Climate Anomalies and Its Impact on U.S. Corn and Soybean Prices

by Yichen Zhu and Atanu Ghoshray

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YICHEN ZHU[a,*], ATANU GHOSHRAY[b]

[a] Global Development Institute, University of Manchester, United Kingdom
[b] Department of Economics, Newcastle University, United Kingdom

Abstract
This paper analyzes the relationship between climate anomalies on corn and soybean prices in the U.S. We choose corn and soybean as these two crops are close substitutes in production and consumption, produced in the same region of the U.S., and compete for acreage. Climate anomalies that can affect temperature and precipitation, are likely to affect growing conditions in the same geographical area where the two different crops are grown, which in turn affect the prices of the two crops. Past studies have indicated that the variability of climatic conditions can impact on the variability of agricultural prices. Accordingly, we investigate the relationship of the two extreme climatic phases, El Niño and La Niña, on corn and soybean prices, by adopting a novel approach, which involves employing a nonlinear interval based time series estimation that takes into consideration both the interval range as well as the level values of the data. This research addresses a gap in past studies by exploiting the variability in the data, which we argue is crucial given the importance of the extreme phases of climate variability, as well as the volatility of agricultural prices. The results show that the variability of grain prices matter and needs to be taken in to account to inform policy decisions in relation to farm risk management and crop planting decisions.

Keywords: Corn price, Soybean price, El Niño Southern Oscillation (ENSO), Variability, Threshold Autoregressive Interval (TARIX) estimation.
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* Corresponding author. Global Development Institute, University of Manchester, United Kingdom. Email address: yichen.zhu@manchester.ac.uk

1. Introduction

For quite some time, there have been warnings about increasing temperatures and declining precipitation having an impact on crop yield and acreage (Lobell et al., 2008; Miao et al., 2016) as well as prices (Ubilava, 2017a). In 2015, the popular press such as *The Wall Street Journal*[1] and *The Guardian*[2] issued a caution about how El Niño followed by La Niña can impact strongly upon agricultural commodity markets. This concern is reasonable because agriculture is a vulnerable industry in the face the weather fluctuations, as uncertainty and risk affect agricultural production (Kennett and Marwan, 2015). According to the Intergovernmental Panel on Climate Change (IPCC, 2014) report, higher temperatures could affect crop production through reduced yields, plant cells getting damaged and higher vapor pressure leading to water stress. Besides, all aspects of food security, including food access, utilization and food price fluctuations are affected through climate change (Porter et al., 2017).

This article analyzes the relationship between climate anomalies on corn and soybean prices in the U.S. We choose corn and soybean as these two crops are considered substitutes in production and consumption. They are both typically produced in the same geographic regions of the U.S. and the planting decisions for both crops are made jointly. As a result, the supply responses of corn and soybeans are a trade-off with respect to acreage allocation decisions (Holt, 1992), in the sense that an increase in corn acreage happens at the expense of a reduction in soybean acreage, and vice versa (Chavas and Holt, 1990). This close competition for acreage is largely driven by the substitutability of these crops, and in recent years, since the Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007, both crops have been used in the production of biofuels (e.g., Eidman, 2007; Gardner, 2007; Anderson and Coble, 2010). Further, the byproducts of corn-based ethanol and soybean-based biodiesel production, contribute to the end-use in livestock production (Beckman et al., 2011) and are close substitutes in livestock feed rations (Holt, 2012). Finally, ethanol from corn and biodiesel from soybean are blended with gasoline and diesel, thereby providing an energy link between the two commodities (Holt, 2012). Given that both the crops are grown in the same geographical area of the U.S. and have similar end uses, thereby competing for acreage, we make a contribution by analyzing how the prices of soybean and corn can be affected by climatic anomalies.

The El Niño Southern Oscillation (ENSO) phenomenon describes the climate anomalies by irregular periodic volatiles in the sea surface temperature (SST) over the central and eastern tropical Pacific Ocean, which radiates extreme weather conditions to much of the tropics and subtropics around the world (Chen and McCarl, 2000; Dai

[1]Craymer, L. (2015) "Winter is coming: La Niña Poised to Storm Markets" *The Wall Street Journal*. December 23.

[2]Meng, K. and S. Hsiang (2015). "El Niño: A Global Weather Event that may save California – and destroy the Tropics" *The Guardian*, September 21.

