the phase. In the case of vegetable oils, Ab Rahman et al. (2013) finds that crude palm oil prices tend to rise during La Niña events, as excessive rainfall and flooding often disrupt production.

La Niña	El Niño

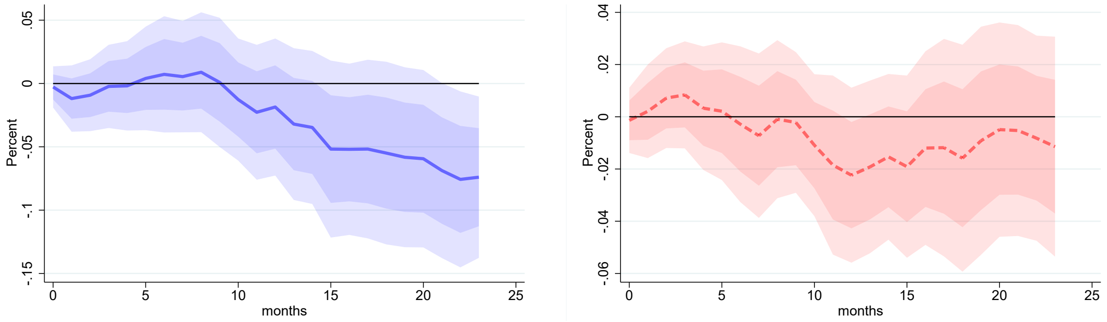
Agriculture index



Energy index



Metals and Minerals index



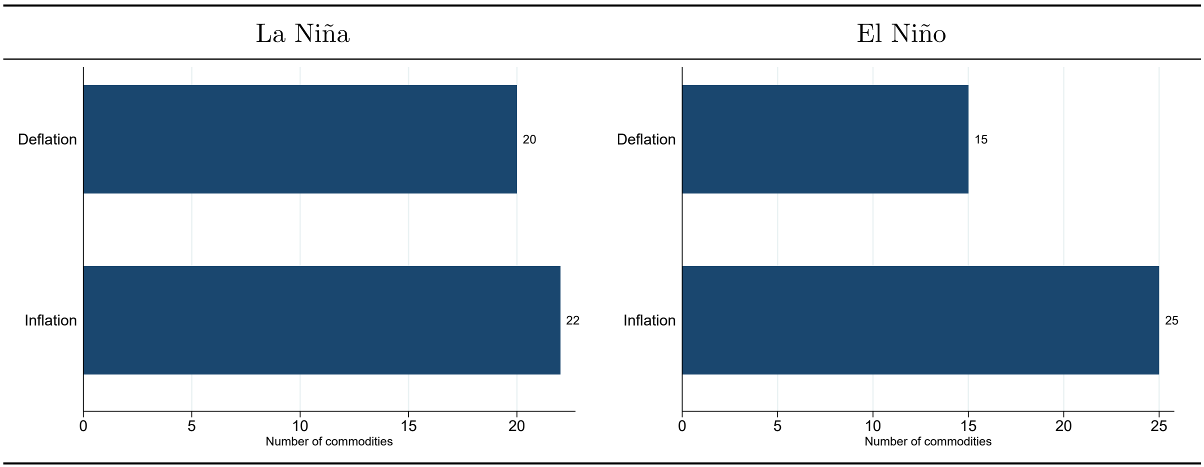
Note: Impulse responses of price indices to 1 sd MEIV2 negative shock during La Niña phase (solid blue) and positive shock during El Niño phase (dashed red) with 68% and 90% confidence bands.

Figure 5: Impact of MEI.v2 on commodities

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 16 in Appendix 8.3. Commodities' reaction to ENSO shocks appears to be dependent on ENSO state (EN or LN).

These non-linearities confirm our empirical strategy.



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

Figure 6: Inflationary or deflationary impact of MEI.v2 on commodities

4.3 Asymmetric response of commodity prices to changing ENSO patterns

An interesting result from Figure 5 is the differentiated response of commodity prices to ENSO depending on whether the ENSO shocks are positive or negative. This asymmetry is reflected both in differences in the magnitude of the price responses and in differences in the direction of the response (price increase or decrease). Several facts stand out. When we consider the commodity price indices grouped according to their nature (agriculture, energy, metals/minerals), it seems that prices are very sensitive to La Niña episodes (coinciding with colder temperatures) and relatively weakly reactive in the event of El Niño episodes (coinciding with warming temperatures). Furthermore, not all prices change in the same direction during a La Nina episode. In some cases, they increase (agricultural products and energy), while in other cases, they decrease (metals and minerals). There are several explanations for these results.

The greater responsiveness of commodity prices to La Niña shocks is a result obtained in other works in the literature (e.g., Ubilava (2017) makes this observation for wheat prices). This can be explained by the fact that episodes of negative (i.e., La Nina) anomalies in ocean surface temperatures last on average longer than anomalies linked to episodes of positive (i.e., El Niño) abnormal, coinciding with warming of temperatures, particularly since the early 2000s (this can be seen in Figure 4). Furthermore, we can see in this figure a greater frequency of extreme temperature events linked to episodes of La Niña. The strong amplitude of its effects on prices comes from the fact that more persistent and severe episodes of La Niña cause exceptional droughts in certain parts of the globe, and generate phenomena such as a greater frequency of tornadoes, cyclones, or floods. These phenomena generate natural disasters that have an effect on harvests (for agricultural products), the yield of mining operations and therefore on the level of inventories (they induce a low inventory stock regime). This corresponds to a supply channel. Moreover, this effect can be reinforced by a demand channel. In fact, forecasts of lower inventory stocks can induce speculative behavior on the commodities markets (particularly on the derivative markets associated with commodities), causing prices to rise.

A second interesting result appears in Figure 5. When prices react to ENSO shocks (typically, in the case of La Nina again, where the IRFs are significantly different from zero), we observe a phenomenon of persistence in the effect of the shocks. There does not seem to be a mean-reverting mechanism once the initial shock leads to a deviation from zero. On the contrary, in the El Niño regime, the effects of the shocks last for a very short time (the zero value crosses the confidence interval of the IRF, which means that the deviations are very small). The combination of these two observations implies that the model produces another type of asymmetry linked to differences in the length of time spent in each regime. La Niña corresponds to an "absorbing" regime, while El Niño corresponds to a "repelling" regime. This has implications in terms of policymaking because it means that in the event of persistent shocks following a sharp drop in temperatures, price stabilization policies may not be viable.

4.4 Model Robustness

To enrich the robustness of the economic analysis, we include four alternative models. First, we include structural break dates based on the approach by Bai and Perron (1998) for the commodity price sets (see Table 5).

Second, we estimate the Baseline model prior to the COVID-19 period (i.e., we exclude 2020 to 2023 from the sample period).

Third, we construct two alternative measures of global output and interest rate by extending the number of countries, albeit with a reduction of the data points in the sample period (1999:01 to 2023:12, due to data availability). The global output and interest rate data are based on data for twenty-one economies represent around 78.5% of global output.[16] Global output and interest rate data are constructed via two variants. The first variant is based on Principal Component Analysis (PCA) using one factor (first principal component) for the global variables (Ratti and

---

[16] We extend the baseline model's coverage of five economies by adding sixteen additional countries: Brazil, Switzerland, Chile, China, Columbia, Czech Republic, Hungary, India, Israel, Mexico, Norway, Poland, South Korea, Sweden, Russia and Turkey. Based on IMF data, these 21 economies represent 78.5% of global output in purchasing power parity (PPP) terms in 2023. 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, and Ginn and Pourroy, 2022).

Vespignani, 2016). The second variant utilizes a GDP-weighted index (Purchasing Price Parity), with weights rebased to sum to one for each period (Dufrénot et al., 2024). Figure 18 plots the the economic data, including the global measures of output growth and interest rate. The top-pane shows a sizable decline in output which occurred during the global financial crisis.[17] The results of the PCA are provided in Table 4, which shows the top three principal components of each global variable for the twenty-one economies. The first principal component captures significant share of the variance relating to output (61.1%) and the interest rate (90.4%).[18] The correlation between the two model variants (i.e., PCA and GDP weighted models) of output and interest rate is 97.6% and 83.4%, respectively.[19]

Figure 19 demonstrates that the baseline model closely matches the models estimated before the COVID-19 period and after controlling for structural breaks. Figure 20 shows that the baseline model aligns closely with the models estimated using the two variants of global economic conditions. Consequently, the baseline model and four alternative models consistently demonstrate that the models are quantitatively similar, reinforcing the robustness of the findings.

---

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

[18] 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.

[19] The contemporaneous correlation is statistically significant for both measures at the 1% level.

5 ENSO under stress: an exposure index

5.1 Index overview

To quantify the impact of changing ENSO patterns on commodity price volatility, we construct a scenario-specific volatility index for each commodity. For each of the four ENSO scenarios — more intense El Niño (s_1), more intense La Niña (s_2), faster transitions during El Niño (s_3) and faster transitions during La Niña (s_4) — we assess whether the commodity's price volatility significantly increases, decreases, or remains unchanged.

