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THE IMPACT OF ENSO CLIMATIC ANOMALIES ON AGRICULTURAL COMMODITY RETURNS: VOLATILITY AND TAIL RISK

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Resumen

El estudio de la evolución del rendimiento de los precios de productos básicos como bienes agrícolas es determinante para la economía tanto doméstica como general. Conocer sus aspectos econométricos nos permite no solo entender patrones de consumo, sino también de inversión.

Este trabajo aborda el impacto de la variable climática ENSO en dichos productos agrícolas, centrándose en ocho bienes específicos. El objetivo es comprender si la influencia de esta variable es decisiva debido a su impacto en la producción. Para ello se aplican modelos econométricos, contrastados con momentos de orden superior realizados como la volatilidad, la asimetría y la curtosis.

Tras trabajar con diferentes modelos, extraemos conclusiones económicas relativas a estas cuestiones que nos permiten caracterizar la estructura de la volatilidad y el riesgo de cola de la distribución cuando analizamos los bienes agrícolas.

Palabras clave: anomalías del ENSO, bienes agrícolas, modelos GJR-GARCH-X, volatilidad realizada, momentos de orden superior, riesgo de cola de la distribución.

Abstract

The study of the evolution of price returns of commodities such as agricultural commodities is determinant for both domestic and general economics. Understanding their econometric properties allows us not only to comprehend consumption patterns, but also investment behavior.

This work addresses the impact of the ENSO climate variable on these agricultural products, focusing on eight specific commodities. The objective is to understand whether the influence of this variable is decisive due to its impact on production. To this end, econometric models are applied, contrasted with realized higher-order moments such as volatility, skewness, and kurtosis.

After working with different models, we extract economic conclusions regarding these issues that allow us to characterize the structure of volatility and tail risk of the distribution when analyzing agricultural commodities.

Keywords: ENSO anomalies, agricultural commodities, GJR-GARCH-X models, realized volatility, higher-order moments, tail risk.

Contents

1 Introduction

One of the main concerns of household economies is the price of basic food products. The shift in these prices affects their consumption decisions and could have a profound impact on their livelihoods so that makes the study of the behavior of the evolution of these prices a key field of investigation for institutions and governments. This work tries to give response to some questions about how returns vary for different commodities, especially nowadays in the current context of massive changes in climate trend, modifying landscapes and generating sudden rainfalls or droughts that reduce or increase the production of the agricultural assets that we study in this work. The commodities analyzed are Cocoa, Orange juice, Coffee, Cotton, Wheat, Corn, Soybean and Sugar. They are cultivated across geographically diverse regions with varying degrees of exposure and vulnerability to climate phenomena, generating a great impact on their prices.

Apart from immediate local supply shocks, agricultural price fluctuations have a wide effect that spreads quickly through the global economy. Unanticipated volatility in these soft commodities generates inflationary pressures that drops consumer purchasing power and it also increases market risk for policymakers, investors, and agricultural producers attempting to protect themselves against severe price changes. This is one reason why understanding what drives this instability is important to develop better risk management strategies, ensure market stability, and address food security challenges. These multiple approaches justify the fact that this topic is studied in important economic institutions worldwide.

An important focus that could be used while addressing this question is the study of the effects produced by the phenomenon of El Niño-Southern Oscillation (ENSO). This phenomenon is one of the main sources to evaluate climate variability and the data measures the temperature of the surface of the sea in a specific region of the Pacific Ocean.

The main goal of this study is to investigate whether ENSO conditions affect the distribution of agricultural commodity returns, with particular emphasis on volatility, asymmetry, and tail risk. We incorporate climatic information related to ENSO in the Pacific Ocean in order to establish a relationship between these agricultural returns and climatic patterns. This focus is relevant because it might help to understand whether climate anomalies can explain how high-order moments such as skewness or kurtosis of agricultural returns shift, especially in the current context of extreme climate events (2026 is expected to be the start of an exceptionally strong El Niño event, forecast by the World Meteorological Organization [1] to reach a 'very strong' intensity with unprecedented persistence into next year 2027). This information is also useful from the economic point of view since in this reference [2] we can see that investors who are averse to risk and exhibit a stable ranking over higher moments tend to favor positively skewed outcomes and could use this information when making a decision.

To achieve this main goal, this study sets the following specific objectives:

- To estimate parametric GARCH and GJR models incorporating the ENSO variable to analyze its significance on conditional volatility at both daily and monthly frequencies.

- To examine non-parametric realized cumulative moments, distinguishing between Realized Volatility and higher-order moments (Skewness and Kurtosis) to capture shifts in tail risk.

- To test our empirical findings with institutional evidence sourced from Banco de España providing meaningful economic interpretations.

The procedure of the study develops as follows. We select eight agricultural commodities retrieved from Yahoo Finance which are Corn, Wheat, Cotton, Coffee, Cocoa, Orange juice, Soybean and Sugar. In chapter 2, we provide general information about the data used, including a descriptive analysis of the agricultural assets that allows us to gain preliminary insights into the data collected. We also add a brief explanation about how the ONI is obtained as well as some graphics to illustrate our findings. In chapter 3, we define the econometric model that involves different variables that we consider, relying principally on the GARCH and GJR models. We estimate regressions in order to obtain the parameters that help us to decide whether the exogenous variable ENSO is significant with the aim of explaining the shifts in commodity returns. We obtain both daily and monthly results and compare them. In this chapter, we distinguish between the methodology followed through different models and the results obtained in each of them. This structure will remain in following chapters in which we present another step in our study, considering realized cumulative moments and repeating the regression procedure as a way to both contrast results and address new information about high-order moments. This works as a complement of the initial information in the descriptive analysis. This analysis will be elaborated in two different sections (chapters 4 and 5), as we differentiate between the preliminary concept of Realized Volatility in chapter 4 and the more complex high-order moments in chapter 5. In chapter 6, we use institutional evidence sourced from Banco de España on this topic to support and contrast our interpretation. Lastly, we include some limitations of these models in chapter 7 and we also provide feasible solutions to implement in future research. All this work along different chapters will be economically interpreted leading us to clustered conclusions in chapter 8 about how important climate factors are while obtaining econometric information in agricultural commodities.

2 Data

This section describes the data used, in particular, different commodity returns and climate data.

2.1 Descriptive analysis of agricultural commodities

The agricultural commodity data is collected from early February 2002 to late March 2026 yielding a total of 6063 observations and we take its log returns to facilitate our analysis.

Before building the model, we need to treat the data selecting the right dataset and cleaning it. In our case, we obtain the data from the web Yahoo Finance [3]. To ensure consistency, we use continuous futures contract prices (unadjusted for roll yield) and filter out non-trading days according to the standard agricultural futures trading calendar. We display the following statistics summary (in %) that contribute to a better understanding of the data that lead us to an initial necessary approach to the data behavior:

Table 1: Summary statistics log returns (2002–2026)

Commodity	**Mean**	**St. Dev.**	**Min**	**Max**	**Skew.**	**Kurt.**
Cocoa	0.0140	2.1591	-26.0570	12.8047	-0.7665	11.7666
Orange juice	0.0118	2.2844	-13.3244	15.4324	-0.1164	6.0580
Coffee	0.0307	2.1103	-11.0892	12.9720	0.1546	4.5968
Cotton	0.0104	1.8651	-27.2925	13.6218	-0.5642	13.7779
Wheat	0.0124	2.0529	-11.2971	19.7014	0.2846	6.1060
Corn	0.0131	1.8146	-26.8620	12.7571	-0.8984	17.1355
Soybean	0.0164	1.6011	-23.4109	20.3209	-0.9424	19.6734
Sugar	0.0148	2.0294	-13.5709	13.0620	-0.1247	5.9927

Note: Returns obtained as $100 \times \ln(P_t/P_{t-1})$. Classic kurtosis (normal = 3).

We can extract several interesting findings from the summary statistics that we have obtained in Table 1. First, almost all agricultural commodities- with the exception of Coffee and Wheat- exhibit negative skewness. This is the expected behavior of the returns given that since the early 2000s, modern agricultural markets have experienced a process of financialization [4] (coinciding with the beginning period of our gathered data). Consequently, these assets increasingly behave like traditional equities, showing higher equity-commodity correlations and volatility spillovers as institutional investors integrate commodity markets with the broader financial system [5]. Therefore, this indicates a higher probability of observing extreme negative returns compared to positive ones, aligned directly with our goal of modelling risk.

Second, all commodities show highly elevated kurtosis values, far exceeding the threshold of 3 for a normal distribution. In particular, Corn, Soybean, and Cotton show extreme kurtosis levels (17.1355, 19.6734, and 13.7779, respectively). This strong leptokurtic behavior, combined with the extreme minimum values (such as Cotton reaching a daily return of -27.2925%), indicates the presence of heavy tails ('fat tails'). This empirical feature strongly justifies our focus on downside risk frameworks—such as semivariances and higher-order realized moments (skewness and kurtosis)—to accurately capture tail risk that standard normal models underestimate.

The time-aggregation dynamics changes depending on the frequency considered so in order to contrast short-term microstructure noise against structural climate behavior, our empirical strategy relies on two distinct dataset analysis:

- **Daily Dataset:** Contains 6,063 daily log-return observations per commodity (2002-2026), capturing high-frequency volatility clustering and immediate market responses.
- **Monthly Dataset:** Aggregates the daily data into a monthly sample consisting of 290 observations per commodity. This monthly setup directly matches the natural cadence of the Oceanic Niño Index (ONI) series, smoothing daily market noise and facilitating the estimation of long-term climate transmission channels.

This graphics below 1 show the returns in commodities for the Cocoa as an example:

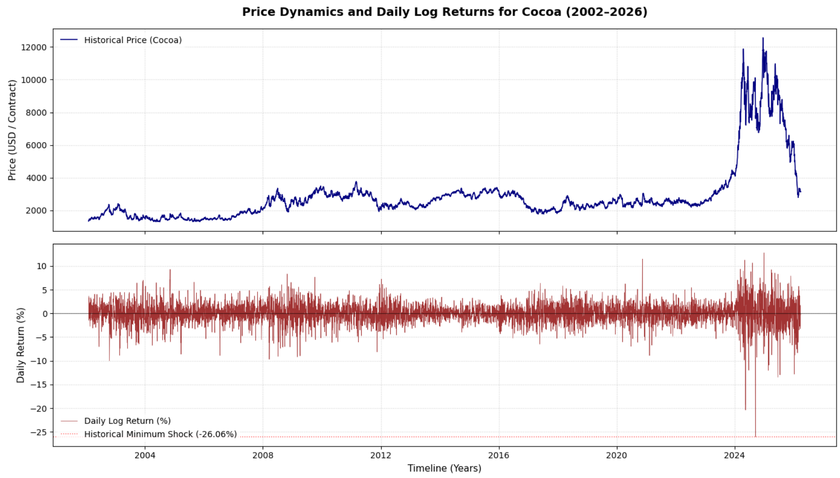


Figure 1: Cocoa Price Dynamics and Daily Log-Returns

Note: The top panel displays historical settlement prices in USD per contract (2002–2026), contrasting two decades of stability (2,000–4,000 USD) with the extreme 2024–2026 rally (8,000–12,000 USD). The bottom panel shows daily log-returns (%), highlighting severe volatility clustering and a sample minimum return of -26.06% in 2024.

2.2 ENSO Climate Data and Real-Time Alignment

To capture the environmental factors influencing these commodity dynamics, we now turn to global climate patterns. The El Niño-Southern Oscillation (ENSO) is one of the main sources to evaluate climate variability as we can observe in this paper [6]. We take this data from the Oceanic Niño Index (ONI), which is a metric employed by the National Oceanic and Atmospheric Administration (NOAA) and its Climate Prediction Center (CPC) [7]. This index measures the anomalies in the sea surface temperature of the Pacific Ocean in the equatorial region bounded by the coordinates 5º N-5ºS and 120ºW-170ºW.

The anomalies are calculated as a 3-month running mean of the Sea Surface Temperature dataset. The procedure to obtain the data requires to filter out the long-term signals of global warming and climate change, so the anomalies are relative to centered 30-year base periods that are dynamically updated by NOAA every 5 years. The ENSO phases are defined based on a threshold of $\pm$ 0.5ºC and we need to distinguish between positive anomalies (EL NIÑO) and negative anomalies (LA NIÑA) because periods dominated by each of these phenomena lead to different consequences whose relationship with the returns is key for our analysis. In other words, we consider that there is El Niño phenomenon in a period if the anomaly this month is $\geq +0.5°$C and La Niña if that anomaly is $\leq -0.5°$C while any value between these 2 thresholds is a neutral value. Another important thing that we have to take into account is that this climatic data is collected monthly so in our daily study we assign that monthly value to every day of that month.

Furthermore, to account for real-time information availability in financial markets, we use lagged ONI values in our regressions. Because NOAA publishes monthly ONI metrics with a structural publication lag, using lagged climate indicators ensures that all climatic information was fully observable to market participants at the time of making investment decisions, avoiding look-ahead bias.

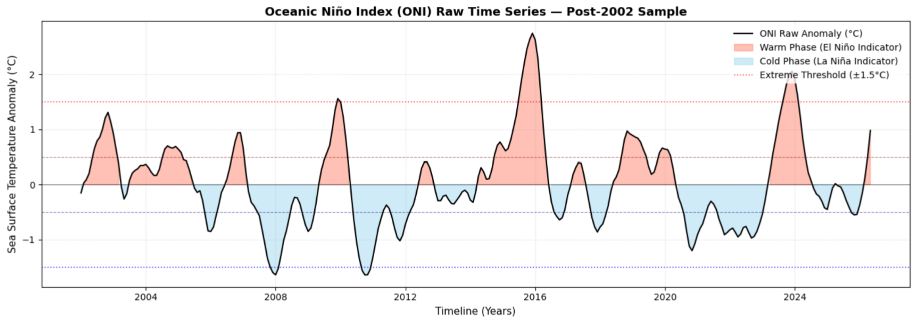


Figure 2: Oceanic Niño Index (ONI) Historical Series (2002–2026)

Note: Data retrieved from the NOAA Climate Prediction Center. The ONI tracks 3-month running averages of Sea Surface Temperature (SST) anomalies in the Niño 3.4 region. Warm phases (El Niño) are defined by ONI $\geq +0.5°C$, reaching a sample maximum of $+2.59°C$, whereas cold phases (La Niña) correspond to ONI $\leq -0.5°C$, with a sample minimum of $-1.78°C$.