2013) and this transmission is known as 'teleconnections'. The El Niño describes the occasional return behavior of the abnormal warm water in the normally cold-water area along the Peruvian coast, and the La Niña describes the cooler-than-normal sea surface temperatures in the central and eastern tropical Pacific Ocean (Ashok and Yamagata, 2009), so that El Niño and La Niña are accompanied with high and low air surface pressure respectively over the tropical western Pacific (Aceituno, 1992). El Niño and La Niña are, therefore, the two extreme phases of the ENSO cycle, which cause a warm SST and cold SST, respectively. Between El Niño and La Niña is the phase termed as ENSO-neutral (Hanley et al., 2003), where temperatures are maintained at the average level. In general, the warmer (cooler) the SST, the stronger the El Niño (La Niña) effects (Timmermann et al., 1999).

Several studies (e.g., Keppenne, 1995; Siegert et al., 2001; Brunner, 2002; Camargo and Sobel, 2005; Schlenker and Roberts, 2009; Ubilava, 2012; 2013; Tack and Ubilava, 2013; Iizumi et al., 2014; Tack and Ubilava, 2015; Ubilava, 2017a; 2017b) have emphasized the link between climate anomalies and agricultural commodity prices. These studies indicate that such anomalies can directly affect yield as well as crop acreage, which in turn, can affect prices. Some of these studies (e.g., Siegert et al., 2001; Camargo and Sobel, 2005) indicate that the magnitude of climate anomalies can cause drought, tropical cyclones, hurricanes and tsunamis due to the ENSO extreme phases, which can lead to large scale crop failure and food insecurity (Limsakul, 2019), as well as damage to storage conditions, transport infrastructure and international logistics (Jaroszweski et al., 2010), thereby exerting upward pressure on agricultural commodity prices (Noy, 2009; Ubilava, 2013; 2017a).

The above studies highlight that extreme weather events as an explanatory variable in examining the dynamics of agricultural prices. Some interesting features can be deduced from past studies. We argue that the choice of data frequency for measuring the impact of weather events on grains should be suitably chosen for constructing econometric models that use weather events as exogenous variables. To this end, we choose to estimate data at a quarterly frequency that aligns with the seasonal variation. Further, given that climate anomalies are leading to weather events that are changing in distribution and intensity (McCarl and Hertel, 2018) we make a contribution by examining the variability of climate change on the variability of prices. We argue that generalizations about average prices in a quarter may mask a significant amount of time scale variability. For example, a similar 'average price' of corn or soybean could arise from two different quarters if point estimates are used but one of the quarters can have more variation compared to another quarter. To this end, we exploit both the average and the interval of the price and weather variable over a quarter to examine the dynamic ENSO-price relationship for corn and soybeans. Accordingly, we make use of a novel Threshold Autoregressive Interval (TARI) procedure, due to Sun et al. (2018), that regresses the interval or range of prices on its own lags, as well as allowing for an exogenous interval climate anomaly as an explanatory variable, thereby modifying the TARI to a Threshold Autoregressive Interval with an exogenous variable, or TARIX model. This procedure allows us to combine nonlinearity by choosing the exogenous climate anomaly to have threshold effects whereby we regress the interval range of weather anomalies on the interval range of corn or soybean prices.

In this manner, we make a contribution by investigating the possible asymmetric relationship of the two extreme phases, El Niño and La Niña, to the interval range of corn and soybean prices; two agricultural commodities that are considered to be close substitutes and compete for acreage, and likely to be affected by climate anomalies. While we consider the El Niño and La Niña phases, we take into consideration both the interval phase of these anomalies as well as the average point estimate. This approach therefore improves upon past studies by exploiting the variability in the data[3]; which is pertinent as larger shocks are more pronounced on agricultural yields, so that considerable deviations in the ENSO anomalies could induce a disproportionate magnitude change in the grain prices (Ubilava, 2017b). Therefore, the point-value series may fail to utilize the range in price changes within an interval of time, thereby ending up using information that is suboptimal; because the data collected at a specific time point during a period is unable to record the interval information (Sun et al., 2019). It is well known that agricultural commodity prices such as corn and soybeans are volatile (Ghoshray, 2019) and the degree of variability of these prices can differ (e.g., different coefficients of variation[4]). In addition, the interval-valued series avoids the unnecessary noises included in the higher-frequency point-valued data series (Sun et al., 2018).