For each commodity i and each ENSO-related climate change scenario $s \in \{s_1, s_2, s_3, s_4\}$ is coded as +1, -1, or 0 respectively:

$$V_{i,s} = \begin{cases} +1 & \text{if volatility increases} \\ 0 & \text{if no significant change} \\ -1 & \text{if volatility decreases} \end{cases}$$

The exposure index ($Index_i$) is computed as the sum of these four responses, resulting in a final index ranging from -4 (all scenarios reduce volatility) to +4 (all scenarios increase volatility). This index provides a measure of each commodity's vulnerability to potential ENSO evolution under climate change. Then, the ENSO Volatility Impact Index for commodity i is given by:

$$\text{Index}_i = \sum_{s=1}^{4} V_{i,s}$$

where the index ranges from:

$$\text{Index}_i \in [-4, +4]$$

For the 67 commodities, we calculate the price impulse 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. Then, we compute, for the 67 commodities, our index of commodity price exposure to the evolution of ENSO. The index, represented on Figure 7, 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.

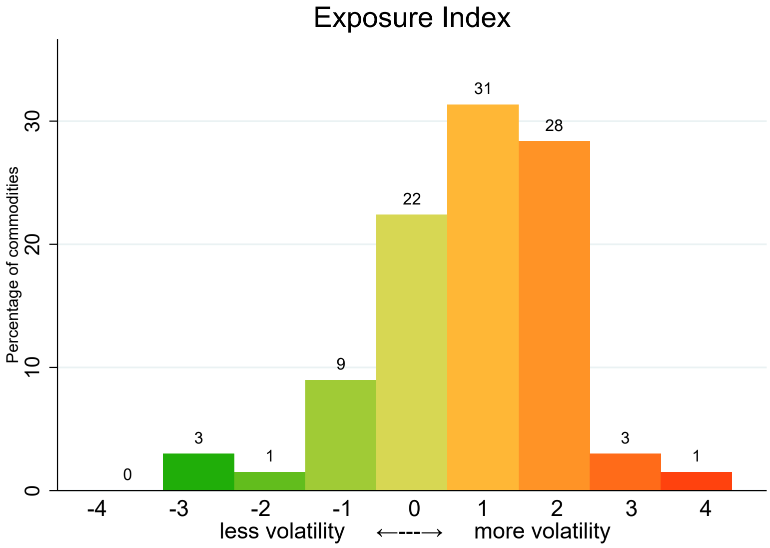


Figure 7: Commodity price exposure to the evolution of ENSO: index overview

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 8, 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 9.

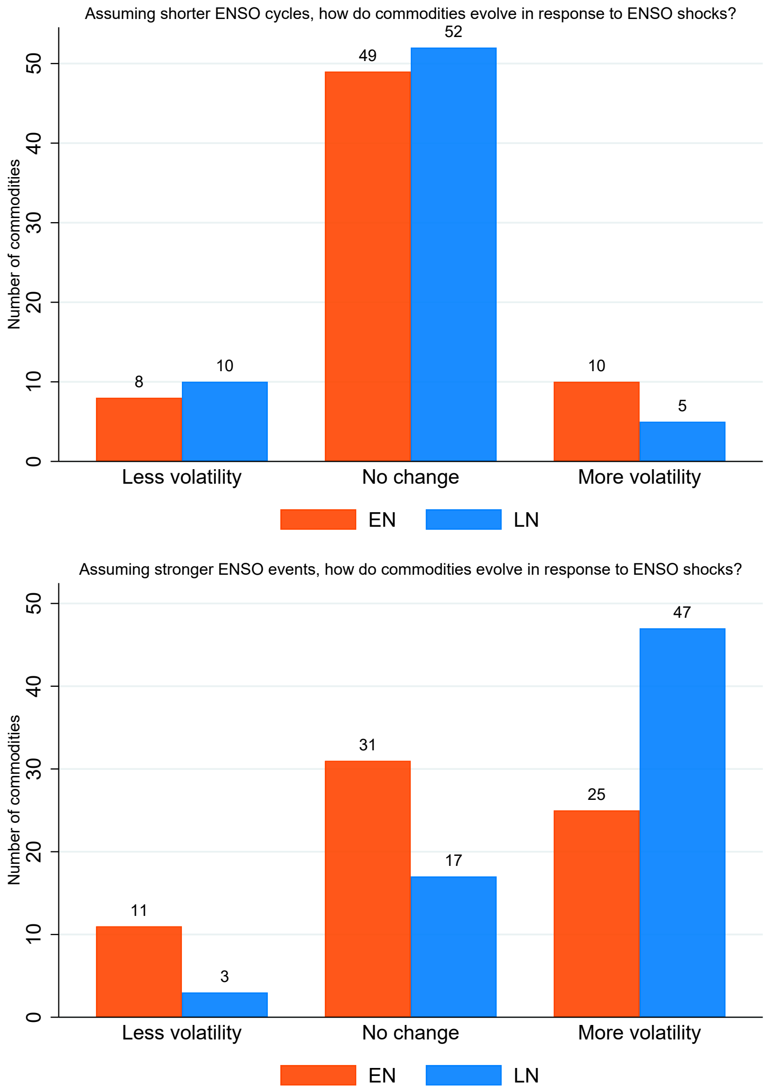
No category stands out from the others. In all cases, significant heterogeneity is observed. One exception to note is that for oil prices, the index systematically takes the value of 0. There are two possible explanations. Firstly, climatic conditions only have a minimal impact on oil prices. Secondly, 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 10 displays our Exposure Index for commodities exposed to financialization (top panel) and for commodities not exposed



Note: Maximum impulse response over 24 months for each commodity based on a 1 sd MEIV2 negative shock during La Niña phase and positive shock during El Niño phase, considering a 90 percent confidence band, 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 8: Changing ENSO patterns impact on commodities

(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-skewed on the top panel, financialization seems to contribute to volatility.

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

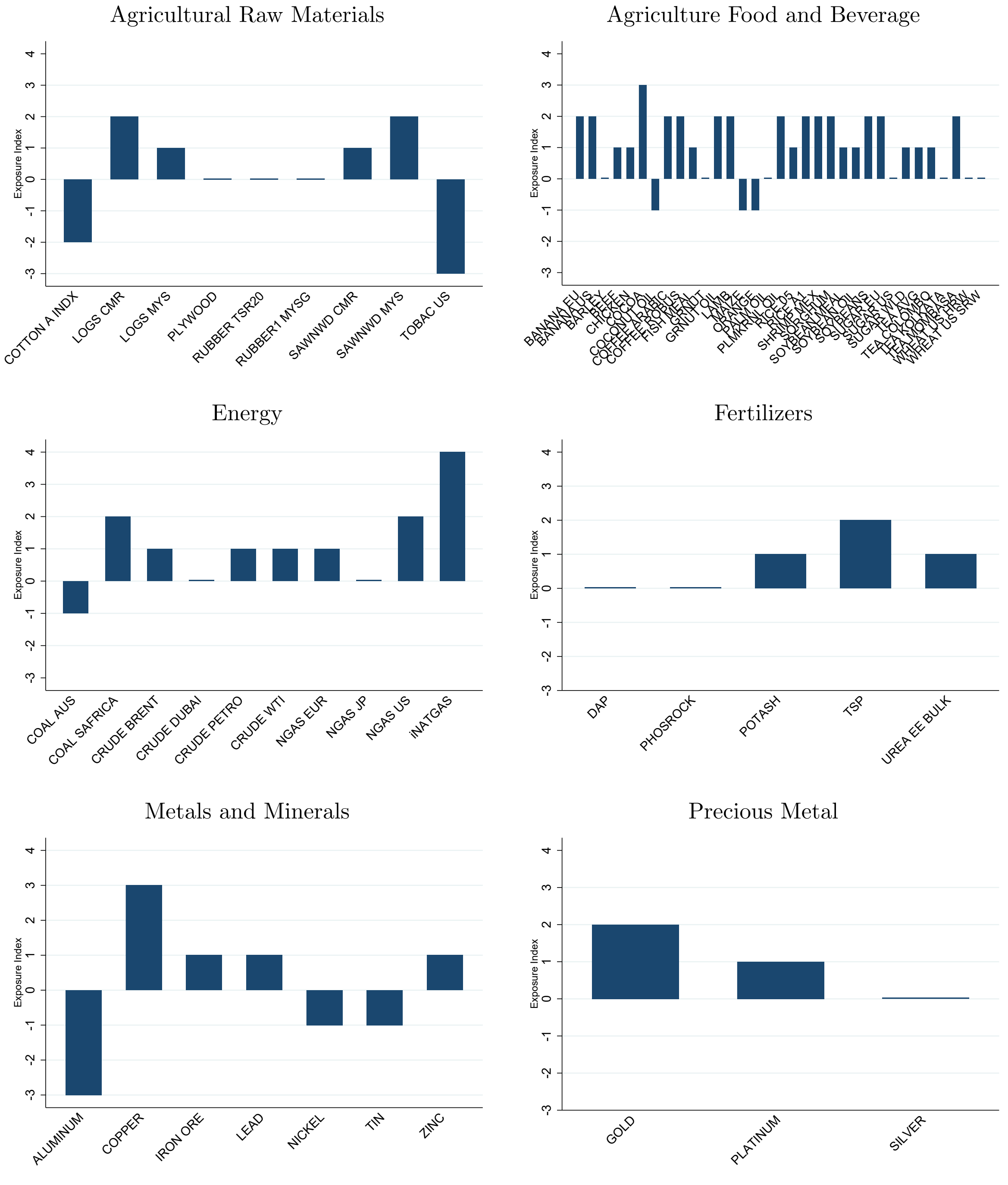
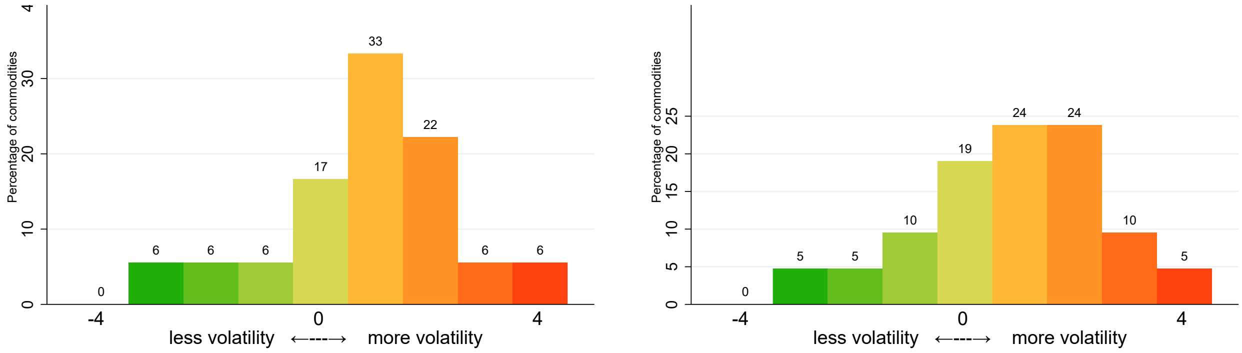