In Figure 2, we can clearly identify the historical occurrences of El Niño and La Niña episodes. Cold phases (La Niña) characterized years such as 2008, 2011, and, with lower intensity, 2006, 2018, and the early 2020s. Conversely, warm phases (El Niño) dominated in 2002, 2010, and particularly during the intense events of 2015–2016 and 2024. The figure also reveals the inception of a new El Niño event developing at the end of the sample period.

3 The GJR-GARCH-X Model

Now, in order to jointly investigate the dynamics of the conditional mean and conditional variance of agricultural returns under climate pressure, we specify an extension of the GARCH framework designed to capture the impact of ENSO events on agricultural commodities. This specification is the GJR-GARCH-X model. While the GJR and GARCH components account for financial leverage effects and volatility persistence, the X represents the exogenous climate variables. Before presenting the full empirical specification, we first formalize what this exogenous component X represents within the information set of the model.

The conditional structure is central if we want to understand this GJR-GARCH-X model. First, let $\mathcal{F}^{\varepsilon}_{t-1} = \sigma(\varepsilon_{t-1}, \varepsilon_{t-2}, ...)$ denote the information generated by the past of return innovations, and let $\mathcal{F}^{X}_{t-1} = \sigma(X_{t-1}, X_{t-2}, ...)$ denote the information generated by the past of the explanatory variables. The full information set is specified as $\mathcal{F}_{t-1} = \mathcal{F}^{\varepsilon}_{t-1} \vee \mathcal{F}^{X}_{t-1}$ where $\vee$ denotes the smallest information set containing both sets defined previously.

We assume that $\varepsilon_t = \sigma_t z_t$, $E(z_t|\mathcal{F}_{t-1}) = 0$ and $E(z_t^2|\mathcal{F}_{t-1}) = 1$. Then, $E(\varepsilon_t|\mathcal{F}_{t-1}) = 0$ and most importantly, $E(\varepsilon_t^2|\mathcal{F}_{t-1}) = Var(\varepsilon_t|\mathcal{F}_{t-1}) = \sigma_t^2$. All this information will be useful along the section, when we define the conditional variance.

3.1 Methodology

3.1.1 Conditional Mean Specification

The conditional mean equation of daily log returns (r_t) is modeled as a first-order Autoregressive process, AR(1), augmented with lagged climate covariates to capture the direct impact of ENSO phases on price changes:

$$r_t = c_0 + c_1 r_{t-1} + \delta^+ C_{t-1}\mathbb{I}_{\{C_{t-1}\geq 0.5\}} + \delta^- |C_{t-1}|\mathbb{I}_{\{C_{t-1}\leq -0.5\}} + \varepsilon_t \tag{1}$$

where:

- c_0 is the constant intercept of the mean process.
- c_1 represents the AR(1) coefficient, which captures market memory and short-term momentum.
- δ^+ and δ^- are the coefficients that quantify the direct impact of extreme El Niño (warm) and La Niña (cold) shocks, respectively, on daily agricultural returns.
- $\mathbb{I}_{\{.\}}$ is an indicator function that acts as a mathematical filter to isolate extreme climate events based on the established absolute threshold of ±0.5°C depending on the phenomena.

The climate covariate C_t represents the Oceanic Niño Index (ONI) at time t.

The disturbance term ε_t in 1 represents the net market innovations and is defined as:

$$\varepsilon_t = \sqrt{h_t} z_t \tag{2}$$

where h_t is the conditional variance. It is important to clarify that rather than assuming standard normality, which typically underestimates the heavy tails (leptokurtosis) of commodity returns, we assume that the standardized innovations z_t follow a standardized Student's t distribution [8]:

$$z_t \sim t_{\text{std}}(0, 1, \nu) \tag{3}$$

where ν represents the degrees of freedom parameter (to be estimated). This parameter is key as it directly captures the tail thickness of the empirical return distributions. The use of this distribution in this work is justified as we have already seen while observing the statistic summary that most of commodities show fat tails and negative skewness.

3.1.2 Conditional Variance Specification

In this subsection, we need to model the time-varying risk and capture the asymmetrical volatility response to market shocks and for that we parameterize the conditional variance h_t using a GJR-GARCH(1,1) specification augmented with environmental covariates.

$$h_t = \omega_t + \alpha\varepsilon_{t-1}^2 + \gamma\mathbb{I}_{\{\varepsilon_{t-1}<0\}}\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{4}$$

where we can consider that $\omega_t = g(X_{t-1})$ which is a time varying intercept but as we need the conditional variance to be positive we will consider ω_t =exp($\omega_0 + \delta' X_{t-1}$) guaranteeing ω_t >0. In this expression, we effectuate an inner product between the vector $\delta = (\omega^+, \omega^-)$ and the vector $X_{t-1} = (C_{t-1}\mathbb{I}_{\{C_{t-1}\geq 0.5\}}, |C_{t-1}|\mathbb{I}_{\{C_{t-1}\leq -0.5\}})$ as we develop in the following subsection. The GARCH part is derived from [9] and the GJR part from [10].

Using now the assumptions detailed in the introduction of this section 3, we can now say that

$$E(\varepsilon_t^2|\mathcal{F}_{t-1}^{\varepsilon}, \mathcal{F}_{t-1}^{X}) = g(X_{t-1}) + \alpha\varepsilon_{t-1}^2 + \gamma\mathbb{I}_{\{\varepsilon_{t-1}<0\}}\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{5}$$

and we can appreciate how the conditional variance uses 2 types of past information. It uses both the GJR-GARCH information contained in past shocks and past conditional variances, and the additional information contained in the history of X_t. X_{t-1} is observed at time $t-1$ so $g(X_{t-1})$ is known when conditioning on $\mathcal{F}_{t-1}$.

By the law of iterated expectations, $E(\varepsilon_t^2|X_{t-1}) = E(E(\varepsilon_t^2|\mathcal{F}_{t-1})|X_{t-1}) = g(X_{t-1}) + \alpha E(\varepsilon_{t-1}^2|X_{t-1}) + \gamma E(\varepsilon_{t-1}^2 \mathbb{I}_{\{\varepsilon_{t-1}<0\}}|X_{t-1}\}) + \beta E(h_{t-1}|X_{t-1})$ using 5.

On the other hand, in this specification, the internal financial dynamics are governed by three key parameters:

- α (the ARCH parameter): Measures the short-term sensitivity of market volatility to recent localized innovations or news. A high α implies that immediate market shocks trigger rapid spikes in risk. This is defined in [9].
- β (the GARCH parameter): Measures the long-term persistence or memory of conditional variance. A high β value indicates that once volatility is triggered, it decays slowly and remains elevated for extended periods. This is also defined in [9].
- γ (the leverage effect parameter): Captures the financial asymmetry of the market. Since the indicator function $\mathbb{I}_{\{\varepsilon_{t-1}<0\}}$ equals 1 when previous returns are negative and 0 otherwise, a positive and statistically significant γ proves that bad news (price drops) generates greater volatility than good news (price increases) of equal magnitude. This is explained in [10].

Under the assumption of symmetric standardized innovations, the unconditional variance of the process takes the form:

$$\mathrm{Var}(\varepsilon_t) = \frac{E[g(X_{t-1})]}{1-\alpha-\beta-\gamma/2} \tag{6}$$

To ensure that this unconditional variance is positive and finite, the model requires the covariance-stationarity constraint $P = \alpha+\beta+\gamma/2 < 1$. The full step-by-step mathematical derivation of this equation 6 and the second-moment stationarity proof are provided in the Appendix C.

One condition that we must impose in our model is that $\alpha+\beta+\frac{\gamma}{2} < 1$. This is a fundamental requirement to ensure stationarity, which guarantees that the variance of the returns is stable. This restriction captures the persistence of volatility and dictates a mean-reverting behavior. The bibliography that motivates the unconditional variance and stationarity condition can be found in [9] and [10].

3.1.3 Exponential Climate-Induced Baseline Variance

The intercept ω_t is dynamically modeled using an exponential structure:

$$\omega_t = exp\left(\omega_0 + \omega^+ C_{t-1}\mathbb{I}_{\{C_{t-1}\geq 0.5\}} + \omega^-|C_{t-1}|\mathbb{I}_{\{C_{t-1}\leq -0.5\}}\right) \tag{7}$$

where:

- ω_0 is the constant log-baseline variance.
- ω^+ and ω^- are the coefficients that capture the net impact of extreme El Niño and La Niña shocks on market risk, respectively.

Splitting the climate index into positive (ω^+) and negative (ω^-) components via indicator functions is technically necessary. Since the ONI is a single continuous dataset representing two opposing meteorological phenomena, this dual-parameter formulation allows us to capture asymmetric responses. It isolates whether ocean warming and ocean cooling exert distinct, non-linear pressures on the overall risk profiles of agricultural commodity markets.

The motivation for specifying an exponential variance intercept is given by how attractive for climate financial modeling is from the theoretical point of view in this case that we use time-varying variables. The exogenous climatic anomalies (ONI) exhibit extreme environmental shocks. If we consider a standard linear GARCH-X specification, we could be generating non-positive baseline variances during extreme El Niño or La Niña episodes, unless artificial non-negative conditions are imposed. One solution to address this potential problem is to consider the exponential formulation which overcomes this limitation and it is able to guarantee strictly positive conditional variances under any climate realization while allowing exogenous shocks to scale market risk flexibly. This exponential form is unneeded in the mean equation—where returns can be negative—or for ARCH/GARCH terms, which rely on non-negative squared components.

Consequently, the climate parameters (ω^+ and ω^-) act multiplicatively on the baseline variance. The percentage change induced by an ENSO shock is directly given by $(\exp(\omega)-1)\times 100\%$, where positive values indicate a volatility expansion and negative values signal a risk-dampening effect.

3.2 Results (daily case)

The empirical estimation results of the GJR-GARCH-X model across the eight agricultural commodities are presented below.

Table 2: GJR-GARCH-X Estimation Results for Corn

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	-0.0513	0.0369	**
c_1 (AR1)	0.0032	0.8210	n.s.
δ^+ (El Niño Impact on Price)	0.0089	0.7710	n.s.
δ^- (La Niña Impact on Price)	0.2786	0.0000	***
ω_0 (Exp Variance Constant)	-0.0000	1.0000	n.s.
α (ARCH)	0.1491	0.0000	***
γ (GJR Asymmetry)	0.1226	0.0175	**
β (GARCH)	0.5370	0.0000	***
ω^+ (El Niño Shock on Variance)	-0.3095	0.0000	***
ω^- (La Niña Shock on Variance)	-0.0020	0.9817	n.s.
ν (Student's t d.f.)	4.5810	0.0000	***

Note: Parameters estimated via Maximum Likelihood assuming a Student's t-distribution ($\nu = 4.58$). For Corn, La Niña shocks (δ^-) exert a highly significant positive impact on returns ($p < 0.01$), whereas El Niño shocks (ω^+) significantly dampen conditional variance ($\omega^+ = -0.3095, p < 0.01$). Conversely, La Niña effects on variance (ω^-) remain statistically insignificant. Standard Ljung-Box diagnostic tests confirm no residual autocorrelation in the mean ($p = 0.2459$) or variance ($p = 0.7572$). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3: GJR-GARCH-X Estimation Results for Wheat

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	-0.0444	0.1348	n.s.
c_1 (AR1)	-0.0054	0.6877	n.s.
δ^+ (El Niño Impact on Price)	-0.0122	0.7699	n.s.
δ^- (La Niña Impact on Price)	0.1103	0.1075	n.s.
ω_0 (Exp Variance Constant)	0.0000	1.0000	n.s.
α (ARCH)	0.1522	0.0000	***
γ (GJR Asymmetry)	-0.0473	0.1063	n.s.
β (GARCH)	0.6114	0.0000	***
ω^+ (El Niño Shock on Variance)	-0.0189	0.7010	n.s.
ω^- (La Niña Shock on Variance)	0.3864	0.0000	***
ν (Student's t d.f.)	8.0269	0.0000	***
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s. not significant.			
LB Diagnostics Mean (p): 0.2595 (OK). LB Diagnostics Variance (p): 0.0000 (ALERT).			

Note: For Wheat, La Niña remains a strong and highly significant driver of conditional variance ($\omega^- = 0.3864, p < 0.01$), confirming that its transmission channel operates primarily through risk rather than price level. El Niño shocks show no statistically significant effect on either mean or variance dynamics.

Table 4: GJR-GARCH-X Estimation Results for Soybean

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	0.0292	0.2379	n.s.
c_1 (AR1)	-0.0081	0.6236	n.s.
δ^+ (El Niño Impact on Price)	-0.0206	0.4789	n.s.
δ^- (La Niña Impact on Price)	0.1741	0.0005	***
ω_0 (Exp Variance Constant)	0.0000	1.0000	n.s.
α (ARCH)	0.1888	0.0000	***
γ (GJR Asymmetry)	0.0165	0.9213	n.s.
β (GARCH)	0.4562	0.6511	n.s.
ω^+ (El Niño Shock on Variance)	-0.3169	0.0000	***
ω^- (La Niña Shock on Variance)	0.0476	0.6435	n.s.
ν (Student's t d.f.)	4.3463	0.0102	**
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s. not significant.			
LB Diagnostics Mean (p): 0.0931 (OK). LB Diagnostics Variance (p): 0.0000 (ALERT).			