This paper is structured as follows: Section 2 outlines the ENSO-price transmission mechanism and measures of ENSO anomalies. This is followed by Section 3 that reviews the literature. Section 4 describes the TARIX procedure to be applied to the data, Section 5 describes the data used in the analysis and some preliminary test results. Section 6 details the key empirical results, and finally, Section 7 concludes.

2. Description of ENSO Measures

The most cited ENSO indicators are the Southern Oscillation Index (SOI) and sea surface temperature (SST) indices employed in several studies (e.g. Keppenne, 1995; Letson and McCullough, 2001; Brunner, 2002; Cashin et al., 2017). SOI is the oldest indicator of the ENSO events, which describes the bimodal variation in sea-level barometric pressure between two stations at Tahiti in the Pacific, and Darwin in Australia (Allan et al., 1991). However, SOI is only based on the sea level pressure at two observation stations, which would cause deviations by short-term fluctuations

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[3] For example, consider a case where the seasonal value of the ENSO indicator is 0.5 in the second quarter in 2016. However, the ENSO index values change from 0.05 to 0.99 from April to June. This wide range needs to be utilized to deliver more information for analyzing the transmission between climate events and commodity prices.

[4] Defined as the ratio of the standard deviation to the mean.

unrelated to ENSO. Besides, these two stations are located at the south of the equator, while ENSO is predominantly along the equator. The other indicator SST, is increasingly used in recent studies since the ocean has been characterized to play an important role in ENSO (Bjerknes, 1969; Rasmusson and Carpenter, 1982). The *Niño 3.4* region, which is a rectangular area of the Pacific Ocean between 5°North-5°South and 170-120°West, has been identified as a suitable ENSO-representative indicator of ENSO cycles (Bamston et al., 1997; Ubilava, 2017b) and the *Niño 3.4* index measures the sea surface temperature (SST) anomalies around the *Niño 3.4* region.

The SST-based measure is a reliable indicator of ENSO occurrence (Tack and Ubilava, 2015) and the commonly utilized climate variable in climate economics studies (Hsiang et al., 2011; Hsiang and Meng, 2015; Ubilava, 2017b). There are three *Niño 3.4* index datasets provided by the National Oceanic and Atmospheric Administration (NOAA)[5]. The better known and popularly applied *Niño 3.4* index depicting ENSO events, is derived from the daily 1/4° Optimally Interpolated SST (OISST.v2) dataset, which is reported from January 1982 and is updated both on a weekly and monthly basis. The OISST-based measure is an average of daily sea surface temperature values interpolated from weekly measures obtained from both satellites and buoys. The anomaly for a given month is denoted by the deviation in this particular month from the average historic *Niño 3.4* values relative to the 1981-2010 base period. Another similar but different *Niño 3.4* index is derived from the monthly Extended Reconstruction SST (ERSST.v5) dataset. To avoid satellite biases, the ERSST is only based on the in situ (ship and buoy) observations (Reynolds et al., 2007). Similar to the OISST index, the ERSST-based *Niño 3.4* uses the fixed 30-year base period (1981-2010) to calculate the anomalies.

A measure, which is the three-month running mean value of SST departures from the average in the *Niño 3.4* region, known as the Oceanic Nino Index (ONI), is considered as an internationally accepted indicator to define the state of the ENSO cycle (Kousky and Higgins, 2007). According to the NOAA, the operational definition for the El Niño condition is characterized by ONI values equal or higher than +0.5°C, and the La Niña episode is characterized by ONI values equal or lower than –0.5°C. When values of the ONI fall into the interval [–0.5°C, +0.5°C], we consider a neutral phase (Royce et al., 2011; Ubilava, 2017b). The classification of the different phases applied to the ONI data from NOAA is shown in Figure 1 below.