Figure 9: Index value by categories

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.

BCOM Index	TR CRB Index

Commodities included in the index



Commodities not included in the index

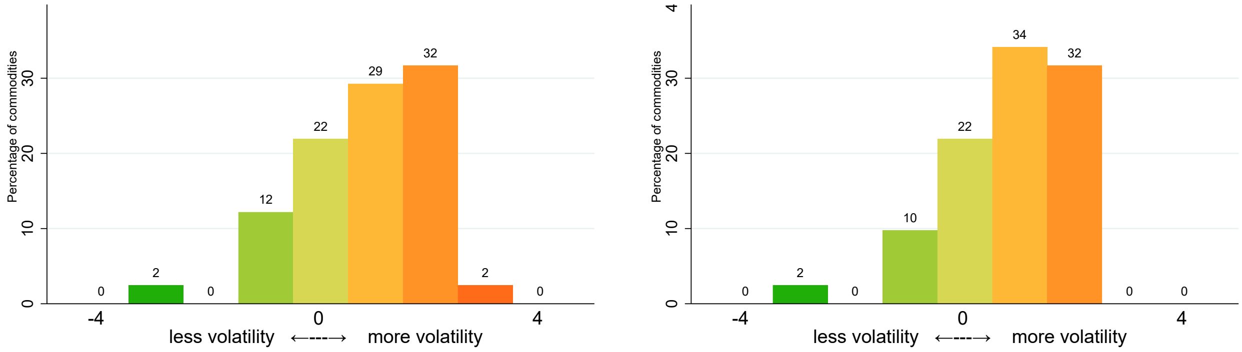


Figure 10: Commodity price exposure and financialization

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 11 displays 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

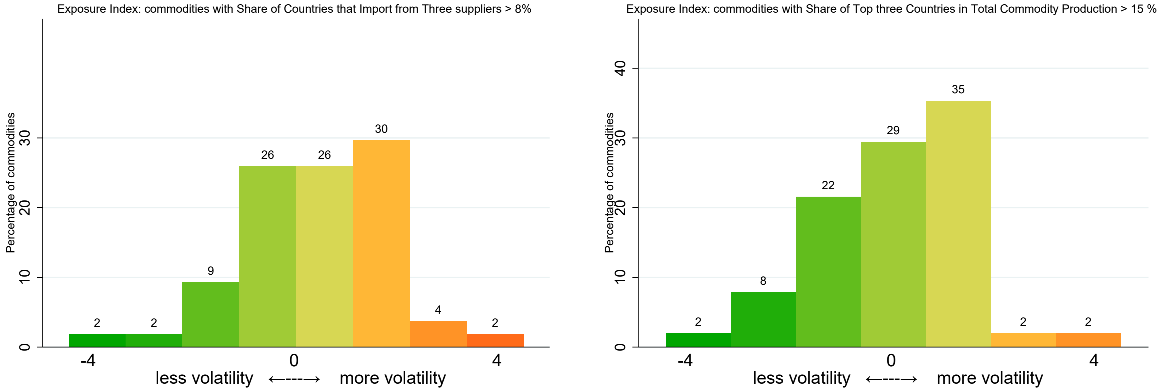
As a result of commodity production concentration (mentioned earlier) access to global commodity markets is essential for many countries. If the global market for a commodity is large, it promotes market liquidity, facilitates access to diversified sources, facilitates arbitrage activities, improves 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 12 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 represents 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 13 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

Exposure Index: commodities with production concentration



Exposure Index: commodities without production concentration

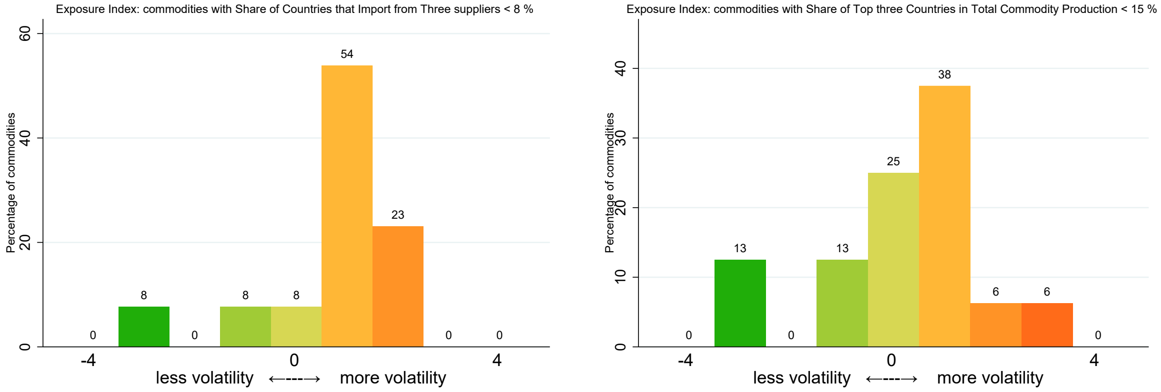
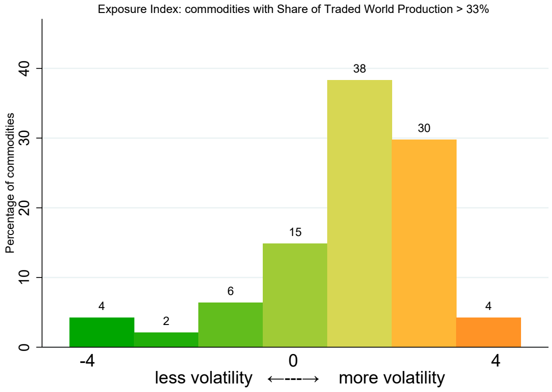


Figure 11: Commodity price exposure and production concentration

Share of Traded World Production

Commodities with large Share of Traded World Production



Commodities with limited Share of Traded World Production

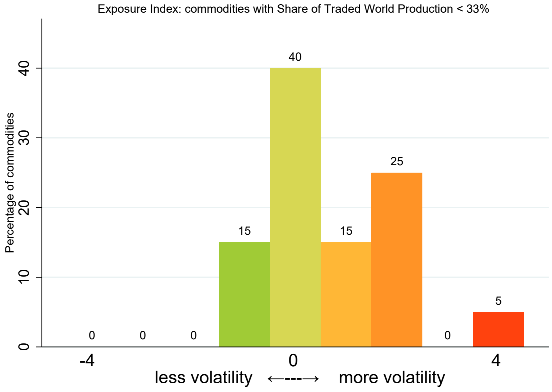
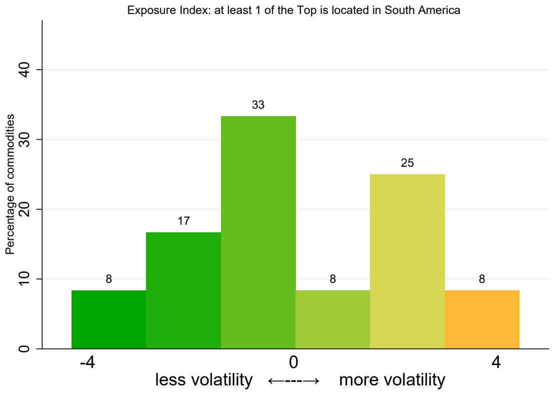


Figure 12: Commodity price exposure and trade

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

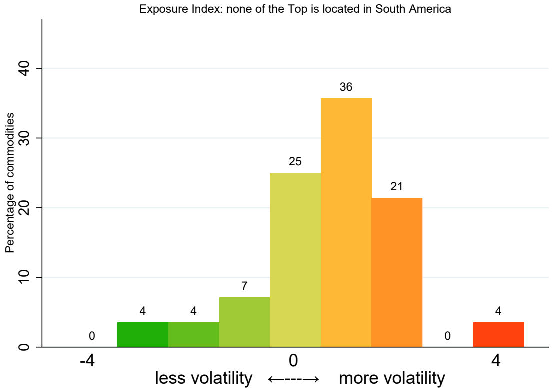


Figure 13: Commodity price exposure and production concentration in South America