Note: For Soybean, La Niña episodes exert a highly significant positive impact on price returns ($\delta^- = 0.1741, p < 0.01$). On the volatility side, El Niño shocks significantly dampen conditional variance ($\omega^+ = -0.3169, p < 0.01$), serving as a stabilizing component, whereas La Niña shows no significant variance effect.

Table 5: GJR-GARCH-X Estimation Results for Sugar

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	-0.0537	0.0713	*
c_1 (AR1)	-0.0102	0.4523	n.s.
δ^+ (El Niño Impact on Price)	0.0305	0.5361	n.s.
δ^- (La Niña Impact on Price)	0.1827	0.0032	***
ω_0 (Exp Variance Constant)	-0.0000	1.0000	n.s.
α (ARCH)	0.1199	0.0000	***
γ (GJR Asymmetry)	0.0204	0.5062	n.s.
β (GARCH)	0.6158	0.0004	***
ω^+ (El Niño Shock on Variance)	0.1585	0.0062	***
ω^- (La Niña Shock on Variance)	0.1701	0.0704	*
ν (Student's t d.f.)	5.8554	0.0000	***
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s. not significant.			
LB Diagnostics Mean (p): 0.0448 (ALERT). LB Diagnostics Variance (p): 0.0000 (ALERT).			

Note: For Sugar, La Niña shocks induce a substantial positive return effect ($\delta^- = 0.1827, p < 0.01$). Conditional variance is significantly elevated by both El Niño ($\omega^+ = 0.1585, p < 0.01$) and, more weakly, La Niña shocks ($\omega^- = 0.1701, p < 0.10$), highlighting that Sugar's risk profile is sensitive to ENSO shocks of either sign.

Table 6: GJR-GARCH-X Estimation Results for Coffee

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	-0.0298	0.3531	n.s.
c_1 (AR1)	-0.0277	0.0308	**
δ^+ (El Niño Impact on Price)	0.0507	0.2951	n.s.
δ^- (La Niña Impact on Price)	0.1320	0.0293	**
ω_0 (Exp Variance Constant)	-0.0000	1.0000	n.s.
α (ARCH)	0.1211	0.0000	***
γ (GJR Asymmetry)	-0.0962	0.0000	***
β (GARCH)	0.7097	0.0275	**
ω^+ (El Niño Shock on Variance)	0.0178	0.7404	n.s.
ω^- (La Niña Shock on Variance)	-0.0338	0.6411	n.s.
ν (Student's t d.f.)	6.5790	0.0000	***
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s. not significant.			
LB Diagnostics Mean (p): 0.7202 (OK). LB Diagnostics Variance (p): 0.0258 (ALERT).			

Note: For Coffee, La Niña shocks display a statistically significant positive effect on price returns ($\delta^- = 0.1320, p < 0.05$). Neither El Niño nor La Niña shows a statistically significant direct impact on conditional variance, although GJR asymmetry ($\gamma = -0.0962, p < 0.01$) remains highly prominent.

Table 7: GJR-GARCH-X Estimation Results for Cocoa

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	0.0082	0.7857	n.s.
c_1 (AR1)	-0.0066	0.6217	n.s.
δ^+ (El Niño Impact on Price)	0.0778	0.0637	*
δ^- (La Niña Impact on Price)	0.0958	0.1001	n.s.
ω_0 (Exp Variance Constant)	0.0000	1.0000	n.s.
α (ARCH)	0.1735	0.0000	***
γ (GJR Asymmetry)	-0.0295	0.3863	n.s.
β (GARCH)	0.6599	0.0000	***
ω^+ (El Niño Shock on Variance)	-0.2779	0.0000	***
ω^- (La Niña Shock on Variance)	-0.0584	0.4768	n.s.
ν (Student's t d.f.)	4.6167	0.0000	***
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s. not significant.			
LB Diagnostics Mean (p): 0.6758 (OK). LB Diagnostics Variance (p): 0.0342 (ALERT).			

Note: For Cocoa, El Niño shocks show a weakly significant positive effect on mean returns ($\delta^+ = 0.0778, p < 0.10$), while La Niña remains insignificant. On the variance side, El Niño shocks exert a highly significant negative effect on conditional variance ($\omega^+ = -0.2779, p < 0.01$), indicating a substantial volatility reduction during warm ENSO phases.

Table 8: GJR-GARCH-X Estimation Results for Orange juice

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	0.0167	0.5920	n.s.
c_1 (AR1)	0.0785	0.0000	***
δ^+ (El Niño Impact on Price)	-0.0019	0.9705	n.s.
δ^- (La Niña Impact on Price)	0.0597	0.3337	n.s.
ω_0 (Exp Variance Constant)	0.0000	1.0000	n.s.
α (ARCH)	0.2384	0.0000	***
γ (GJR Asymmetry)	-0.0570	0.1047	n.s.
β (GARCH)	0.6305	0.0000	***
ω^+ (El Niño Shock on Variance)	0.0062	0.9463	n.s.
ω^- (La Niña Shock on Variance)	0.0059	0.9514	n.s.
ν (Student's t d.f.)	4.7128	0.0000	***
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s. not significant.			
LB Diagnostics Mean (p): 0.1634 (OK). LB Diagnostics Variance (p): 0.0697 (OK).			

Note: For Orange juice, neither El Niño nor La Niña parameters reach statistical significance in the mean or variance equations. Volatility dynamics are primarily driven by standard GARCH persistence ($\beta = 0.6305, p < 0.01$) and strong ARCH effects ($\alpha = 0.2384, p < 0.01$).

Table 9: GJR-GARCH-X Estimation Results for Cotton

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	-0.0252	0.3010	n.s.
c_1 (AR1)	0.0137	0.3196	n.s.
δ^+ (El Niño Impact on Price)	0.0105	0.7212	n.s.
δ^- (La Niña Impact on Price)	0.1289	0.0251	**
ω_0 (Exp Variance Constant)	-0.0000	1.0000	n.s.
α (ARCH)	0.1296	0.0015	***
γ (GJR Asymmetry)	0.1307	0.0334	**
β (GARCH)	0.5524	0.0384	**
ω^+ (El Niño Shock on Variance)	-0.2156	0.0008	***
ω^- (La Niña Shock on Variance)	0.3043	0.0041	***
ν (Student's t d.f.)	4.3001	0.0000	***
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s. not significant.			
LB Diagnostics Mean (p): 0.4074 (OK). LB Diagnostics Variance (p): 0.0002 (ALERT).			

Note: For Cotton, La Niña shocks exert a positive effect on price returns ($\delta^- = 0.1289, p < 0.05$) alongside a strong, highly significant variance expansion ($\omega^- = 0.3043, p < 0.01$). Conversely, El Niño shocks act as a prominent volatility dampener ($\omega^+ = -0.2156, p < 0.01$).

We can summarize the empirical evidence of the effects of extreme ENSO phases (El Niño and La Niña) on the studied agricultural markets. The following table show all the statistical significance of the climatic coefficients for both the mean equation (returns) and the variance equation (risk), giving us a complete vision of the significancies on our model.

Table 10: Summary of Significance for Climatic Parameters (GJR-GARCH-X)

	Impact on Returns (Mean)		**Impact on Variance (Risk)**	
Commodity	**El Niño** (δ^+)	**La Niña** (δ^-)	**El Niño** (ω^+)	**La Niña** (ω^-)
Corn	n.s.	(+) ***	(−) ***	n.s.
Wheat	n.s.	n.s.	n.s.	(+) ***
Soybean	n.s.	(+) ***	(−) ***	n.s.
Sugar	n.s.	(+) ***	(+) ***	(+) *
Coffee	n.s.	(+) **	n.s.	n.s.
Cocoa	(+) *	n.s.	(−) ***	n.s.
Orange juice	n.s.	n.s.	n.s.	n.s.
Cotton	n.s.	(+) **	(−) ***	(+) ***

Note: The sign in parentheses (+ or −) refers to the sign of the estimated coefficient.

Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, n.s. not significant.

We can find in Appendix A a sensitivity analysis of the model without leverage effect as a way to contrast our findings and results.

After displaying these tables we can make some observations about the empirical results which reveal a huge asymmetry in how the 2 ENSO phases interfere in the evolution of agricultural commodity markets. In the mean equations, La Niña (δ^-) tends to be positive and statistically significant across most commodities while El Niño (δ^+) remains largely non-significant.

If we talk about volatility, which is more interesting for our study, El Niño (ω^+) acts as a significant variance reducing shock for Corn, Soybean, Cocoa and Cotton (although increasing shock for Sugar), whereas La Niña (ω^-) exhibits a great positive impact in Wheat and Cotton and a light positive impact on Sugar. These results help us establish that climatic anomalies do not affect global agricultural markets uniformly, but they influence in different ways depending on the commodity, perhaps due to the fact that these commodities are cultivated in different regions that experiment different degree of affection from the ENSO.

However, a critical econometric behavior appears when observing the GARCH persistence parameter (β). Almost all commodities show lower estimated persistence values than expected, compared to standard financial literature, where β typically remains around 0.90 in daily data as we can perceive for example in [11]. This lower estimated persistence could be driven by the structural specification of our model, which forces an exponential variance intercept to guarantee positive variance estimates under exogenous climate shocks, as well as the direct absorption of variance dynamics by the ENSO covariates. In order to verify this, robustness checks were conducted using a linearized version of the model, which revealed higher persistence estimates closer to 0.90; yet, the linearized model remains highly sub-optimal as it risks generating non-positive variance predictions.

3.3 Monthly case

The daily high-frequency specification offers a distinct statistical advantage by providing a large sample size (N), which enhances parameter estimation precision. However, it introduces an inherent temporal mismatch: daily commodity futures returns are paired with an exogenous ENSO index (ONI) that is reported only at a monthly frequency. To operationalize the daily model, monthly ONI values were mapped identically across all trading days within each corresponding month—an approximation that may introduce minor local distortions in climate signal transmission. To address this frequency friction and evaluate parameter stability, we aggregate daily returns into monthly series, establishing a direct one-to-one temporal match with the ONI dataset. Estimating the GJR-GARCH-X model at this aggregated frequency eliminates daily micro-structural noise; however, it comes at the cost of significantly reducing degrees of freedom. Rather than viewing these two frameworks as competing, we present the monthly estimates as a complementary diagnostic. The daily model provides high-frequency volatility dynamics, while the monthly model serves as a robustness check that aligns signal frequencies. Consistency in climate parameter signs and significance across both temporal scales validates the structural reliability of our empirical findings.

Table 11: GJR-GARCH-X Estimation Results for Corn (Monthly Data)

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	-1.0239	0.3667	n.s.
c_1 (AR1 Memory Effect)	-0.1964	0.0755	*
δ^+ (El Niño Impact on Price)	0.1449	0.8138	n.s.
δ^- (La Niña Impact on Price)	6.3817	0.0001	***
ω_0 (Exp Variance Constant)	4.0682	0.0376	**
α (ARCH Effect)	0.4511	0.2655	n.s.
γ (GJR Asymmetry / Leverage)	-0.2340	0.8139	n.s.
β (GARCH Persistence)	0.0000	1.0000	n.s.
ω^+ (El Niño Shock on Variance)	-0.5295	0.0182	**
ω^- (La Niña Shock on Variance)	-0.4190	0.2018	n.s.
ν (Student's t d.f.)	7.8159	0.2830	n.s.

Note: Parameters estimated via Maximum Likelihood assuming a Student's t-distribution. Diagnostics: Ljung-Box Mean ($p = 0.5636$, OK), Ljung-Box Variance ($p = 0.5113$, OK). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. not significant.
Interpretation: For Corn, monthly La Niña episodes exerts a massive, highly statistically significant positive impact on return levels ($\delta^- = 6.3817$, $p < 0.01$). On the volatility side, El Niño shocks act as a significant variance dampener ($\omega^+ = -0.5295$, $p < 0.05$).

Table 12: GJR-GARCH-X Estimation Results for Wheat (Monthly Data)

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	0.3991	0.5327	n.s.
c_1 (AR1 Memory Effect)	-0.1259	0.0429	**
δ^+ (El Niño Impact on Price)	-0.7552	0.3674	n.s.
δ^- (La Niña Impact on Price)	1.5070	0.2585	n.s.
ω_0 (Exp Variance Constant)	0.0000	1.0000	n.s.
α (ARCH Effect)	0.0283	0.3729	n.s.
γ (GJR Asymmetry / Leverage)	-0.0283	0.4200	n.s.
β (GARCH Persistence)	0.9616	0.0000	***
ω^+ (El Niño Shock on Variance)	-0.3100	0.6457	n.s.
ω^- (La Niña Shock on Variance)	1.5628	0.0766	*
ν (Student's t d.f.)	18.3027	0.2129	n.s.

Note: Diagnostics: Ljung-Box Mean ($p = 0.5280$, OK), Ljung-Box Variance ($p = 0.9774$, OK). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. not significant.
Interpretation: Wheat returns exhibit strong GARCH persistence ($\beta = 0.9616$, $p < 0.01$). While climatic parameters remain mostly neutral in the mean, La Niña shocks generate weakly significant volatility expansion ($\omega^- = 1.5628$, $p < 0.10$).