[5] Source: https://www.cpc.ncep.noaa.gov/data/indices/

Figure 1: Time series plots of the ONI using data from NOAA

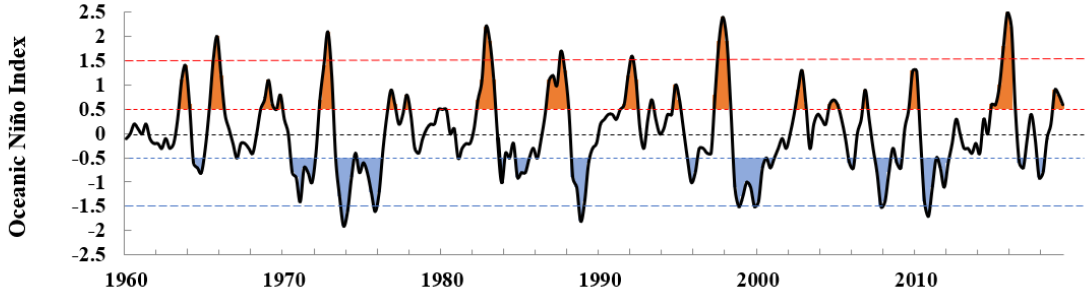


Figure 1 above shows the warm and cold anomalies. Values outside the ONI interval [–0.5°C, +0.5°C] are stippled to indicate El Niño and La Niña episodes, respectively. The areas shaded in red denote the warm anomalies which exceed the upper limit of the ONI interval [–0.5°C, +0.5°C] and denote the El Niño episodes. Similarly, the areas shaded in blue denote the cooler anomalies falling below the lower limit of the ONI interval [–0.5°C, +0.5°C] and thereby denoting the La Niña episodes.

3. Literature review

Several studies analyze the relationship between ENSO anomalies and agricultural commodity prices through the supply (production, transportation) and demand channels. Keppenne (1995) examines how soybean, corn and wheat futures contracts traded on the Chicago Mercantile Exchange are affected by ENSO conditions by applying a multichannel singular spectrum analysis approach. Using a time window of 48-months on the ENSO indicators and soybean prices, he identifies a link between ENSO and soybean prices. Using SOI for climate anomalies, he finds that soybean futures prices are more responsive to the La Niña events than to El Niño events. In the case of corn and wheat, no relationship is found. However, the study falls short of establishing a causal relationship. In a related study, Letson and McCullough (2001) revisit the ENSO-soybean price relationship using cash prices instead of futures, and SST instead of SOI for climate anomalies. Using the Granger causality test for short-run predictability, their findings show no causality between soybean cash prices and ENSO anomalies.

Brunner (2002) examined the ENSO effects on a group of primary commodity prices. Using a VAR model and employing data over a period spanning from 1963 to 1998, he considers the impact of ENSO separately on 30 non-oil primary commodity price indices, along with consumer price index and real GDP. He finds ENSO to account for around 20% of real commodity price fluctuations. This result indicates that the ENSO cycle has considerable explanatory power on the volatility of real commodity prices, in particular real food prices. Laosuthi and Selover (2007) conduct an analysis for 22 individual nations, with particular reference to developing countries which are most susceptible to extreme ENSO events. They employ SOI as the indicator of the magnitude of ENSO events and conduct correlation and Granger causality tests, finding evidence of El Niño effects on the prices of corn, coconuts, palm oil, rice and sorghum. In general, a positive correlation is found between climate anomalies and commodity price inflation. Chimeli et al. (2008) select the state of Ceará to represent a semi-arid region of Brazil, and study the impact of climate uncertainty on the corn market. Using SST to measure climate anomalies, they conduct a semi-parametric algorithm regression to forecast the quantity and prices of corn in the state of Ceará. Their results show that an increase in SST during the rainy season leads to a decrease in corn yields and a small positive impact on corn prices. Algieri (2014) quantifies the impact of ENSO on wheat prices by adopting a vector error correction model (VECM). The data includes monthly observations of the U.S. No. 1 hard red winter export prices, El Niño region 3.4 sea surface temperature (SST) anomalies index, and Southern Oscillation Index (SOI) over the sample period 1980 to 2012. He finds that adverse weather conditions caused by La Niña adversely impact wheat production and thereby raise wheat prices.