6 Conclusion

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

Our identification strategy proceeds in three steps: (1) We first establish the current relationship between the ENSO cycle and commodity prices. 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 and 67 international commodity price sets. For each commodity, we estimate the price response to an ENSO shock — defined as the unanticipated component of ENSO anomalies. We measure this response separately for El Niño (EN) and La Niña (LN) episodes. The results serve as our benchmark: the current situation without climate change. (2) Climate change is expected to increase the incidence of extreme ENSO events (higher intensity) and accelerate the transition between EN and LN phases (higher frequency). We explain how we capture the impact of these changes though the definition of anomalies and to a parameter (gamma) that reflects the speed of transition. (3) We then estimate the response of commodity prices to ENSO shocks under altered climatic conditions: first, assuming a higher incidence of extreme events (higher intensity); second, assuming faster phase transitions (higher frequency). This approach lets us compare how prices react to ENSO shocks with and without climate change. To make the results easier to interpret, we summarize the comparisons in a single index. For each of the four cases, the index gains one point if climate change increases price volatility, loses one point if it decreases volatility, and stays the same if the difference is not significant. As a result, the index ranges from –4 to +4 for each commodity, showing whether climate change tends to make prices more or less volatile. Finally, we explore the economic mechanisms that might explain this relationship between climate change and price volatility. To do so, we analyze how the index varies with factors such as financialization, production concentration, trade exposure, and production localization.

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 ENSO 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 ENSO 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-thirds of commodity prices are impacted by a non-expected evolution of the ENSO cycle (or ENSO shock), generally with nonlinearity associating climatic conditions with commodity prices.

Our index that captures commodity price exposure to the evolution of ENSO, due to climate change, also bring important results. We show that in most cases, climate change is likely to result in greater volatility of commodity prices. 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 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. In contrast, the origin of the production of the commodity plays a little role: ENSO does not only affect South American countries; ENSO is a global phenomenon, therefore the global economy is likely to be impacted.

The results of this research have immediate and long-term policy implications regarding adaptation to climate change. A starting point for short-term policy is to establish sources of vulnerability that could create economic risks. The findings of this paper serve to do just that in a global factor environment by analyzing the propagation mechanisms through which ENSO shocks influence commodity price changes. 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 policy makers with regard 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 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 sense, increased commodity volatility can complicate their mission of price stability. Finally, our research underscores the importance 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.

Our work is likely to give rise to several future areas of research.

As we have seen, the asymmetrical effects of ENSO shocks generate persistent phenomena in the reaction of commodity prices. Regime-switching models make the implicit assumption that the dynamics studied are short-moted, i.e. that following a disturbance, prices are supposed to return quickly to their pre-disturbance level. This does not seem to be the case here. An alternative to regime-switching models would be to adopt the framework of long-memory models, where commodity prices are modeled as ARFIMA (autoregressive fractionally integrated moving average) or Gengenbauer (to capture the presence of long cycles in the series) processes.

Another avenue of research would be to model more specifically the heterogeneity linked to the differentiated dynamics of the different commodities. In fact, in this work, we concentrated on the heterogeneity of reactions over time (in this case by considering different ENSO regimes). Taking into account the heterogeneity of the "individual" dimension in our series requires us to abandon the assumption of homogeneity of the coefficients by adapting our model to the case of dynamic panel data. This would have several advantages. In addition to differentiating the reactions of the various categories of commodities, this type of model would make it possible to link the differentiated degrees of persistence to the duration of the cycles (short, medium and long) of the various commodities.

Finally, commodity prices in physical markets are closely tied to the prices of financial assets derived from these markets, such as options and futures. These financial instruments reflect the expectations of buyers and sellers regarding the impact of the ENSO cycle on food products, metals, minerals, and carbon-based energy sources. Investigating whether this financial market behavior amplifies or mitigates the effects of ENSO would be a valuable direction for future research.

7 Bibliography

Ab Rahman, A. K., Abdullah, R., Balu, N., and Shariff, F. M. (2013). The impact of la niña and el niño events on crude palm oil prices: An econometric analysis. Oil Palm Ind Econ J, 13:38–51.

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., and Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? Journal of Macroeconomics, 65:103207.

Adams, Z. and Glück, T. (2015). Financialization in commodity markets: A passing trend or the new normal? Journal of Banking & Finance, 60:93–111.

Albertus, M. (2019). The effect of commodity price shocks on public lands distribution: Evidence from Colombia. World Development, 113:294–308.

Alexander, M., Bladé, I., Newman, M., Lanzante, J., Lau, N.-C., and Scott, J. (2002). The atmospheric bridge: The influence of ENSO teleconnections on air–sea interaction over the global oceans. Journal of Climate, 15(16):2205–2231.

An, S.-I., Ham, Y.-G., Kug, J.-S., Jin, F.-F., and Kang, I.-S. (2005). El Niño–La Niña asymmetry in the coupled model intercomparison project simulations. Journal of Climate, 18(14):2617–2627.

An, S.-I. and Wang, B. (2000). Interdecadal change of the structure of the ENSO mode and its impact on the ENSO frequency. Journal of Climate, 13(12):2044–2055.

Anttila-Hughes, J. K., Jina, A. S., and McCord, G. C. (2021). ENSO drives child undernutrition in the global tropics.

Atems, B. and Sardar, N. (2021). Exploring asymmetries in the effects of El Niño-Southern Oscillation on US food and agricultural stock prices. The Quarterly Review of Economics and Finance, 81:1–14.

Auerbach, A. and Gorodnichenk, Y. (2012). Measuring the output responses to fiscal policy. American Economic Journal: Economic Policy, 4(2):1–27.

Baffes, J. and Kabundi, A. (2023). Commodity price shocks: Order within chaos? Resources Policy, 83:103640.

Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. Econometrica, pages 47–78.

Barlow, M., Nigam, S., and Berbery, E. (2001). ENSO, pacific decadal variability, and US summertime precipitation, drought, and stream flow. Journal of Climate, 14(9):2105–2128.

Barnston, A. (2015). Why are there so many ENSO indexes, instead of just one. NOAA Climate. gov.

Basak, S. and Pavlova, A. (2016). A model of financialization of commodities. The Journal of Finance, 71(4):1511–1556.

Battiston, S., Dafermos, Y., and Monasterolo, I. (2021). Climate risks and financial stability.

Berry, B. J. and Okulicz-Kozaryn, A. (2008). Are there ENSO signals in the macroeconomy. Ecological Economics, 64(3):625–633.

Bertrand, A., Lengaigne, M., Takahashi, K., Avadi, A., Poulain, F., and Harrod, C. (2020). El Niño Southern Oscillation (ENSO) effects on fisheries and aquaculture, volume 660. Food and Agriculture Organization.

Boneva, L., Ferrucci, G., and Mongelli, F. P. (2022). Climate change and central banks: what role for monetary policy? Climate Policy, 22(6):770–787.

Brönnimann, S., Xoplaki, E., Casty, C., Pauling, A., and Luterbacher, J. (2007). ENSO influence on Europe during the last centuries. Climate Dynamics, 28(2-3):181–197.

Brunner, A. D. (2002). El Nino and world primary commodity prices: warm water or hot air? Review of Economics and Statistics, 84(1):176–183.

Buhr, B., Volz, U., Donovan, C., Kling, G., Lo, Y. C., Murinde, V., and Pullin, N. (2018). Climate change and the cost of capital in developing countries.

Cai, W., Borlace, S., Lengaigne, M., Van Rensch, P., Collins, M., Vecchi, G., Timmermann, A., Santoso, A., McPhaden, M. J., and Wu, L. (2014). Increasing frequency of extreme El Niño events due to greenhouse warming. Nature climate change, 4(2):111–116.

Cai, W., Santoso, A., Collins, M., Dewitte, B., Karamperidou, C., Kug, J.-S., Lengaigne, M., McPhaden, M., Stuecker, M., and Taschetto, A. (2021). Changing El Niño–Southern Oscillation in a warming climate. Nature Reviews Earth & Environment, 2(9):628–644.

Callahan, C. W. and Mankin, J. S. (2023). Persistent effect of El Niño on global economic growth. Science, 380(6649):1064–1069.

Campos, R. G., Estefania-Flores, J., Furceri, D., and Timini, J. (2023). Geopolitical fragmentation and trade. Journal of Comparative Economics, 51(4):1289–1315.

Carleton, T. A. and Hsiang, S. M. (2016). Social and economic impacts of climate. Science, 353(6304):aad9837.

Cashin, P., Mohaddes, K., and Raissi, M. (2017). Fair weather or foul? The macroeconomic effects of El Niño. Journal of International Economics, 106:37–54.

Cevik, S. and Jalles, J. (2024). Eye of the storm: The impact of climate shocks on inflation and growth. Review of Economics, 75(2):109–138.

Chen, C., McCarl, B., and Adams, R. (2001). Economic implications of potential ENSO frequency and strength shifts. Climatic Change, 49(1):147–159.

Ciccarelli, M. and Mojon, B. (2010). Global inflation. The Review of Economics and Statistics, 92(3):524–535.