Table 13: GJR-GARCH-X Estimation Results for Soybean (Monthly Data)

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	-0.0908	0.8740	n.s.
c_1 (AR1 Memory Effect)	-0.0553	0.4312	n.s.
δ^+ (El Niño Impact on Price)	-0.0151	0.9833	n.s.
δ^- (La Niña Impact on Price)	3.4402	0.0052	***
ω_0 (Exp Variance Constant)	2.4643	0.1216	n.s.
α (ARCH Effect)	0.2804	0.2538	n.s.
γ (GJR Asymmetry / Leverage)	-0.1612	0.3909	n.s.
β (GARCH Persistence)	0.6363	0.1203	n.s.
ω^+ (El Niño Shock on Variance)	-0.4806	0.2926	n.s.
ω^- (La Niña Shock on Variance)	-0.1254	0.8894	n.s.
ν (Student's t d.f.)	7.3195	0.0080	***

Note: Diagnostics: Ljung-Box Mean ($p = 0.0390$, ALERT), Ljung-Box Variance ($p = 0.3182$, OK). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. not significant.
Interpretation: For Soybean, La Niña episodes exert a strong positive return shock ($\delta^- = 3.4402$, $p < 0.01$). Fat tails are strongly supported by a low degrees of freedom parameter ($\nu = 7.3195$, $p < 0.01$).

Table 14: GJR-GARCH-X Estimation Results for Sugar (Monthly Data)

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	-0.2782	0.6639	n.s.
c_1 (AR1 Memory Effect)	0.0689	0.2811	n.s.
δ^+ (El Niño Impact on Price)	0.9667	0.4435	n.s.
δ^- (La Niña Impact on Price)	1.9702	0.1385	n.s.
ω_0 (Exp Variance Constant)	2.1811	0.0004	***
α (ARCH Effect)	0.0316	0.7013	n.s.
γ (GJR Asymmetry / Leverage)	-0.0127	0.8924	n.s.
β (GARCH Persistence)	0.7680	0.0000	***
ω^+ (El Niño Shock on Variance)	0.8768	0.0001	***
ω^- (La Niña Shock on Variance)	1.0279	0.0001	***
ν (Student's t d.f.)	7.6374	0.0114	**

Note: Diagnostics: Ljung-Box Mean ($p = 0.2516$, OK), Ljung-Box Variance ($p = 0.2890$, OK). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. not significant.
Interpretation: Sugar represents a unique market where climate variability acts as a universal risk multiplier: both El Niño ($\omega^+ = 0.8768$, $p < 0.01$) and La Niña ($\omega^- = 1.0279$, $p < 0.01$) significantly expand conditional variance.

Table 15: GJR-GARCH-X Estimation Results for Coffee (Monthly Data)

Theoretical Parameter	**Estimated Value**	p**-value**	**Significance**
c_0 (Mean Constant)	-0.5013	0.5275	n.s.
c_1 (AR1 Memory Effect)	-0.1261	0.0364	**
δ^+ (El Niño Impact on Price)	0.8413	0.3932	n.s.
δ^- (La Niña Impact on Price)	2.3053	0.0940	*
ω_0 (Exp Variance Constant)	2.3995	0.0109	**
α (ARCH Effect)	0.1011	0.1784	n.s.
γ (GJR Asymmetry / Leverage)	-0.1011	0.3460	n.s.
β (GARCH Persistence)	0.8039	0.0000	***
ω^+ (El Niño Shock on Variance)	0.0144	0.9742	n.s.
ω^- (La Niña Shock on Variance)	0.1900	0.7445	n.s.
ν (Student's t d.f.)	8.8096	0.0469	**

Note: Diagnostics: Ljung-Box Mean ($p = 0.9367$, OK), Ljung-Box Variance ($p = 0.9754$, OK). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. not significant.
Interpretation: For Coffee, La Niña shocks induce a statistically significant positive price response ($\delta^- = 2.3053$, $p < 0.10$), while climate shocks show neutral direct variance impacts.

Table 16: GJR-GARCH-X Estimation Results for Cocoa (Monthly Data)

Theoretical Parameter	**Estimated Value**	p**-value**	**Significance**
c_0 (Mean Constant)	0.4126	0.9989	n.s.
c_1 (AR1 Memory Effect)	-0.2402	0.9980	n.s.
δ^+ (El Niño Impact on Price)	1.0307	0.9987	n.s.
δ^- (La Niña Impact on Price)	1.0289	0.9996	n.s.
ω_0 (Exp Variance Constant)	0.0000	1.0000	n.s.
α (ARCH Effect)	0.1667	0.9994	n.s.
γ (GJR Asymmetry / Leverage)	-0.1200	0.9990	n.s.
β (GARCH Persistence)	0.8723	0.9979	n.s.
ω^+ (El Niño Shock on Variance)	1.2925	0.9995	n.s.
ω^- (La Niña Shock on Variance)	1.6928	0.9995	n.s.
ν (Student's t d.f.)	12.1088	0.9986	n.s.

Note: Diagnostics: Ljung-Box Mean ($p = 0.8486$, OK), Ljung-Box Variance ($p = 0.7176$, OK). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. not significant.
Interpretation: Optimization flat landscape observed possibly due to high recent volatility. Despite parameter insensitivity, diagnostic tests confirm clean standardized residuals with no ARCH effects remaining.

Table 17: GJR-GARCH-X Estimation Results for Orange juice (Monthly Data)

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	-0.0850	0.9079	n.s.
c_1 (AR1 Memory Effect)	-0.1477	0.0143	**
δ^+ (El Niño Impact on Price)	0.9650	0.4368	n.s.
δ^- (La Niña Impact on Price)	1.7381	0.1935	n.s.
ω_0 (Exp Variance Constant)	1.6420	0.1221	n.s.
α (ARCH Effect)	0.0000	1.0000	n.s.
γ (GJR Asymmetry / Leverage)	0.0684	0.5250	n.s.
β (GARCH Persistence)	0.8879	0.0000	***
ω^+ (El Niño Shock on Variance)	0.6626	0.0893	*
ω^- (La Niña Shock on Variance)	0.6989	0.3772	n.s.
ν (Student's t d.f.)	8.1676	0.0774	*

Note: Diagnostics: Ljung-Box Mean ($p = 0.2677$, OK), Ljung-Box Variance ($p = 0.4751$, OK). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. not significant.
Interpretation: Orange juice volatility is characterized by high GARCH persistence ($\beta = 0.8879$, $p < 0.01$) alongside a weakly significant variance expansion driven by El Niño ($\omega^+ = 0.6626$, $p < 0.10$).

Table 18: GJR-GARCH-X Estimation Results for Cotton (Monthly Data)

Theoretical Parameter	**Estimated Value**	**p-value**	**Significance**
c_0 (Mean Constant)	0.0761	0.8927	n.s.
c_1 (AR1 Memory Effect)	-0.1678	0.0096	***
δ^+ (El Niño Impact on Price)	-0.0019	0.9978	n.s.
δ^- (La Niña Impact on Price)	3.3696	0.0087	***
ω_0 (Exp Variance Constant)	0.4889	0.5112	n.s.
α (ARCH Effect)	0.0951	0.1238	n.s.
γ (GJR Asymmetry / Leverage)	-0.0951	0.0533	*
β (GARCH Persistence)	0.9121	0.0000	***
ω^+ (El Niño Shock on Variance)	0.2275	0.6571	n.s.
ω^- (La Niña Shock on Variance)	1.7667	0.0008	***
ν (Student's t d.f.)	6.2130	0.0017	***

Note: Diagnostics: Ljung-Box Mean ($p = 0.4997$, OK), Ljung-Box Variance ($p = 0.4938$, OK). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. not significant.
Interpretation: Cotton shows a dual climate transmission mechanism: La Niña episodes push monthly returns up significantly ($\delta^- = 3.3696$, $p < 0.01$) and simultaneously spark strong variance expansion ($\omega^- = 1.7667$, $p < 0.01$).

Table 19: Summary of Climate Coefficient Significances Across Commodity Markets (Monthly)

	Impact on Returns (Mean)		**Impact on Variance (Risk)**	
Commodity	**El Niño (δ^+)**	**La Niña (δ^-)**	**El Niño (ω^+)**	**La Niña (ω^-)**
Corn	n.s. (+)	*** (+)	** (-)	n.s. (-)
Wheat	n.s. (-)	n.s. (+)	n.s. (-)	* (+)
Soybean	n.s. (-)	*** (+)	n.s. (-)	n.s. (-)
Sugar	n.s. (+)	n.s. (+)	*** (+)	*** (+)
Coffee	n.s. (+)	* (+)	n.s. (+)	n.s. (+)
Cocoa	n.s. (+)	n.s. (+)	n.s. (+)	n.s. (+)
Orange juice	n.s. (+)	n.s. (+)	* (+)	n.s. (+)
Cotton	n.s. (-)	*** (+)	n.s. (+)	*** (+)

Note: Sign in parentheses (+) or (−) denotes the empirical direction of the point estimate. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. not significant.
Core Empirical Insight: La Niña episodes (δ^-) represent the dominant price driver across agricultural commodities (Corn, Soybean, Cotton, and Coffee). Conversely, volatility dynamics (ω^+/ω^-) exhibit commodity-specific behaviors, with Sugar and Cotton experiencing significant volatility expansion during severe ENSO events.

Comparing the conditional variance parameters (ω^+, ω^-) across daily and monthly estimation frequencies in tables 10 and 19 reveals key insights into how climate risk propagates through commodity markets over different frequencies:

- **Filtering Microstructure Noise:** When we change from daily to monthly data, we filter out better short-term market noise and speculative swings. This gives us a much clearer picture of how persistent ENSO phases structurally influence in conditional volatility.

- **Amplified Volatility Transmission in Soft Commodities:** The monthly aggregation makes risk dynamics stronger in highly vulnerable markets. We can take Sugar as an example. This commodity shifts from a localized variance expansion in daily data to a robust dual-risk regime in monthly data, where both El Niño ($\omega^+ = 0.8768$, $p < 0.01$) and La Niña ($\omega^- = 1.0279$, $p < 0.01$) significantly elevate conditional volatility. Similarly, Cotton exhibits a strong, sustained variance expansion during La Niña episodes ($\omega^- = 1.7667$, $p < 0.01$).

- **Variance Dampening and Asymmetric Risk Shocks:** Across both time horizons, warm ENSO events (El Niño) frequently act as volatility dampeners for major grain markets such as Corn ($\omega^+ = -0.5295$, $p < 0.05$), stabilizing variance dynamics compared to the destabilizing supply-side disruptions that La Niña phases show.

Overall, the comparative evidence confirms that climate-induced volatility is not a daily artifact that changes, but a persistent structural risk channel that drives market volatility over a monthly horizon. Although there are some clear discrepancies between the daily and monthly models—mainly because monthly aggregated data smooths out short-term fluctuations—the overall results regarding conditional variance remain remarkably consistent. Across both time frequencies, the estimated coefficients generally preserve consistent economic signs, with climatic signals becoming more pronounced at the monthly frequency. This stability confirms that the climate impact on market variance is robust and not just an artifact of the chosen data frequency.

Once we have presented the results from both the daily and monthly data summarized in tables 10 and 19, we can extract key conclusions regarding the limitations and importance of this framework, as well as next steps. While the GJR-GARCH-X specification serves as a valuable baseline, it presents parametric and numerical trade-offs when modeling extreme climate risk.

On the one hand, the optimization algorithm drives the baseline scale parameter (ω_0) close to zero, rendering it non-informative in specific commodity assets (such as monthly Wheat) due to hybrid integration of an exponential variance intercept with a linear GJR.

On the other hand, diagnostic testing via the Ljung-Box test on squared residuals exhibits several serial dependence alerts across most commodities (with the exception of Corn and Orange juice). This indicates that the parametric recursion does not fully absorb the complex conditional heteroskedasticity that characterizes agricultural markets under extreme climate shocks.

Rather than invalidating the parametric analysis, these combined limitations and optimization frictions, attenuated persistence, and residual serial correlation—provide an econometric justification for transitioning to a non-parametric analysis. By leveraging high-frequency intraday data, the Realized Volatility (RVol) framework solves parametric issues and structural constraints altogether, directly observing market risk in continuous time during extreme ENSO episodes. Consequently, Realized Volatility is introduced not only as an alternative method, but as a model-free strategy that resolves the rigidities of GARCH-type specifications and sets the base for last analytical chapters.

4 Realized volatility

While the GJR-GARCH-X treated in the previous section provides a measure of variance persistence, Realized metrics ($RVol$, RSk, RK) offer essential intra-month detail regarding daily tail risk and asymmetric behavior which are the two notions that we want to address now, this is the reason that motivates their use in our study. Along these sections we use both $RVol$, RSk, RK and $RVol_{i,t}$, $RSk_{i,t}$, $RK_{i,t}$ while referring to the same realized concepts.

4.1 Methodology

4.2 General model

In this section we study the monthly *Realized Volatility* ($RVol_{i,t}$) for each commodity which is computed as the square root of the sum of squared daily returns within month t (following [12]):

$$RVol_{i,t} = \sqrt{\sum_{j=1}^{N_t} r_{i,j,t}^2} \tag{8}$$

where $r_{i,j,t}$ represents the daily innovations (residuals) obtained after filtering the conditional mean of the daily log returns on trading day j during month t for each commodity i via an appropriate autoregressive (ARMA) process . This way, we can remove serial correlation from raw returns so that we ensure $\varepsilon_{i,t}$ shows uncorrelated daily unexpected shocks. N_t is the total number of active trading days in that specific month.

It is important not to confuse Realized Volatility ($RVol_{i,t}$) with the Realized Variance ($RVar_{i,t}$), which is defined as: $RVar_{i,t} = \sum_{j=1}^{N_t} r_{i,j,t}^2$ as we contrast in the paper [13] Therefore, we can establish that

$$RVar_{i,t} = RVol_{i,t}^2. \tag{9}$$

Although realized skewness and realized kurtosis are discussed in subsequent chapters, we present them based on realized volatility.