Dai, A. (2013). Increasing drought under global warming in observations and models. Nature Climate Change, 3(1):52–58.

Damette, O., Mathonnat, C., and Thavard, J. (2024). Climate and sovereign risk: The Latin American experience with strong ENSO events. World Development, 178:106590.

De Marco, F., Limodio, N., Eufinger, C., Gorostiaga, J. P., Richter, B., Martini, F., Steffen, Z., Theunisz, C., and Lattanzio, G. (2023). The financial transmission of a climate shock: El Nino and US banks. Available at SSRN, 4279194.

De Winne, J. and Peersman, G. (2018). Agricultural price shocks and business cycles - a global warning for advanced economies. Technical report.

De Winne, J. and Peersman, G. (2021). The adverse consequences of global harvest and weather disruptions on economic activity. Nature Climate Change, 11(8):665.672.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. Journal of Economic Literature, 52(3):740–98.

Diaz, H. F., Hoerling, M. P., and Eischeid, J. K. (2001). ENSO variability, teleconnections and climate change. International Journal of Climatology: A Journal of the Royal Meteorological Society, 21(15):1845–1862.

Dufrénot, G., Ginn, W., and Pourroy, M. (2024). Climate pattern effects on global economic conditions. Economic Modelling, 141:106920.

Dufrénot, G., Ginn, W., Pourroy, M., and Sullivan, A. (2024). Does state dependence matter in relation to oil price shocks on global economic conditions? Studies in Nonlinear Dynamics Econometrics.

Fabris, N. (2020). Financial stability and climate change. Journal of Central Banking Theory and Practice, 9(3):27–43.

Flori, A., Pammolli, F., and Spelta, A. (2021). Commodity prices co-movements and financial stability: A multidimensional visibility nexus with climate conditions. Journal of Financial Stability, 54(C).

Generoso, R., Couharde, C., Damette, O., and Mohaddes, K. (2020). The growth effects of El Nino and La Nina: Local weather conditions matter. Annals of Economics and Statistics, (140):83–126.

Ginn, W. (2023a). The impact of economic policy uncertainty on stock prices. Economics Letters, page 111432.

Ginn, W. (2023b). World output and commodity price cycles. International Economic Journal, pages 1–25.

Ginn, W. and Pourroy, M. (2022). The contribution of food subsidy policy to monetary policy in India. Economic Modelling, 113:105904.

Giuzio, M., Krušec, D., Levels, A., Melo, A. S., Mikkonen, K., and Radulova, P. (2019). Climate change and financial stability. Financial Stability Review, 1.

Gorodnichenko, Y. and Auerbach, A. J. (2013). Fiscal Multipliers in Recession and Expansion. University of Chicago Press.

Gouel, C. and Laborde, D. (2021). The crucial role of domestic and international market-mediated adaptation to climate change. Journal of Environmental Economics and Management, 106:102408.

Guo, Z., Zhou, T., and Wu, B. (2017). The asymmetric effects of El Niño and La Niña on the East Asian winter monsoon and their simulation by CMIP5 atmospheric models. Journal of Meteorological Research, 31(1):82–93.

Gutierrez, L. (2017). Impacts of El Niño-Southern Oscillation on the wheat market: A global dynamic analysis. PloS one, 12(6):e0179086.

Hansen, J., Hodges, A., and Jones, J. (1998). ENSO influences on agriculture in the southeastern United States. Journal of Climate, 11(3):404–411.

Henseler, M. and Schumacher, I. (2019). The impact of weather on economic growth and its production factors. Climatic change, 154(3-4):417–433.

Hsiang, S., Meng, K., and Cane, M. (2011). Civil conflicts are associated with the global climate. Nature, 476(7361):438–441.

Hu, K., Huang, G., Huang, P., Kosaka, Y., and Xie, S.-P. (2021). Intensification of El Niño-induced atmospheric anomalies under greenhouse warming. Nature Geoscience, 14(6):377–382.

Iizumi, T., Luo, J.-J., Challinor, A. J., Sakurai, G., Yokozawa, M., Sakuma, H., Brown, M. E., and Yamagata, T. (2014). Impacts of El Niño Southern Oscillation on the global yields of major crops. Nature communications, 5(1):3712.

IMF (2023). Divergences, navigating global. World Economic Outlook.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. American Economic Review, 95(1):161–182.

Kabundi, A. N., Mlachila, M. M., and Yao, J. (2022). How persistent are climate-related price shocks? implications for monetary policy. Technical report, International Monetary Fund.

Kang, W., Tang, K., and Wang, N. (2023). Financialization of commodity markets ten years later. Journal of Commodity Markets, 30:100313.

Kashif, A., Qasim, M. Z., Huaming, S., Muntasir, M., Haider, M., and Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. Environmental Science and Pollution Research, 29:42539–42559.

Kose, M., Otrok, C., and Whiteman, C. (2003). International business cycles: World, region, and country-specific factors. American Economic Review, 93(4):1216–1239.

Kranz, T., Bennani, H., and Neuenkirch, M. (2024). Monetary policy and climate change: Challenges and the role of major central banks. Technical report, University of Trier, Department of Economics.

Legler, D. M., Bryant, K. J., and O'brien, J. J. (1999). Impact of ENSO-related climate anomalies on crop yields in the US. Climatic Change, 42:351–375.

Li, Y., Yi, F., Wang, Y., and Gudaj, R. (2019). The Value of El Niño-Southern Oscillation Forecasts to China's Agriculture. Sustainability, 11(15):1–23.

Liu, Y., Cai, W., Lin, X., Li, Z., and Zhang, Y. (2023). Nonlinear El Niño impacts on the global economy under climate change. Nature Communications, 14(1):5887.

Mainardi, S. (2011). Cropland use, yields, and droughts: spatial data modeling for Burkina Faso and Niger. Agricultural Economics, 42(1):17–33.

McPhaden, M., Santoso, A., and Cai, W. (2020). Introduction to El Niño Southern Oscillation in a changing climate. El Niño Southern Oscillation in a Changing Climate, pages 1–19.

McPhaden, M., Zebiak, S., and Glantz, M. (2006). ENSO as an integrating concept in earth science. Science, 314(5806):1740–1745.

Mekasha, T. J., Molla, K. G., Tarp, F., and Aikaeli, J. (2022). Commodity price fluctuations and child malnutrition. World Development, 158:105927.

Melo-Velandia, L. F., Orozco-Vanegas, C. A., and Parra-Amado, D. (2022). Extreme weather events and high Colombian food prices: A non-stationary extreme value approach. Agricultural Economics, 53(S1):21–40.

Mohtadi, S. and Castells-Quintana, D. (2021). The distributional dimension of the resource curse: Commodity price shocks and income inequality. Structural Change and Economic Dynamics, 59:63–78.

Monfort, A., Renne, J.-P., Rüffer, R., and Vitale, G. (2003). Is economic activity in the G7 synchronized? common shocks versus spillover effects. Common Shocks Versus Spillover Effects (November 2003).

Mourtzinis, S., Ortiz, B., and Damianidis, D. (2016). Climate change and ENSO effects on southeastern US climate patterns and maize yield. Scientific reports, 6(1):29777.

Mueller, V. and Osgood, D. (2009). Long-term consequences of short-term precipitation shocks: evidence from Brazilian migrant households. Agricultural Economics, 40(5):573–586.

Mukherjee, K. and Ouattara, B. (2021). Climate and monetary policy: do temperature shocks lead to inflationary pressures? Climatic change, 167(3-4):32.

Nam, K. (2021). Investigating the effect of climate uncertainty on global commodity markets. Energy Economics, 96:105123.

Patnaik, I., Shah, A., and Bhattacharya, R. (2011). Monetary policy transmission in an emerging market setting. Number 11-15. International Monetary Fund.

Pointner, W. and Ritzberger-Grünwald, D. (2019). Climate change as a risk to financial stability. Financial Stability Report, 38:30–45.

Ramey, V. and Zubairy, S. (2018). Government spending multipliers in good times and in bad: evidence from US historical data. Journal of Political Economy, 126(2):850–901.

Ratti, R. A. and Vespignani, J. L. (2016). Oil prices and global factor macroeconomic variables. Energy Economics, 59:198–212.

Ray Biswas, R. and Rahman, A. (2023). Adaptation to climate change: A study on regional climate change adaptation policy and practice framework. Journal of Environmental Management, 336:117666.

Romero, D. (2025). Domestic linkages and the transmission of commodity price shocks. Journal of International Economics, 153:104041.

Ropelewski, C. and Halpert, M. (1987). Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. Monthly Weather Review, 115(8):1606–1626.

Rosenzweig, C., Iglesias, A., Yang, X., Epstein, P., and Chivian, E. (2001). Climate change and extreme weather events. Global Change and Human Health, 2(2):90.

Sarachik, E. and Cane, M. (2010). The El Nino-southern oscillation phenomenon. Cambridge University Press.

Smith, S. and Ubilava, D. (2017). The El Niño Southern Oscillation and economic growth in the developing world. Global Environmental Change, 45:151–164.

Stan, K., Watt, G. A., and Sanchez-Azofeifa, A. (2021). Financial stability in response to climate change in a northern temperate economy. Nature Communications, 12(1):7161.

Strabel, J. and Wurgler, J. (2021). What do you think about climate finance? CEPR Discussion Papers 16622, C.E.P.R. Discussion Papers.

Su, Y.-J., Liao, P.-A., and Chang, H.-H. (2025). How does food market respond to natural disaster shocks? evidence from the cabbage wholesale market. World Development, 190:106950.

Svartzman, R., Bolton, P., Despres, M., Pereira Da Silva, L. A., and Samama, F. (2021). Central banks, financial stability and policy coordination in the age of climate uncertainty: A three-layered analytical and operational framework. Climate Policy, 21(4):563–580.

Tack, J. and Ubilava, D. (2015). Climate and agricultural risk: measuring the effect of ENSO on U.S. crop insurance. Agricultural Economics, 46(2):245–257.

Tang, K. and Xiong, W. (2012). Index investment and the financialization of commodities. Financial Analysts Journal, 68(6):54–74.

Timmermann, A., Oberhuber, J., Bacher, A., Esch, M., Latif, M., and Roeckner, E. (1999). Increased El Niño frequency in a climate model forced by future greenhouse warming. Nature, 398(6729):694–697.

Tol, R. S. (2024). A meta-analysis of the total economic impact of climate change. Energy Policy, 185:113922.

Ubilava, D. (2012a). El Niño, La Niña, and world coffee price dynamics. Agricultural Economics, 43(1):17–26.

Ubilava, D. (2012b). El Niño, La Niña, and world coffee price dynamics. Agricultural Economics, 43(1):17–26.

Ubilava, D. (2013). El Niño southern oscillation and the fishmeal–soya bean meal price ratio: regime-dependent dynamics revisited. European Review of Agricultural Economics, 41(4):583–604.

Ubilava, D. (2017). The ENSO effect and asymmetries in wheat price dynamics. World Development, 96:490–502.

Ubilava, D. (2018). The role of El Nino Southern Oscillation in commodity price movement and predictability. American Journal of Agricultural Economics, 100(1):239–263.

Ventosa-Santaulària, D., Tapia, E., and Pérez-Peña, A. (2024). Inflation dynamics under different weather regimes: Evidence from Mexico. Ecological Economics, 220:108179.

Vink, S. and Robbins, S. (2012). Mine water management in variable climate regimes. International Mine Water Association, Annual Conference.

Yeh, S.-W., Cai, W., Min, S.-K., McPhaden, M., Dommenget, D., Dewitte, B., Collins, M., Ashok, K., An, S.-I., and Yim, B.-Y. (2018). ENSO atmospheric teleconnections and their response to greenhouse gas forcing. Reviews of Geophysics, 56(1):185–206.

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.

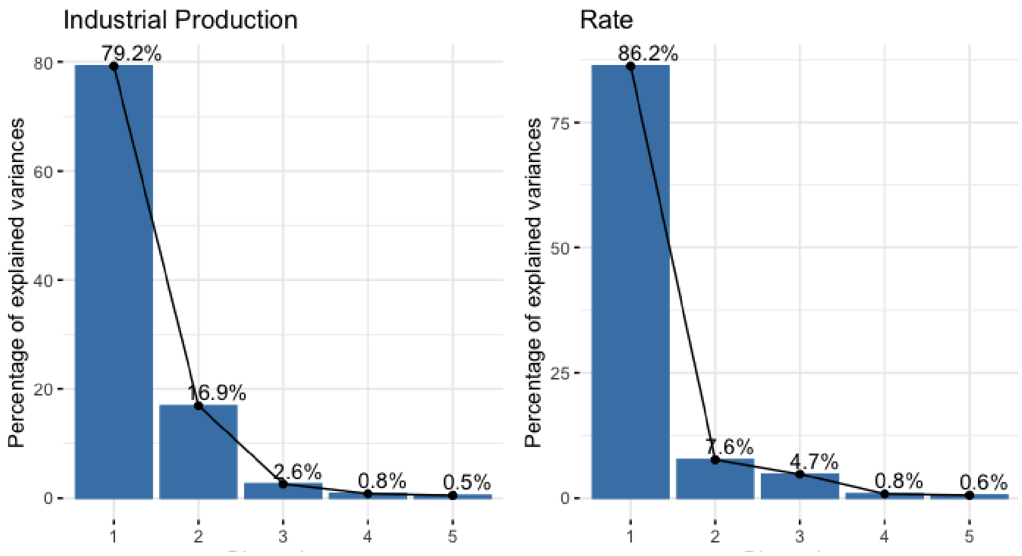
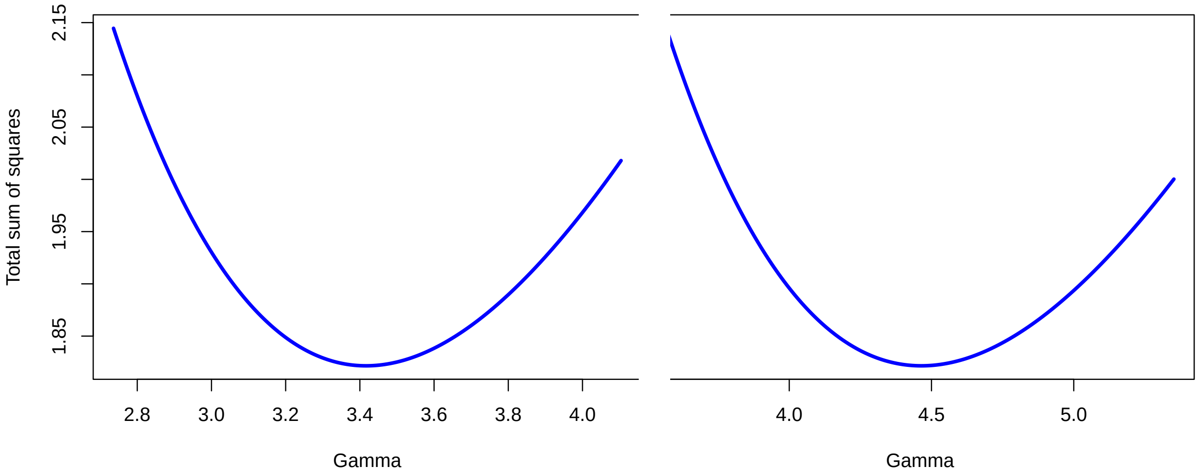


Figure 14: Scree Plots for Global Variables

8.2 Transition speed

Climate change may affect the ENSO cycle by shortening the transition time between phases (El Niño to La Niña and vice versa). As these transitions become more rapid, the parameter γ is expected to increase. Consequently, under climate change, the estimated value of γ should rise over time. To test this hypothesis, we estimate γ by dividing the MEI.v2 series into two subsamples: 1980–2000 and 2000–2020. The results are presented in Figure 15. During the first period (1980–2000), $\hat{\gamma}$ was approximately 3.4, whereas in the second period (2000–2020), it increased to about 4.5.