To analyze the persistence of this volatility and the potential impact of climate anomalies, we estimate the following AR(p) specification in logarithms using this reference [14]:

$$\ln(RVol_{i,t}) = \alpha_i + \sum_{j=1}^{p} \beta_{i,j} \ln(RVol_{i,t-j}) + \gamma_{i,1} C_{t-1} \mathbb{I}_{\{C_{t-1} \geq 0.5\}} + \gamma_{i,2} |C_{t-1}| \mathbb{I}_{\{C_{t-1} \leq -0.5\}} + \varepsilon_{i,t} \tag{10}$$

where α_i is the intercept, $\beta_{i,j}$ captures the volatility persistence (with the stationarity condition $|\beta| < 1$), and $C_{t-1}\mathbb{I}_{\{C_{t-1}\geq 0.5\}}$ and $|C_{t-1}|\mathbb{I}_{\{C_{t-1}\leq -0.5\}}$ are the lagged dummy variables representing the presence of El Niño and La Niña phenomena, respectively. From now in advance, we use indistinctively NIÑO_{t-1} and NIÑA_{t-1} or $C_{t-1}\mathbb{I}_{\{C_{t-1}\geq 0.5\}}$ and $|C_{t-1}|\mathbb{I}_{\{C_{t-1}\leq -0.5\}}$. Specifically, $\gamma_{i,1}$ measures the impact of lagged El Niño shocks, while $\gamma_{i,2}$ measures the impact of La Niña shocks in previous epochs on the log-volatility process. The term $\varepsilon_{i,t}$ represents the i.i.d. error term. Also, the lag order p is dynamically selected for each commodity using the Ljung-Box test to eliminate residual autocorrelation and will be used this way among the regressions that we can find in the Results subsection 4.3.

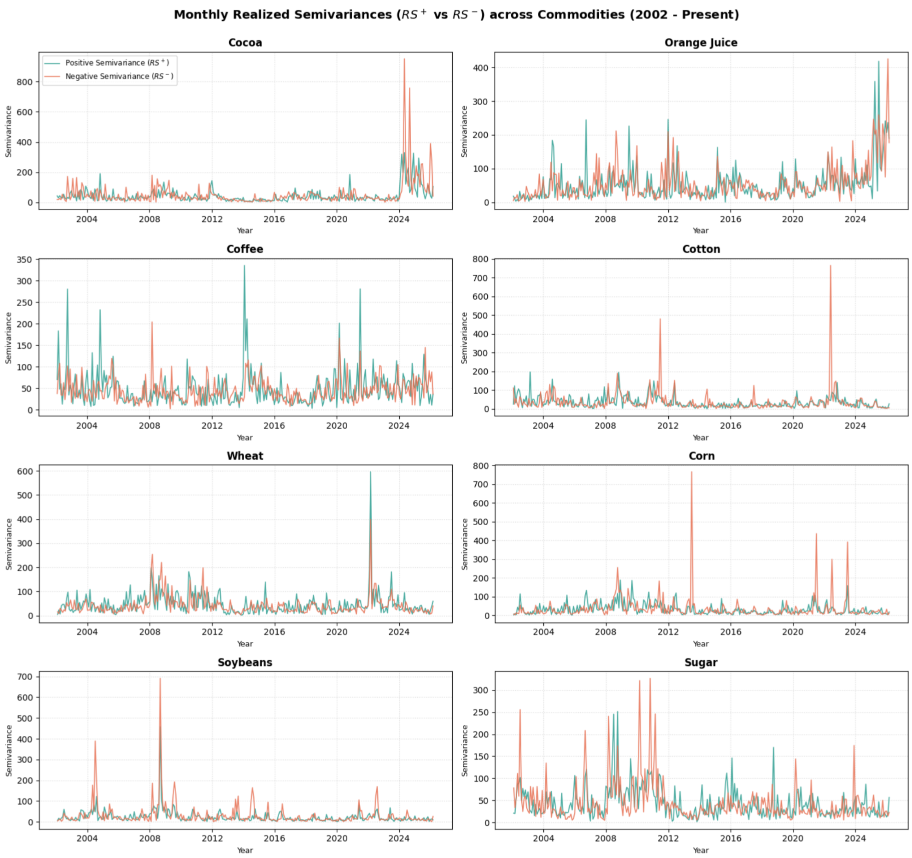
4.2.1 Semivariances

Once we have obtained the daily innovations which are used to build the realized volatility, we can decompose $RVol_{i,t}$ into its good and bad counterparts, positive and negative semivariances, following this reference [15]. These are the variances attributed to positive and negative daily price innovations within each month. We define them as follows:

$$POS_{i,t} = \sum_{j=1}^{N_t} r_{i,j,t}^2 I\{r_{i,j,t} > 0\}$$

$$NEG_{i,t} = \sum_{j=1}^{N_t} r_{i,j,t}^2 I\{r_{i,j,t} < 0\}$$

with $r_{i,j,t}$ obtained as daily innovations explained in the previous section 4.2. We can display the following graphics with the time evolution of positive and negative returns in eight commodities that will be useful as a visual support.



This figures illustrates the monthly trajectory of realized positive (RS^+) and negative (RS^-) semivariances across all eight agricultural commodities from 2002 to the present. The visual evidence reveals significant temporal heterogeneity rather than a uniform macroeconomic response. For instance, while early years (2002–2010) exhibit heightened volatility in Sugar, the year 2014 emerges as a particularly turbulent period specifically for Coffee and Corn. Furthermore, major global shocks do not affect all markets equally: while the 2020 COVID-19 pandemic triggered volatility in several assets, Soybean remained remarkably stable during that period, displaying near-flat semivariance dynamics during the last 15 years. The 2008 major crisis affected some commodities from this analysis although it is not highly remarkable.

An inspection of the asymmetry across panels demonstrates distinct commodity-specific patterns. Positive semivariance (RS^{+}) visibly dominates in Coffee and Wheat, where the highest variance spikes correspond to upward return shocks. Conversely, in Soybean, Corn, Cocoa, and Cotton, the most extreme historical spikes are overwhelmingly negative (RS^{-}), indicating that downside volatility accounts for the largest tail-risk events in these markets. Furthermore, Orange juice and Sugar display a more balanced behavior, with positive and negative semivariances tracking each other closely without a persistent structural dominance of either component. Finally, the graphics show that the scale changes depending on the product. While Coffee, Orange juice and Sugar exhibit little spikes, reaching at the maximum point 300-400 $\%^2$ (corresponding to monthly realized volatility of 17.3% or 20%), the rest of commodities achieve even 800 $\%^2$ (corresponding to monthly realized volatility of 28.3%).

We can establish different measures for the volatility asymmetry of these semivariances. This is crucial as it allows us to determine whether market risk is predominantly driven by positive or negative return shocks. The first one is through a formula that gives us a coefficient set up between -1 (negative semivariance dominates) and 1 (positive semivariance dominates) This formula is specified this way based on the bibliography compiled in this paper [16]:

$$A_{i,t} = \frac{POS_{i,t} - NEG_{i,t}}{POS_{i,t} + NEG_{i,t}}$$

It is important to note that a positive value of $A_{i,t}$ does not imply positive expected returns. Instead, it indicates that positive-return realizations account for a larger share of total realized volatility than negative ones during that specific period.

4.2.2 Interquartile Range regression

If we want to check how robust are these initial asymmetry results exposed in the previous subsection 4.2.1, we can set an alternative dispersion measure based on Interquartile Range ($IQR_{i,t} = P_{75} - P_{25}$) also denoted simply as IQR which will help us to determinate how central values of the monthly data explain positivity and negativity on semivariances. Traditional semivariances are the squared sum of daily innovations and this methodology is highly sensitive to extreme daily price shocks, but with this measure focused on the 50% of the distribution, we can confirm or reject that the asymmetry in returns is due to influence of outliers.

The procedure is as follows. First, we split the daily innovations within each month into positive ($\varepsilon_{i,t} > 0$) and negative ($\varepsilon_{i,t} < 0$) subsets. Then for each month we compute positive and negative Interquartile Range ($IQR^{+}_{i,t}$ and $IQR^{-}_{i,t}$) which will be the difference between the 75% and 25% percentiles of positive and negative innovations respectively in each period. Now that we have defined these concepts, we can construct an alternative Relative Asymmetry Ratio:

$$Ratio(IQR_{i,t}) = \frac{IQR^{+}_{i,t} - IQR^{-}_{i,t}}{IQR^{+}_{i,t} + IQR^{-}_{i,t}}$$

This ratio works identical to the standard semivariance asymmetry ratio bounded by -1 and 1 in 4.2.1. A positive value shows that positive innovations exhibit a broader central spread than negative ones, signalling upside risk. Conversely, a negative value reflects greater dispersion among negative shocks, indicating downside risk. By isolating the interquartile spread from extreme tail events, this test serves as a solid validation check for the baseline semivariance metrics.

There also exists an alternative way to evaluate central dispersion which usage is justified as it can be helpful in order to check robustness and that is the Interquartile Range regression based on the IQR computed as detailed in 4.2.2. We estimate the following autoregressive climate specification using the same structure of this equation 10:

$$\ln(IQ_{i,t}) = \alpha_i + \sum_{j=1}^{p} \beta_{i,j} \ln(IQ_{i,t-j}) + \gamma_{i,1} C_{t-1} \mathbb{I}_{\{C_{t-1} \geq 0.5\}} + \gamma_{i,2} |C_{t-1}| \mathbb{I}_{\{C_{t-1} \leq -0.5\}} + \varepsilon_{i,t} \quad (11)$$

where again α_i is the intercept, $\beta_{i,j}$ captures the volatility persistence (with the stationarity condition $|\beta| < 1$), and NIÑO_{t-1} and NIÑA_{t-1} are the lagged dummy variables representing the presence of El Niño and La Niña phenomena, respectively. $\gamma_{i,1}$ measures the impact of lagged El Niño shocks, while $\gamma_{i,2}$ measures the impact of La Niña shocks in previous epochs on the log-volatility process. The term $\varepsilon_{i,t}$ represents the i.i.d. error term. Also, the lag order p is dynamically selected for each commodity using the Ljung-Box test to eliminate residual autocorrelation and will be used this way among the regressions that we can find in the Results subsection 4.3.

4.3 Results

Table 20: Estimation Results for Monthly Realized Volatility ($\ln(RVol_{i,t})$)

Commodity	**Intercept**	β_1	β_2	β_3	**NIÑO**	**NIÑA**	R^2 **Base**	R^2 **Climate**
Cocoa	0.2589**	0.3779***	0.1978***	0.2950***	0.0347	0.0418	0.5688	0.5719
Orange juice	0.5171***	0.2416***	0.2743***	0.2570***	0.0014	-0.0296	0.3944	0.3956
Coffee	1.0995***	0.3418***	0.1574***	—	-0.0021	-0.0141	0.1884	0.1889
Cotton	0.6589***	0.3646***	0.2960***	—	-0.0226	0.0873**	0.3777	0.3894
Wheat	0.8122***	0.4152***	0.1946***	—	-0.0087	0.1015**	0.3511	0.3681
Corn	0.7686***	0.4050***	0.2104***	—	-0.0764**	0.0151	0.3202	0.3320
Soybean	0.6648***	0.5437***	0.1804***	-0.0830	-0.0834**	0.0121	0.4264	0.4394
Sugar	0.7438***	0.4340***	0.2009***	—	0.0408	0.0781**	0.3495	0.3601

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models are estimated using Ordinary Least Squares (OLS) where the dependent variable is $\ln(RVol_t)$, constructed from daily mean-filtered residuals ($\varepsilon_{i,t}$). The autoregressive lags β_p are selected iteratively for each commodity to eliminate residual autocorrelation (Ljung-Box test). R^2 Base refers to the model controlling solely for market memory ($AR(p)$), while R^2 Climate incorporates the El Niño and La Niña ENSO indicators.

Taking into account market memory, we have included higher-order autoregressive lags ($\beta_1, \beta_2, \beta_3$). These coefficients captures the volatility persistence while ensuring clean, serially uncorrelated residuals. Across commodities, first-lag persistence (β_1) ranges from 0.2416 in Orange juice to 0.5437 in Soybean, with secondary and tertiary lags (β_2 and β_3) playing a statistically significant role in absorbing multi-month volatility dynamics. Furthermore, the inclusion of ENSO indicators enhances the explanatory power (R^2 Base vs. R^2 Climate) across several agricultural markets, particularly for grains and soft fibers. The adjusted R^2 is corrected when the number of explanatory variables increases and, in concrete, for the commodities where the ENSO variables are significant, the increase in the R^2 Climate is bigger. We observe notable gains in R^2 for Wheat (from 35.11% to 36.81%), Cotton (from 37.77% to 38.94%), Soybean (from 42.64% to 43.94%), Sugar (from 34.95% to 36.01%), and Corn (from 32.02% to 33.20%). This confirms that climatic indicators provide meaningful explanatory power regarding agricultural risk. Lastly, the estimated climate coefficients reveal divergent structural impacts. La Niña (NIÑA) significantly inflates monthly realized volatility in Wheat ($\beta_{\text{NIÑA}} = 0.1015$, $p < 0.05$), Sugar ($\beta_{\text{NIÑA}} = 0.0781$, $p < 0.05$), and Cotton ($\beta_{\text{NIÑA}} = 0.0873$, $p < 0.05$), indicating that colder-than-average ocean anomaly phases generate pronounced market instability and supply uncertainty. Conversely, El Niño (NIÑO) exerts a significant risk-dampening effect on Soybean ($\beta_{\text{NIÑO}} = -0.0834$, $p < 0.05$) and Corn ($\beta_{\text{NIÑO}} = -0.0764$, $p < 0.05$), consistent with the stabilizing effect of warmer ENSO conditions.

Comparing the results from the daily GJR-GARCH-X model with those from the monthly Realized Volatility (RVol) model allows for evaluating the temporal persistence of climate impacts on market risk. From a methodological point of view, both similarity and discrepancies are expected between the two approaches due to their distinct time horizons. While the GJR-GARCH framework captures the immediate, high-frequency impact of climate shocks on daily conditional variance, the RVol model measures the total risk mass accumulated over an entire month. By incorporating market memory ($\log(RVol_{i,t-1})$) as a control variable in the monthly specification, the threshold for statistical significance increases. This dual framework thereby identifies whether El Niño and La Niña phenomena act merely as short-term transitory shocks or show a structurally persistent effect at a monthly scale.

After computing all the semivariances in the logarithmic case and apply both methods, we obtain the following results:

Table 21: Robustness Comparison of Volatility Asymmetry Metrics

Commodity	**Baseline Ratio**	**IQR Ratio**	**Baseline Risk**	**IQR Risk**
Cocoa	-0.0028	-0.0146	Downside Risk	Downside Risk
Orange juice	-0.0322	-0.0077	Downside Risk	Downside Risk
Coffee	-0.0131	+0.0074	Downside Risk	Upside Risk
Cotton	+0.0283	+0.0321	Upside Risk	Upside Risk
Wheat	+0.0268	+0.0019	Upside Risk	Upside Risk
Corn	+0.0187	+0.0004	Upside Risk	Upside Risk
Soybean	-0.0095	-0.0154	Downside Risk	Downside Risk
Sugar	+0.0141	+0.0206	Upside Risk	Upside Risk

As we can see, the results in table 21, at least concerning to the sign are almost identical except from Coffee but results are close enough anyway so we have contrasted the robustness of our tests. We can see that Cocoa, Orange juice and Soybean display a negative trend while Cotton, Wheat, Corn and Sugar exhibit positive results.

The key structural reason behind this empirical coincidence is explained by the nature of return volatility in agricultural commodities. While the baseline semivariance metric aggregates squared daily innovations (ε_i^2), making it susceptible to heavy tails and extreme market movements, the interquartile range ($IQR = P_{75} - P_{25}$) isolates the central 50% of daily observations. The fact that both metrics identify the exact same dominant risk direction suggests that the observed asymmetry is not an artifact driven by a few isolated extreme daily shocks (outliers). Instead, it demonstrates that directional volatility risk is an intrinsic, persistent feature of the core return distribution across commodity markets.

Table 22: Model results of Interquartile log-range $\ln(\mathrm{IQR}_t)$ and climate impact

Commodity	**Intercept**	β_1	β_2	β_3	**NIÑO**	**NIÑA**	**R² Base**	**R² Climate**
Cocoa	0.1680***	0.3602***	0.1589**	0.2309***	0.0231	0.0306	0.3808	0.3821
Orange juice	0.3244***	0.3456***	0.2609***	—	-0.0103	-0.0232	0.2657	0.2661
Coffee	0.5106***	0.3389***	—	—	0.0524	0.0434	0.1226	0.1297
Cotton	0.2062***	0.3215***	0.2948***	—	-0.0223	0.0990*	0.3138	0.3241
Wheat	0.4037***	0.2781***	0.1801***	—	0.0227	0.1551***	0.1945	0.2223
Corn	0.2306***	0.4834***	0.1446**	—	-0.0827**	0.0157	0.3518	0.3628
Soybean	0.1946***	0.4038***	0.1857***	—	-0.0916**	0.0327	0.2984	0.3146
Sugar	0.3102***	0.3481***	0.1897***	—	0.0668*	0.0785	0.2313	0.2420

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We can extract some insight from this table 22, not only from the parameter estimates themselves, but also in comparison with the previous $RVol_{i,t}$ specification. In agricultural grains, the findings across $RVol_{i,t}$ and $IQR_{i,t}$ are highly aligned. La Niña increases volatility in Wheat across all models ($\beta_{\text{NINA}} = 0.1551, p < 0.01$). Similarly, El Niño dampens volatility in Soybean ($\beta_{\text{NINO}} = -0.0916, p < 0.05$) and Corn ($\beta_{\text{NINO}} = -0.0827, p < 0.05$). This cross-metric consistency confirms that ENSO shocks shift the entire central return distribution rather than generating short-lived market noise. In contrast, for Sugar, La Niña is statistically significant in the $RVol_{i,t}$ specifications but loses strict significance at the 10% level in the $IQR_{i,t}$ model ($p = 0.1255$), while El Niño becomes marginally significant ($\beta_{\text{NINO}} = 0.0668, p = 0.0984$). This indicates that while climate shocks strongly impact overall variance ($RVol_{i,t}$), their effect on the core interquartile dispersion ($IQR_{i,t}$) is slightly more dispersed between phases, with El Niño picking up part of the monthly volatility shock. Finally, we find persistence in market memory. Across all commodities, the first-order lag (β_1) remains highly significant ($p < 0.01$) and almost all commodities show the second-order lag (β_2) highly significant as well, confirming that volatility clustering is an intrinsic property of core commodity return distributions.

Comparing the monthly realized volatility ($\ln(RVol_{i,t})$) in table 20 and interquartile log-range ($\ln(IQR_{i,t})$) in table 22 estimations with the daily GJR-GARCH-X conditional variance results from Section 3 in table 10 reveals strong structural alignment alongside horizon-specific nuances. First, the cross-metric consistency between total volatility ($\ln(RVol_{i,t})$) and central dispersion ($\ln(IQR_{i,t})$) is remarkable for grain commodities: La Niña consistently inflates risk in Wheat ($\beta_{\text{NIÑA}} = 0.1015, p < 0.05$ in $RVol_{i,t}$; $\beta_{\text{NIÑA}} = 0.1551, p < 0.01$ in $IQR_{i,t}$), while El Niño significantly dampens volatility in Soybean ($\beta_{\text{NIÑO}} = -0.0834, p < 0.05$ vs. $-0.0916, p < 0.05$) and Corn ($\beta_{\text{NIÑO}} = -0.0764, p < 0.05$ vs. $-0.0827, p < 0.05$). This indicates that ENSO anomalies not only generate short-lived daily noise, but rather change the entire monthly return distribution.

If we cross this results with the high-frequency GJR-GARCH-X model, the monthly realized models are almost identical concerning to the directional response of daily conditional variance, particularly for agricultural grains and soft fibers where climate transmission shows strong temporal persistence. However, we identify a divergence in the overall goodness of fit (R^2): while the daily GJR-GARCH-X model captures immediate daily volatility clusters, the monthly realized models achieve substantially higher explanatory power (with R^2 reaching up to 57.19% in Cocoa and 43.94% in Soybean). Furthermore, the loss of statistical significance for La Niña in Sugar under $IQR_{i,t}$ ($p = 0.1255$) relative to $RVol_{i,t}$ ($p < 0.05$) highlights that while ENSO shocks affect total monthly volatility mass, their impact on the core central 50% spread can occasionally be absorbed or dispersed over longer multi-month horizons, proving the importance of work with different time horizons together in complementary models.

5 Realized skewness and Realized kurtosis

In this work, we have already widely analyzed the role of realized volatility, incredibly helpful if we want to study magnitude of risk in commodity markets. While this metric gives valuable information, it does not contribute to explain price shock direction or extreme spikes frequency, motivating the introduction of third and fourth distribution moments of daily returns seen as monthly data. These are respectively, the realized skewness and realized kurtosis which fit better to this focus.

To know whether ENSO shocks alter the central dispersion of price returns or drive extreme tail behavior, we compare classic high-order realized moments against robust, quantile-based metrics. While classic Realized Skewness ($RSk_{i,t}$) and Realized Kurtosis ($RKu_{i,t}$) aggregate cubed and quadrupled daily returns ($r^3_{i,j,t}, r^4_{i,j,t}$), robust metrics isolate specific parts of the distribution. Specifically, we employ $RobSk_{i,t}$ and $RobKu_{i,t}$, which rely on distribution quartiles and octiles respectively, alongside the Interquartile Range ($IQR_{i,t}$). If climate anomalies impact classic moments but vanish under robust metrics, the transmission mechanism is uniquely tail-driven rather than a shift in central dispersion. Obtaining this information is key to understanding the returns distribution and addressing tail risk.

5.1 Methodology

5.1.1 Realized skewness

Following the information provided in these papers [13],[17] and also this identity 9, we define Realized skewness as follows:

$$RSk_{i,t} = \frac{\sqrt{N_t}\sum_{j=1}^{N_t} r^3_{i,j,t}}{RVol^3_{i,t}} \tag{12}$$

where N_t is the number of days in each month, i represents the different commodities, j explains the day , t is the month and RVol is the realized volatility already defined in previous sections (8). Values of RSk above 0 indicate that positive spikes returns dominate the month while negative RSk show that spikes returns drop dominates.

We also calculate Robust skewness through a formula which is useful to verify whether climate impact affect the whole distribution or only the outliers. The Bowley formula is based in quantiles, can be found in this reference [18] and is specified as:

$$RobSk_{i,t} = \frac{Q_{i,3}(t) - 2Q_{i,2}(t) + Q_{i,1}(t)}{Q_{i,3}(t) - Q_{i,1}(t)} \tag{13}$$

where $Q_{i,1}(t), Q_{i,2}(t), Q_{i,3}(t)$ represent first, second and third quartile of daily returns in month t of asset i. This measure evaluates the skewness in the central part of the distribution.

Now, we take a regression with both metrics and we find insights about the behavior of skewness among different perspective and also compared to RVol.

Unlike Realized Volatility, Realized Skewness (we can use RSk and $RobSk$ for simplicity) naturally reaches positive and negative values, preventing logarithmic transformations. For Realized Kurtosis (we can use RKu and $RobKu$ for simplicity), and in alignment with our baseline results for Volatility in levels (Appendix), models are estimated in levels. This approach preserves direct scale interpretability while capturing the climate dynamics on higher-order moments. Settled that, the regression used is:

$$Sk_{i,t} = \alpha_i + \sum_{k=1}^{p} \beta_{i,k} Sk_{i,t-k} + \gamma_{i,1} C_{t-1} \mathbb{I}_{\{C_{t-1} \geq 0.5\}} + \gamma_{i,2} |C_{t-1}| \mathbb{I}_{\{C_{t-1} \leq -0.5\}} + \varepsilon_{i,t} \tag{14}$$

where $Sk_{i,t} \in \{RSk_{i,t}, RobSk_{i,t}\}$, α_i is the intercept, and $\beta_{i,k}$ controls for market memory. The climate indicators $\text{NIÑO}_{t-1} = C_{t-1}\mathbb{I}_{\{C_{t-1}\geq 0.5\}}$ and $\text{NIÑA}_{t-1} = |C_{t-1}|\mathbb{I}_{\{C_{t-1}\leq -0.5\}}$ capture lagged El Niño and La Niña ocean temperature anomalies, respectively. The autoregressive lag order $p \in \{1, 2, 3\}$ is selected separately for each commodity using the Ljung-Box test on the regression residuals to eliminate serial correlation.

5.1.2 Realized kurtosis

We treat now the fourth moment. Again, following the information in these papers [13],[17] and taking into account that 9, we define Realized kurtosis as follows:

$$RKu_{i,t} = \frac{N_t \sum_{j=1}^{N_t} r_{i,j,t}^4}{RVol_{i,t}^4} \tag{15}$$

where N_t is the number of days in each month, i represents the different commodities, j explains the day, t is the month and RVol is the realized volatility already defined in previous sections (8). Higher realized kurtosis indicates a greater concentration of total intraperiod variation in relatively large daily returns, i.e., stronger tail concentration.

One of our goals is analyze what we observe if we isolate influence from outliers while measuring kurtosis, so we can use the octiles of the distribution to obtain the following measure based on this reference [19]:

$$RobKu_{i,t} = \frac{(E_{i,7}(t) - E_{i,5}(t)) + (E_{i,3}(t) - E_{i,1}(t))}{E_{i,6}(t) - E_{i,2}(t)} \tag{16}$$

where $E_{i,1}(t), ..., E_{i,8}(t)$ correspond to the eight different octiles of data from month t. We are focusing on the central part of the distribution.

Analogically to previous realized moments, we specify now both regressions and compare them.

$$Ku_{i,t} = \alpha_i + \sum_{k=1}^{p} \beta_{i,k} Ku_{i,t-k} + \gamma_{i,1} C_{t-1} \mathbb{I}_{\{C_{t-1} \geq 0.5\}} + \gamma_{i,2} |C_{t-1}| \mathbb{I}_{\{C_{t-1} \leq -0.5\}} + \varepsilon_{i,t} \tag{17}$$

where $Ku_{i,t} \in \{RKu_{i,t}, RobKu_{i,t}\}$, α_i is the intercept, and $\beta_{i,k}$ controls for market memory. The climate indicators $\text{NIÑO}_{t-1} = C_{t-1}\mathbb{I}_{\{C_{t-1}\geq 0.5\}}$ and $\text{NIÑA}_{t-1} = |C_{t-1}|\mathbb{I}_{\{C_{t-1}\leq -0.5\}}$

capture lagged El Niño and La Niña ocean temperature anomalies, respectively. The autoregressive lag order $p \in \{1, 2, 3\}$ is dynamically selected for each commodity using the Ljung-Box test on the regression residuals to eliminate serial correlation.