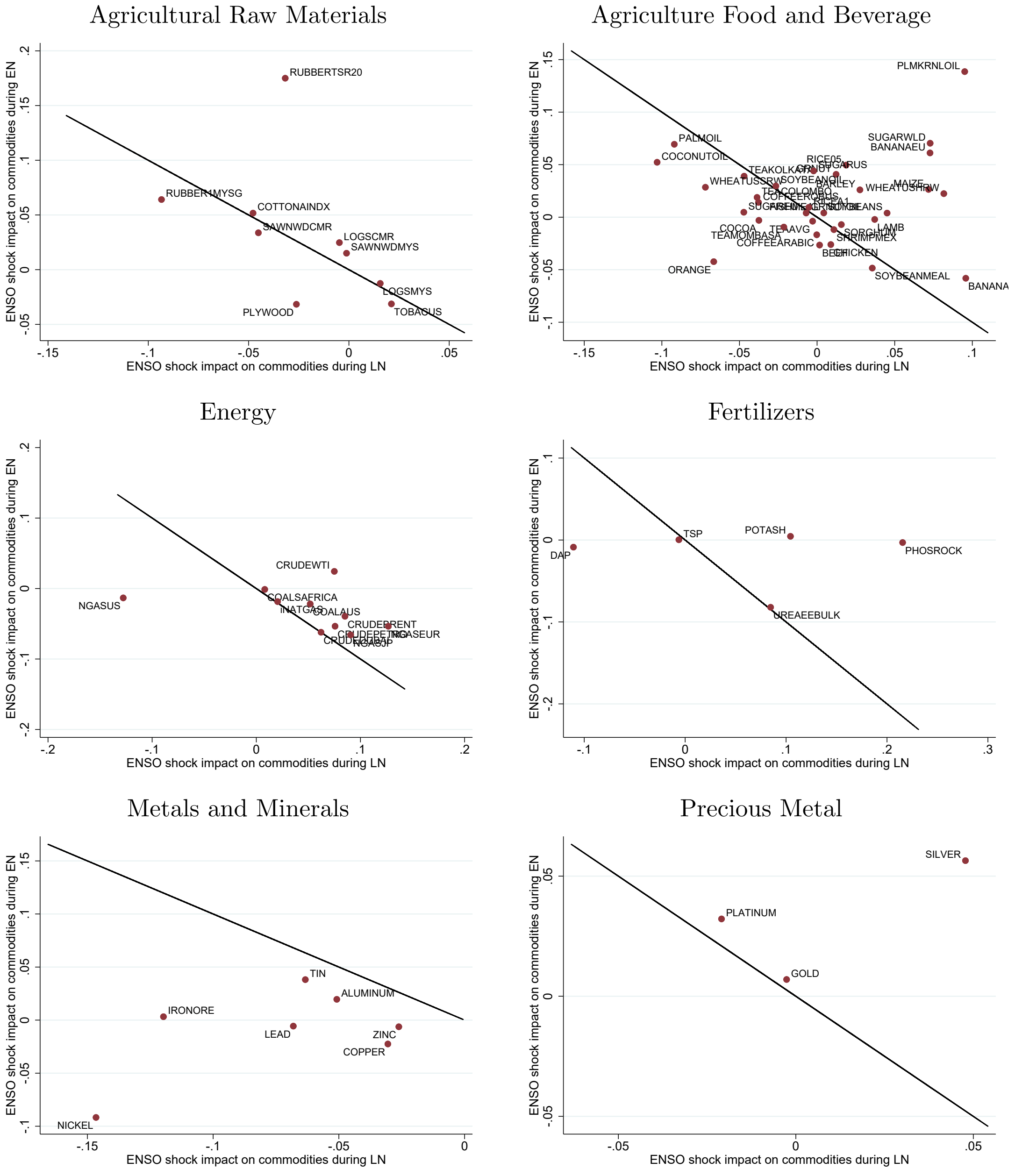


$\hat{\gamma}$ estimated over 1970-1990 $\hat{\gamma}$ estimated over 1990-2010

Figure 15: Shortening transition times: historical $\hat{\gamma}$

8.3 Nonlinearities

A limitation of the results presented on Figure 5 is that they are based on aggregated variables. We therefore carried out the same exercise for each of the 67 commodities, one by one. We plot the reactions, grouped by commodity type on Figure 16. 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.

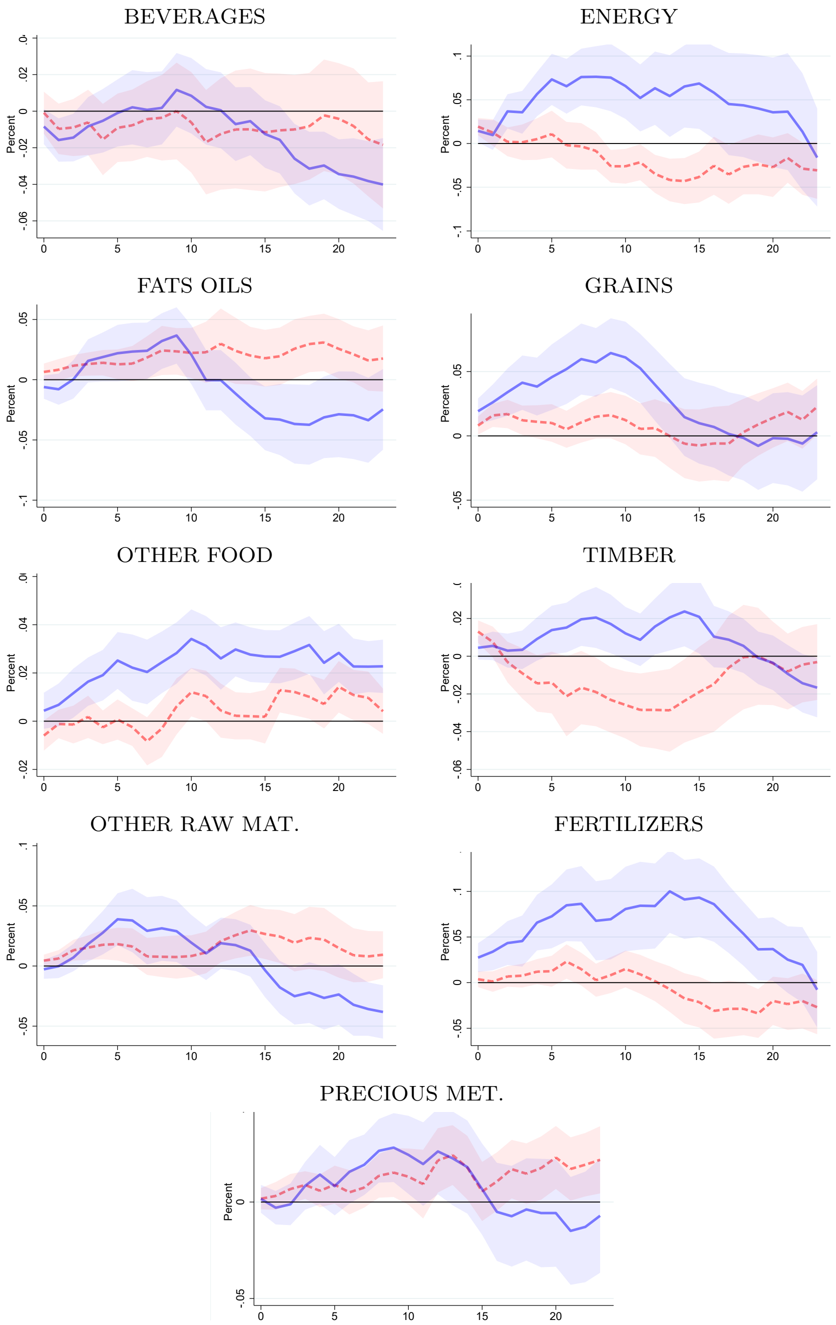


Note: Impulse response function at its maximum value over 24 months for each commodity based on a 1 sd MEIV2 negative shock during La Niña phase and positive shock during El Niño phase.

Figure 16: Reactions to ENSO shocks grouped by commodity categories

8.4 Additional IRF

In addition to the impulse response functions presented in Figure 5 for the major commodity, we also provide additional IRFs on major commodities in Figure 17 below.

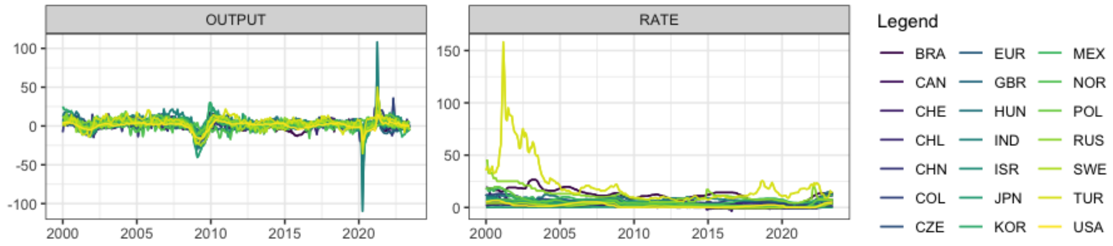


Note: Impulse responses of price indices to 1 sd MEIV2 negative shock during La Niña phase (solid blue) and positive shock during El Niño phase (dashed red) with 68% confidence bands.

Figure 17: Impact of MEI.v2 on additional commodities

8.5 Robustness analysis

Economic Data



World Economic Data

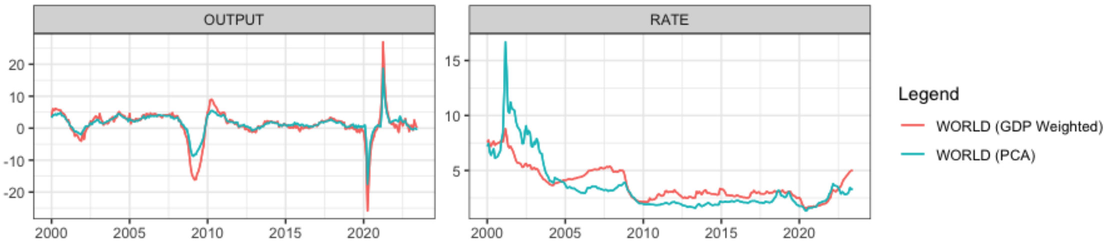


Figure 18: Global Economic Data

	Global Output	Global Interest Rate
First Principal Component	63.1%	90.9%
Second Principal Component	8.0%	5.4%
Third Principal Component	5.7%	1.3%

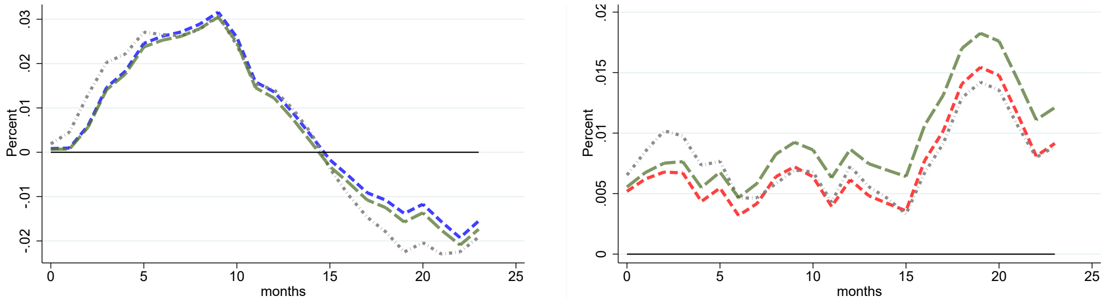
Table 4: Variation Explained by First Three Principal Components (Alternative Model)