5.2 Results

Table 23: Monthly skewness ENSO impact: Classic (RSk) vs. Robust (RobSk)

	Realized Skewness Classic (RSk)		**Robust Skewness (RobSk)**	
Commodity	**NIÑO ($t-1$)**	**NIÑA ($t-1$)**	**NIÑO ($t-1$)**	**NIÑA ($t-1$)**
Cocoa	0.0951 (0.393)	0.1290 (0.364)	-0.0181 (0.579)	-0.0011 (0.979)
Orange juice	0.1272 (0.256)	-0.0696 (0.626)	0.0561* (0.095)	0.0512 (0.230)
Coffee	-0.0065 (0.946)	0.0925 (0.453)	-0.0481 (0.158)	0.0346 (0.426)
Cotton	0.0069 (0.954)	0.2435 (0.109)	-0.0451 (0.171)	-0.0540 (0.199)
Wheat	-0.2374** (0.018)	-0.1463 (0.252)	-0.0269 (0.419)	-0.0020 (0.962)
Corn	-0.0562 (0.650)	0.2940* (0.067)	0.0172 (0.621)	0.0538 (0.229)
Soybean	0.0850 (0.448)	0.4287*** (0.003)	0.0024 (0.943)	-0.0016 (0.969)
Sugar	0.0432 (0.683)	-0.1149 (0.395)	-0.0075 (0.817)	0.0400 (0.335)

Notes: p-values in parentheses. Models with $AR(1)$ structure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We appreciate that the ENSO impact in the skewness is done by extreme shocks. We highlight the case of Soybean and how in La Niña episodes we can see that the classic model exhibit a significant coefficient (which disappears in the robust model). One feasible interpretation is that as La Niña triggers extreme dry whether in main producer regions of this commodity, we get strong punctual shocks ($RSk > 0$). We can also talk about Wheat in El Niño case where there is a drop in the skewness in the SK model ($\beta_1 = -0.2374$) while we do not appreciate any effect RobSk, situation that might be explained by the good agricultural previsions that El Niño brings (accentuating rains) dropping future market.

Table 24: Monthly Kurtosis ENSO impact: Classic (RKu) vs. Robust (RobKu)

	Realized Kurtosis Classic (RKu)		**Robust Kurtosis (RobKu)**	
Commodity	**NIÑO ($t-1$)**	**NIÑA ($t-1$)**	**NIÑO ($t-1$)**	**NIÑA ($t-1$)**
Cocoa	-0.3886** (0.020)	-0.0686 (0.744)	-0.0584 (0.235)	0.0257 (0.682)
Orange juice	0.1770 (0.389)	0.0338 (0.897)	0.0850 (0.162)	0.0746 (0.335)
Coffee	-0.1695 (0.159)	-0.1108 (0.470)	-0.0594 (0.219)	-0.0650 (0.292)
Cotton	0.1138 (0.638)	0.1163 (0.706)	0.0339 (0.519)	-0.0334 (0.619)
Wheat	-0.2415* (0.072)	-0.0638 (0.707)	-0.0175 (0.678)	0.0309 (0.565)
Corn	-0.0003 (0.999)	-0.4746 (0.135)	0.0165 (0.745)	0.0667 (0.304)
Soybean	-0.1976 (0.279)	-0.1535 (0.509)	-0.0238 (0.607)	-0.0839 (0.156)
Sugar	0.0160 (0.927)	0.1013 (0.650)	-0.0584 (0.284)	0.0651 (0.349)

Notes: p-values in parentheses. Models with $AR(1)$ structure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We perceive some relevant insights from this table related specifically to Cocoa while the El Niño phenomena. We realize that if we check the classic kurtosis, the climate variable exhibits a significant negative coefficient whereas this effect disappears at robust version. This drop might indicate that extreme volatility shocks are less frequent. Future market tends to experience lack of surprises or violent shocks so price dynamics is more fluent through the month. Finally, as we do not observe any statistic significance along Robust Kurtosis for climate indexes, we can theorize that ENSO anomalies do not alter central values of distribution but exclusively the extremes.

5.3 Synthesis: Interplay Between Realized Volatility, Skewness, and Kurtosis

An evaluation of agricultural risk requires integrating the findings from the first studied moment ($\text{RVol}_{i,t}$) 20 with higher-order conditional dynamics ($\text{RSk}_{i,t}$ and $\text{RK}_{i,t}$) in tables 23 and 24. While Realized Volatility reflects the overall scale or magnitude of price dispersion—where ENSO shocks account for statistically significant shifts in total risk for commodities like Wheat ($\beta_{\text{NIÑA}} = 1.0617, p < 0.01$), Sugar, Cotton, Soybean, and Corn—it remains inherently symmetric. Crucially, comparing the classic realized moment regressions against their robust counterparts 23 and 24 reveals that climate anomalies propagate through commodity distributions via asymmetric, tail-driven transmission channels rather than uniform shifts in central dispersion.

The joint behavior of higher-order moments allows us to obtain a better understanding of climate-induced volatility. For instance, during La Niña phases, Soybean display an increase in classic Realized Skewness ($\beta_{\text{NIÑA}} = 0.4287, p < 0.01$), whereas this effect entirely vanishes under robust skewness ($\text{RobSk}_{i,t}$). Similarly, El Niño significantly reduces classic Realized Kurtosis in Cocoa ($\beta_{\text{NIÑO}} = -0.3886, p < 0.05$), an effect that likewise disappears when isolating the distribution's central octiles via robust metric ($\text{RobKu}_{i,t}$). Because climate significance is exclusively present in standard higher moments—which aggregate cubed and quadrupled daily returns ($r^3_{i,j,t}, r^4_{i,j,t}$)—and absent across all robust quantile metrics, we establish that ENSO shocks do not alter the core interquartile spread ($\text{IQR}_{i,t}$). Instead, climate anomalies generate volatility principally by driving low-frequency outer-tail events (extreme daily price spikes or drops), elevating downside risk and tail risk for risk-averse market participants.

6 Economic Interpretation and Institutional Evidence

To assess the external validity and economic relevance of our empirical findings, we contrast our econometric results with recent institutional evidence published by the Banco de España [20]. Their macroeconomic analysis examines the transmission mechanisms of ENSO shocks to European consumer food prices, which coincide with several of the commodities analyzed in this work, providing a robust real-world benchmark that complements our asset-pricing framework.

First, our descriptive and econometric results regarding commodity-specific heterogeneity are similar to the sector-level dynamics identified by the central bank. Specifically, our data highlights severe negative skewness and extreme tail risk in commodities like Cocoa (kurtosis of 11.77, daily minimum return of -26.06%). This aligns directly with the structural supply disruptions documented in Ghana or Ivory Coast in [20], where El Niño induced severe rainfall followed by intense droughts triggered severe crop diseases and historic price spikes. Conversely, our GJR-GARCH-X results and the central bank's findings confirm clear market-specific effects for grains. Specifically, La Niña increases market risk in Wheat ($\omega^- = +$, $p < 0.01$), whereas El Niño reduces daily risk in Corn and Soybean ($\omega^+ = -$, $p < 0.01$). Meanwhile, Coffee shows no significant variance changes (n.s.), likely due to geographic substitution between different producing regions.

Second, the central bank's findings support our principal premise: ENSO anomalies generate asymmetric and persistent shifts in higher-order moments rather than simple linear variance changes. While early macroeconomic literature (1970s-1980s) associated El Niño exclusively with inflationary price spikes [20], other factors like modern trade integration or adaptation technologies have attenuated and transformed these transmission channels. Consequently, extreme climate events manifest primarily through sudden tail-risk realization and distribution skewness—precisely the higher-order dynamics obtained in our realized moment estimations.

In summary, these institutional similarities validate that the unconditional skewness and tail behavior modeled in our study are not econometric artifacts, but rather the direct market reflection of macro-climate transmission channels. Understanding these asymmetric climate-finance dynamics provides critical insights for risk-averse investors optimizing portfolio allocations, as well as for central banks monitoring systemic food inflation risks in the context of intensifying climate change.

7 Limitations and future research

7.1 GARCH-MIDAS

One interesting approach that we can make consists in incorporate the GARCH-MIDAS model as we can observe in this paper [21]. This is an idea conceived for future research in this field as it can constitute an interesting evolution of the GJR-GARCH-X model, addressing the present limitation that we have. While daily analysis covers one point of view (high frequency) and monthly analysis covers another point of view (matching data), they can be seen as complementary, but the main problem is that the daily data can not be compared to other models. The GARCH-MIDAS model helps our research with that trouble combining both daily agricultural data with monthly ENSO data in a model that avoid both possibly bad approximations and low frequency and giving us a powerful tool with two strong objectives. It allows us to compare the daily analysis and to contrast the monthly one.

While the daily analysis via GJR-GARCH-X captures high-frequency financial dynamics and the monthly specifications align with the periodicity of climatic indices, direct cross-model comparability remains restricted due to frequency misalignment.

To overcome this limitation in future research, the GARCH-MIDAS framework proposed offers a natural extension. This model decomposes conditional variance into a daily short-run component ($g_{i,t}$) and a monthly slow-moving trend (τ_t):

$$\sigma_{i,t}^2 = \tau_t g_{i,t} \tag{18}$$

where $g_{i,t}$ captures daily volatility clustering, and τ_t directly incorporates monthly ENSO shocks via a weighted lag scheme:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\mathrm{ENSO}_{t-k} \tag{19}$$

Furthermore, this framework can be extended to asymmetric climate effects ($\theta_E \neq \theta_L$) and higher-order realized moments (Realized Skewness and Kurtosis) to evaluate climate-driven tail risk within Value-at-Risk specifications.

7.2 Value-at-Risk (VaR) and Expected Shortfall (ES)

A natural extension of this research involves assessing the tail risk implications of climate-induced skewness in agricultural commodity markets. Following the theoretical framework of [18], ignoring higher-order distribution moments can lead to a severe underestimation of extreme downside risks, particularly in commodity markets which tend to asymmetric supply and demand shocks. Therefore, a possible idea for future research is to evaluate how climate-driven asymmetry alters tail risk measures such as Value-at-Risk (VaR) and Expected Shortfall (ES) across agricultural assets.

In line with [18], future studies could adopt the third-order Cornish-Fisher (CF3) expansion to separate the marginal effect of unconditional skewness on tail risk from kurtosis contributions. Since agricultural commodities share key structural dynamics with energy markets—such as seasonal demand patterns, storage constraints, and high vulnerability to exogenous supply disruptions—applying the CF3-adjusted VaR and ES frameworks may provide more accurate risk management tools and optimize hedging strategies for agricultural market participants.

8 Conclusions

The primary objective established at the beginning of this research was to examine whether climatic conditions derived from ENSO anomalies in the Pacific Ocean systematically affect the return distribution of agricultural commodities, with a specific focus on conditional volatility, asymmetry, and tail risk. Addressing this core question is particularly relevant in the current macroeconomic environment, where extreme weather events increasingly disrupt global supply chains. From a financial perspective, identifying climate-driven shifts in higher-order moments—such as skewness and kurtosis—provides vital insight for risk-averse investors who exhibit explicit moment preferences when structuring portfolios.

To assess how these initial goals were fulfilled, the following points address our empirical findings in relation to the three central objectives of this research:

- **Parametric Volatility Dynamics (GJR-GARCH-X and AR(p) models):** Our first objective was to evaluate the impact of the ENSO index on conditional volatility across daily and monthly frequencies. The empirical evidence confirms this objective: integrating the ONI indicator into our autoregressive specifications leads to statistically significant gains in explanatory power (R^2) for major crops like Wheat, Sugar, Cotton, Corn, and Soybean. Furthermore, the parametric estimates reveal clear structural asymmetry: La Niña conditions significantly inflate monthly realized volatility in Wheat, Sugar, and Cotton due to severe supply disruptions in key growing basins, whereas El Niño shows a stabilizing or even decreasing risk effect on feed crops such as Corn and Soybean.

- **Realized Higher-Order Moments and Quantile-Based Metrics:** Our second objective was to analyze non-parametric realized cumulative moments (Realized Volatility, Skewness, and Kurtosis) against robust quantile-based metrics (IQR, Bowley skewness, and Moors kurtosis) to isolate tail risk transmission. In accomplishing this objective, we show that agricultural returns exhibit leptokurtosis and negative skewness. Crucially, comparing standard moments with robust measures reveals that climate shocks do not alter the core day-to-day interquartile return distribution; instead, climate significance is uniquely concentrated in the extreme tails ($RSk_{i,t}$ and $RKu_{i,t}$). As emphasized by [18], failing to account for these asymmetric tail shifts leads to a severe underestimation of downside risk during adverse climate phases.

- **Institutional Evidence and Macroeconomic Alignment:** Our third objective was to contrast our empirical asset pricing findings with institutional macroeconomic evidence, in this case from Banco de España, to provide meaningful economic interpretations. The results confirm a strong alignment between econometrically estimated market risk and real-world supply dynamics. For instance, the severe tail asymmetry and volatility in Cocoa reflect localized extreme weather disruptions in Ghana or Ivory Coast Africa, whereas commodities like Wheat and Coffee display international trade diversion and supply adjustments that absorb local disruptions.

In summary, incorporating climate indicators such as the ONI provides crucial predictive value for managing agricultural tail risk.

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A Robustness Analysis: Model Sensitivity and Frequency Aggregation

To evaluate the stability of our baseline empirical findings, this appendix presents two robustness tests which we compare:

1. A test of the daily GARCH-X specification by removing the financial asymmetry parameter ($\gamma = 0$) so we do not study the GJR model anymore.

2. An analogical evaluation of the model without GJR part at a monthly frequency to test signal persistence and align the parametric framework with monthly Realized Volatility metrics.

A.1 GARCH-X model without GJR

Table 25: **Robustness analysis: GARCH-X model estimation without GJR skewness** ($\gamma = 0$)

	Impact on Returns (Mean)		**Impact on Variance (Risk)**	
Commodity	**El Niño** (δ^+)	**La Niña** (δ^-)	**El Niño** (ω^+)	**La Niña** (ω^-)
Corn	n.s. (+0.0081)	*** (+0.2797)	*** (-0.3147)	n.s. (+0.0085)
Wheat	n.s. (-0.0128)	n.s. (+0.1113)	n.s. (-0.0171)	*** (+0.3817)
Soybean	n.s. (-0.0206)	*** (+0.1743)	*** (-0.3177)	n.s. (+0.0484)
Sugar	n.s. (+0.0301)	*** (+0.1820)	*** (+0.1600)	* (+0.1693)
Coffee	n.s. (+0.0534)	** (+0.1301)	n.s. (+0.0314)	n.s. (-0.0438)
Cocoa	* (+0.0796)	* (+0.0969)	*** (-0.2740)	n.s. (-0.0556)
Orange juice	n.s. (-0.0016)	n.s. (+0.0611)	n.s. (+0.0104)	n.s. (+0.0215)
Cotton	n.s. (+0.0109)	** (+0.1216)	*** (-0.2181)	*** (+0.2870)

Significant levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. = no significant. Between brackets is indicated the estimated value of the coefficient.

A.2 Monthly GARCH-X Aggregation and Cross-Frequency Comparison

Daily GARCH specifications explains immediate market volatility and high-frequency fluctuations. However, estimating conditional variance at a monthly frequency aligns the parametric framework directly with the monthly scale of the Oceanic Niño Index (ONI). This aggregation also allows for a direct comparison with the Realized Volatility measures developed in 8.

To perform this robustness test, we adjust the baseline GARCH-X model equations to monthly data. Table 26 details the specific estimation results for Corn as a baseline case, while Table 27 presents the full cross-commodity comparative results.

Table 26: Estimation results from monthly model GARCH-X exp-ω with Student's t distribution

Section	**Theoretical parameter**	**Estimate value**	***p*-value**
A. Equation of the mean (μ_t)			
	Constant (c_0)	-0.9777	0.1448
	AR(1) memory (c_1)	-0.1942**	0.0182**
	El Niño impact (δ^+)	0.0937	0.8815
	La Niña impact (δ^-)	6.2599***	0.0000***
B. Variance equation (σ_t^2)			
	Constant (ω_0)	3.9225***	0.0000***
	ARCH effect (α_1)	0.3660**	0.0336**
	GARCH memory (β_1)	0.0785	0.6658
	El Niño shock (ω^+)	-0.5267**	0.0270**
	La Niña shock (ω^-)	-0.4228	0.2305
	Degrees of freedom (ν)	7.2339**	0.0156**
C. (Tests of Ljung-Box)			
	Mean residuals, $Q(10)$	p-val: 0.5380	OK (Without autocorrelation)
	Variance residuals, $Q^2(10)$	p-val: 0.4032	OK (Homoskedastic)

Significant levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 27: Brief comparative of estimate parameters of model GARCH-X (Monthly)

Parameter	**Corn**	**Wheat**	**Soybean**	**Sugar**	**Coffee**	**Cocoa**	**Orangejuice**	**Cotton**
c_0	-0.9777	0.4156	-0.1860	-0.2992	-0.4744	0.3122	-0.1535	0.0395
c_1	-0.1942**	-0.1230*	-0.0442	0.0692	-0.1313**	-0.2194***	-0.1530**	-0.1351*
δ^+	0.0937	-0.9094	-0.0183	0.9920	0.8246	0.9673	1.0329	0.0550
δ^-	6.2599***	1.3818	3.5380***	1.9940	2.3156*	0.4865	1.8161	3.2571**
ω_0	3.9225***	0.6031	2.6277*	2.2210***	2.6015*	1.1735	1.0804	1.7077*
α_1	0.3660**	0.0000	0.1891	0.0231	0.0496	0.1695	0.0440*	0.0714
β_1	0.0785	0.9630***	0.5927	0.7624***	0.7901***	0.7732***	0.9078***	0.7964***
ω^+	-0.5267**	-0.2678	-0.4167	0.8690***	-0.0872	0.9211	0.8085**	0.3351
ω^-	-0.4228	1.2679	-0.0152	1.0253***	0.0886	1.2038	1.0114	1.3692**
ν	7.2339**	17.2367	7.1156***	7.5821***	8.5922**	16.5546	8.3453*	6.3461***
$Q(10)$ p-val	0.5380	0.5226	0.0320	0.2464	0.9391	0.8264	0.2735	0.5312
$Q^2(10)$ p-val	0.4032	0.9525	0.3292	0.2682	0.9897	0.9344	0.2092	0.7700

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 28: Summary of significance for climatic parameters

	Impact on Returns (Mean)		**Impact on Variance (Risk)**	
Commodity	**El Niño (δ^+)**	**La Niña (δ^-)**	**El Niño (ω^+)**	**La Niña (ω^-)**
Corn	n.s.	(+) ***	(−) **	n.s.
Wheat	n.s.	n.s.	n.s.	n.s.
Soybean	n.s.	(+) ***	n.s.	n.s.
Sugar	n.s.	n.s.	(+) ***	(+) ***
Coffee	n.s.	(+) *	n.s.	n.s.
Cocoa	n.s.	n.s.	n.s.	n.s.
Orange juice	n.s.	n.s.	(+) **	n.s.
Cotton	n.s.	(+) **	n.s.	(+) **

Sign of estimated coefficient in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We perceive high persistence (β_1). Monthly variance exhibits strong memory across most markets confirming slow decay of monthly shocks. But there are some differences depending on the commodity. Sugar, Orange juice, and Cotton experience significant volatility expansions during ENSO events. Sugar is sensitive to both phases, while Orange juice responds to El Niño and Cotton to La Niña. Finally, Corn displays a negative, significant variance response during El Niño, reinforcing the stabilizing effect of El Niño on grain yield expectations.

Another topic we can discuss from the tables is the interpretation of heavy tails. The degrees of freedom parameter ν is low and significant across almost all commodities which could contribute to provide empirical evidence for heavy-tailed behavior and validating the Student's-t distribution.

A.2.1 Discussion of Monthly Findings and Cross-Frequency Comparison

The empirical findings obtained across the monthly specifications provide a comprehensive view of climate transmission, while offering valuable insights when compared directly to the daily baseline results:

- **Impact on Mean Returns (δ^- and δ^+) — Daily vs. Monthly:** In both frequencies, La Niña (δ^-) consistently acts as the primary driver of positive return shocks across key crops. In the daily specification, La Niña triggers statistically significant price increases in Corn, Wheat, Soybean, Sugar, Coffee, and Cotton. When aggregating data to a monthly scale, this price realignment effect remains highly robust and statistically significant for Corn, Soybean, Coffee, and Cotton. Severe droughts associated with La Niña disrupt major production hubs, forcing structural upward price adjustments that persist across timescales. Conversely, El Niño (δ^+) shows no significant direct impact on return levels across any commodity in either the daily or monthly specifications.

- **Impact on Conditional Variance (ω^- and ω^+) — Daily vs. Monthly:** At a daily frequency, El Niño (ω^+) consistently dampens variance across most crops (such as Corn, Soybean, Cocoa, and Cotton). In the monthly model, this variance-stabilizing effect during El Niño remains statistically significant for Corn, reinforcing the expectation of favorable growing conditions for grains. However, the monthly aggregation reveals broader volatility expansions for soft commodities during ENSO events: Sugar experiences volatility surges under both phases, Orange juice shows heightened variance under El Niño, and Cotton reacts to La Niña.

- **Variance Persistence (β_1):** Moving from daily to monthly frequency filters out high-frequency market noise, yielding very high variance persistence (β_1) across most soft commodities. This confirms that once a climate shock affects the market, its impact on conditional uncertainty decays slowly over time.

- **Residual Distribution (ν):** The estimated degrees of freedom parameter ν remains low and statistically significant across almost all commodities in both daily and monthly specifications. This formally confirms heavy-tailed residual behavior regardless of sampling frequency and validates the choice of the Student's-t distribution.

In conclusion, comparing daily and monthly frameworks confirms that La Niña acts as a major structural supply shock for grains and soft fibers. The core transmission mechanism is remarkably robust to frequency aggregation, impacting both price levels and conditional uncertainty.

B Realized volatility

In order to capture the climatic impacts in scale units, we also estimate the model without logarithmic transformations, using an AR(1).

$$RVol_{i,t} = \alpha_i + \sum_{j=1}^{p} \beta_i RVol_{i,t-j} + \gamma_{i,1} C_{t-1} \mathbb{I}_{\{C_{t-1} \geq 0.5\}} + \gamma_{i,2} |C_{t-1}| \mathbb{I}_{\{C_{t-1} \leq -0.5\}} + \varepsilon_{i,t} \quad (20)$$

In the linear equation, the parameters mantain the same theoretical definition.

Table 29: Monthly Realized Volatility Regression Results with Climate Variables (In Levels)

Commodity	Intercept	β_1	β_2	β_3	NIÑO	NIÑA	R^2 Base	R^2 Climate
Cocoa	0.9303*	0.3773***	0.2168***	0.2786***	0.5081	0.5365	0.5621	0.5674
Orange juice	2.0680***	0.2652***	0.2419***	0.2993***	-0.0798	-0.2690	0.4037	0.4046
Coffee	5.1670***	0.2976***	0.1495**	—	-0.0336	-0.2183	0.1455	0.1467
Cotton	2.9746***	0.3715***	0.2321***	—	-0.2528	0.8502**	0.3242	0.3394
Wheat	3.7071***	0.3737***	0.1874***	—	-0.1331	1.0617***	0.2990	0.3192
Corn	3.5365***	0.3458***	0.2164***	—	-0.6886**	-0.0287	0.2494	0.2611
Soybean	2.6674***	0.5625***	0.0587	—	-0.6380**	0.0033	0.3800	0.3906
Sugar	2.9147***	0.4184***	0.2176***	—	0.3521	0.7892**	0.3487	0.3605

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models are estimated using Ordinary Least Squares (OLS) in levels without logarithmic transformations. The dependent variable is the Monthly Realized Volatility ($RVol_{i,t}$), calculated from daily mean-filtered residuals ($\varepsilon_{i,t}$). The autoregressive structure β_p is dynamically selected for each commodity to eliminate residual autocorrelation. R^2 Base refers to the model controlling solely for market memory ($AR(p)$), while R^2 Climate incorporates the El Niño and La Niña ENSO indicators.

We can now repeat the comparison between semivariances ratio and IQR ratio in the linear case without applying logs and we get these results:

Table 30: Volatility Asymmetry Ratios and IQR Robustness Test by Commodity

Commodity	Baseline Ratio	IQR Ratio	Baseline Risk	IQR Risk
Cocoa	-0.0028	-0.0146	Downside Risk	Downside Risk
Orange juice	-0.0322	-0.0077	Downside Risk	Downside Risk
Coffee	-0.0131	+0.0074	Downside Risk	Upside Risk
Cotton	+0.0283	+0.0321	Upside Risk	Upside Risk
Wheat	+0.0268	+0.0019	Upside Risk	Upside Risk
Corn	+0.0187	+0.0004	Upside Risk	Upside Risk
Soybean	-0.0095	-0.0154	Downside Risk	Downside Risk
Sugar	+0.0141	+0.0206	Upside Risk	Upside Risk

If we compare these results with the log results we can identify that they are identical. No matter the commodity, in both ratio metrics we find the exact same sign and dominant risk classification regardless of whether log-transformations are applied.

This consistency confirms that we get robust findings independent of the return calculation method. While log-transformations are commonly used in econometrics to stabilize variance, they can sometimes show extreme positive values. In our work, both specifications stand that our asymmetry results reflect core market dynamics.

C Derivation of the Unconditional Variance and Stationarity Condition

To establish the analytical form of the unconditional variance for the GJR–GARCH–X specification with an X-driven time-varying intercept, we begin from the conditional variance expression:

$$\sigma_t^2 = g(X_{t-1}) + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 I(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{21}$$

By expressing return innovations as $\varepsilon_{t-1} = \sigma_{t-1} z_{t-1}$, where $\{z_t\}$ represents an i.i.d. standardized innovation process with $E[z_t] = 0$ and $E[z_t^2] = 1$, Equation (21) can be compactly rewritten as a stochastic recurrence equation:

$$\sigma_t^2 = g(X_{t-1}) + A_{t-1}\sigma_{t-1}^2 \tag{22}$$

where A_{t-1} is a random coefficient defined as:

$$A_{t-1} = \beta_1 + \alpha_1 z_{t-1}^2 + \gamma_1 z_{t-1}^2 I(z_{t-1} < 0) \tag{23}$$

Taking unconditional expectations on both sides of Equation (22), and utilizing the independence of z_{t-1} relative to past volatility states σ_{t-1}^2, we obtain:

$$E[\sigma_t^2] = E[g(X_{t-1})] + E[A_{t-1}]E[\sigma_{t-1}^2] \tag{24}$$

Under the structural assumption of a symmetric standardized distribution for z_t, the expectation of the asymmetric indicator term evaluates to $E[z_t^2 I(z_t < 0)] = \frac{1}{2}E[z_t^2] = \frac{1}{2}$. Consequently, the expected value of A_{t-1} simplifies to:

$$E[A_{t-1}] = \alpha_1 + \beta_1 + \frac{\gamma_1}{2} \tag{25}$$

Assuming covariance stationarity, the second-order unconditional moment remains time-invariant, such that $E[\sigma_t^2] = E[\sigma_{t-1}^2] = \bar{\sigma}^2 = \mathrm{Var}(\varepsilon_t)$. Substituting Equation (25) into Equation (24) yields:

$$\bar{\sigma}^2 = E[g(X_{t-1})] + \left(\alpha_1 + \beta_1 + \frac{\gamma_1}{2}\right)\bar{\sigma}^2 \tag{26}$$

To guarantee that the process possesses a finite and strictly positive unconditional variance, we impose the second-moment stationarity condition:

$$P = \alpha_1 + \beta_1 + \frac{\gamma_1}{2} < 1 \tag{27}$$

provided that $E[g(X_{t-1})] < \infty$ and that $g(X_{t-1})$ follows a strictly stationary process. Rearranging terms in Equation (26) under condition (27) yields the closed-form unconditional variance:

$$\mathrm{Var}(\varepsilon_t) = \bar{\sigma}^2 = \frac{E[g(X_{t-1})]}{1 - \alpha_1 - \beta_1 - \frac{\gamma_1}{2}} \tag{28}$$