Commodity	**Break Dates**	**Commodity**	**Break Dates**
Agriculture	12/2013, 12/2020	**Energy**	6/2005, 10/2019
Metmin	9/2009, 6/2011		
ALUMINUM	5/1991, 12/2006	ORANGE	6/1997, 10/2006
BANANAEU	6/2000, 4/2007	PALMOIL	3/1999, 1/2020
BANANAUS	10/1990, 2/2000	PHOSROCK	3/2004
BARLEY	1/1997, 10/1994	PLATINUM	8/2022
BEEF	8/2018, 6/2014	PLMKRNLOIL	1/2010
CHICKEN	5/1990, 4/2013	PLYWOOD	12/2001, 1/2003
COALAUS	1/2013, 12/2003	POTASH	12/2013
COALSAFRICA	3/2015, 4/2011	RICE05	7/2014, 5/2002
COCOA	1/1991	RICEA1	3/2001, 11/1998
COCONUTOIL	2/1993, 7/2008	RUBBER1MYSG	6/1997, 12/2005
COFFEEARABIC	4/1996, 8/2010	RUBBERTSR20	2/2001
COFFEEROBUS	11/2001, 9/2002	SAWNWDCMR	12/2022, 5/2021
COPPER	8/2022, 1/2021	SAWNWDMYS	5/2017, 5/2021
COTTONAINDX	7/2001, 3/2017	SHRIMPMEX	3/2010, 9/1992
CRUDEBRENT	12/1997, 12/2007	SILVER	3/1990, 1/2004
CRUDEDUBAI	5/1998, 3/2017	SORGHUM	9/1997, 11/2010
CRUDEPETRO	7/1988, 10/1996	SOYBEANMEAL	8/2013, 11/1987
CRUDEWTI	6/1998, 8/2005	SOYBEANOIL	9/2005, 2/1988
DAP	1/2014	SOYBEANS	9/2009, 12/2012
FISHMEAL	5/2016, 5/1998	SUGAREU	12/2014, 1/1995
GOLD	11/2022, 10/2011	SUGARUS	4/1997, 3/2015
GRNUT	2/2014, 2/1994	SUGARWLD	5/2018, 5/2009
GRNUTOIL	3/1993	TEAAVG	5/2023
iNATGAS	1/1987, 10/1999	TEACOLOMBO	1/2012, 4/1990
IRONORE	3/1987	TEAKOLKATA	6/2023, 8/2010
LAMB	4/1999, 7/2014	TEAMOMBASA	4/2007, 1/2004
LEAD	9/1998, 11/1987	TIN	7/2005, 12/2009
LOGSCMR	9/2015, 6/2007	TOBACUS	10/2020
LOGSMYS	6/2015, 10/2006	TSP	7/1990
MAIZE	6/1993, 7/2007	UREAEEBULK	5/2014, 9/1988
NGASEUR	4/2009, 5/2011	WHEATUSHRW	6/2009, 5/1989
NGASJP	11/1987, 1/2019	WHEATUSSRW	5/2016, 11/2010
NGASUS	8/2006, 2/2000	ZINC	10/2015, 6/2004
NICKEL	07/1988, 11/2003		

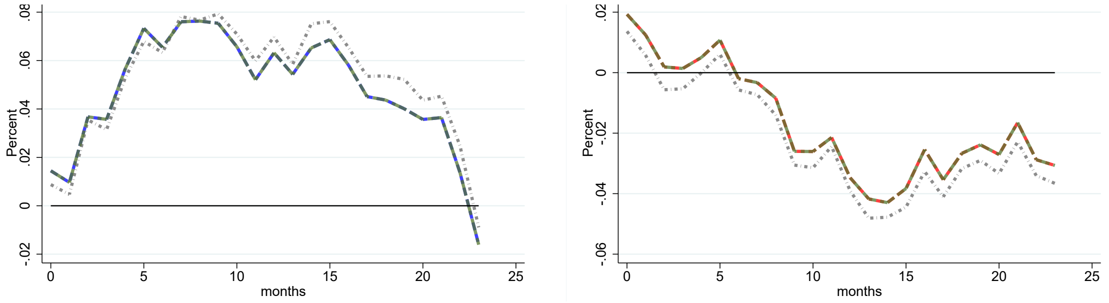
Table 5: Structural Break Dates by Commodity

La Niña El Niño

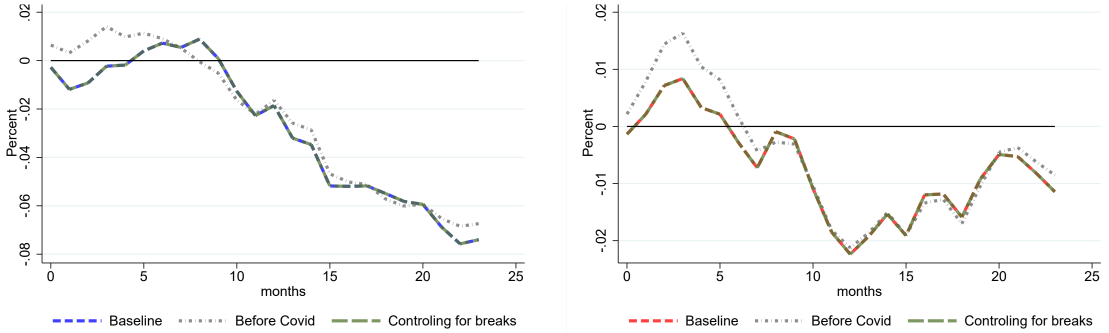
Agriculture index



Energy index



Metals and Minerals index

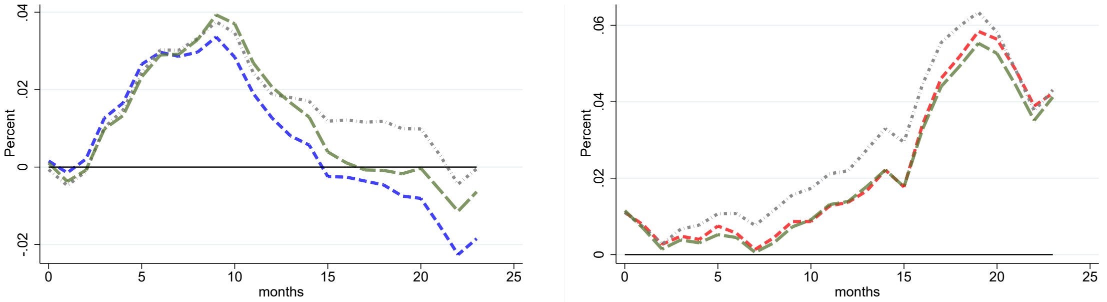


Note: Impulse responses of price indices to 1 sd MEIV2 negative shock during La Niña phase and positive shock during El Niño phase.

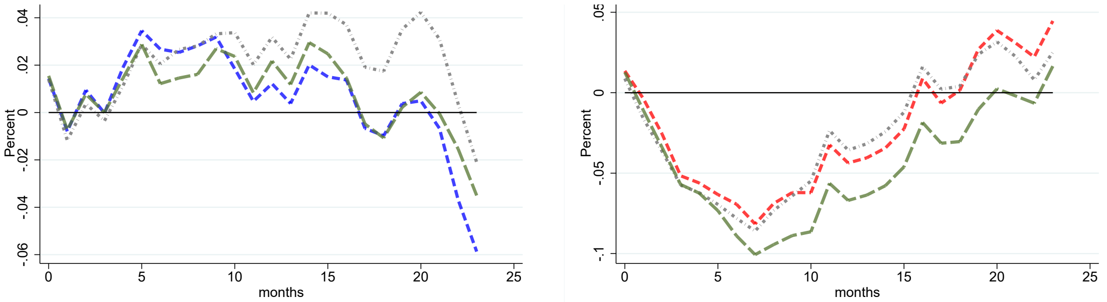
Figure 19: Impact of MEI.v2 on commodities, controlling for breaks and for the COVID-19 period

La Niña	El Niño

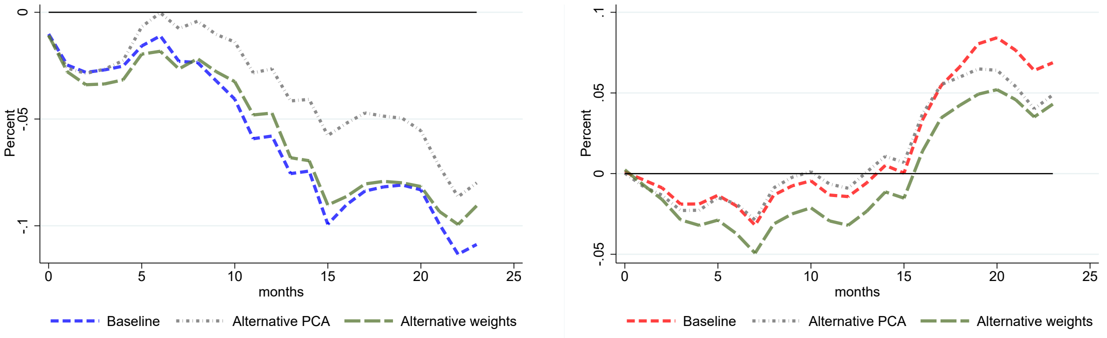
Agriculture index



Energy index



Metals and Minerals index



Note: Impulse responses of price indices to 1 sd MEIV2 negative shock during La Niña phase and positive shock during El Niño phase.

Figure 20: Impact of MEI.v2 on commodities, alternative estimations for world output and world interest rate