A string of influential studies by Ubilava (2012; 2013; 2017a; 2017b) has been carried out analyzing the ENSO-commodity price relationship. For example, Ubilava (2012) analyzes the ENSO-coffee price relationship by employing monthly price data for four different classes of coffee, being Columbian Mild Arabica, Other Mild Arabica, Brazilian Naturals, and Robusta. Using a smooth transition autoregression (STAR) framework, he finds that ENSO events affect coffee prices, and the relationship is asymmetric. In particular, Ubilava (2012) finds that the El Niño-Robusta coffee price relationship is positive but negative for ENSO-Arabica prices, while the opposite is true during the La Niña periods. In another related study, Ubilava and Holt (2013) assess the ENSO effects on world vegetable oil prices covering the period from January 1972 to December 2010. They adopt a smooth transition vector error correction (STVEC) model in the spirit of Rothman et al. (2001), which is a multivariate version of the STAR framework. They find that the responses of vegetable oil prices to ENSO shocks are different to the different ENSO phases. In another study, Ubilava (2013) revisits the fishmeal-soybean-meal price ratio and analyzes it in conjunction with the ENSO anomalies. Using a STAR modelling framework on a sample of monthly observations covering the period from 1982 to 2012, he finds regime-dependent behavior in the fishmeal-soybean-meal price ratio, with evidence of asymmetry. More recently, using more than three decades of monthly data, Ubilava (2017b) employs a vector smooth transition autoregression (VSTAR) approach to analyze the ENSO-price relationship in the world wheat market and concludes that wheat prices respond differently to the two extreme ENSO phases. He finds that wheat prices tend to drop after El Niño events and rise following La Niña shocks, and with more persistent price responses during La Niña conditions than El Niño conditions. La Niña negatively affects wheat production, which can deplete the international grain reserves, and prices spike in such a low-inventory regime (Algieri, 2014). These findings are in common with the conclusions of Iizumi et al. (2014), who report the differential price performance within two extreme phases of ENSO. In a more comprehensive study, Ubilava (2017a) estimates the impact of ENSO climate anomalies across an extensive list of primary commodity prices over the period 1980 to 2016. Employing the TV-STAR modelling framework due to Lundbergh et al. (2003), he notes that the ENSO events only affect selected prices and therefore depend largely on the type of commodities (e.g., some vegetable oils and protein meals respond most robustly to ENSO anomalies, while no effects of SST on grains). These mixed results are underscored by Iizumi et al. (2014), where they document the differences in averaged yield anomaly between El Niño (La Niña) years and neutral years, constructing the overall impacts of ENSO extreme episodes on global yields are uncertain. They also highlight the various reactions of the crop yields during El Niño and La Niña years, and the grain price variations across export regions.

On balance, the extant literature concludes a causal relation between climate anomalies and commodity prices. When focusing on selected grain prices, however, the evidence of causality on balance seems limited. According to the IPCC (2014), rainfall is changing in distribution and intensity as a result of climate anomalies. Farmers have to adapt to these changing conditions by adjusting the crop mix (McCarl and Hertel, 2018) and soybeans and corn is a case in point. The variability in agricultural commodity prices is well known, and we address this issue by reexamining the impact of climate anomalies on grain prices taking into account both changes in mean and variance. In section 5, we show that the variability of soybean prices is different to that of corn. Given that these two grains compete for acreage in the U.S., we make a conjecture that the interval-based analysis of the ENSO relation with corn and soybean prices is likely to be different, thereby leading to policy conclusions that need to be made based on the issue of the high-low range of corn and soybean prices. Besides, as discussed earlier, from a methodological perspective, the novel interval-based TARIX procedures are superior to the point-based STAR and TV-STAR models by allowing us to produce more efficient parameter estimates and statistical inferences for the ENSO-price relations, by exploiting the variability range of climate anomalies on agricultural prices and thereby avoiding undesirable noise in the high-frequency point-valued observations (see Sun et al., 2018). This is particularly useful if soybean prices are relatively more variable than corn. To our knowledge, this approach of interval time series estimation has not been applied in the context of climate anomalies and agricultural commodity prices, and we address this gap in the literature with specific relation to two competing grains in the U.S.

4. Threshold autoregressive interval framework

In this section, we begin by providing a brief description of the threshold autoregressive interval (TARI) proposed by Sun et al. (2018). We also describe the TARIX model, which is an extension of TARI that includes exogenous explanatory interval variables.

The TARI model can be described as follows:

$$Y_t = \begin{cases} \alpha_{01} + \alpha_{11} I_0 + \beta_{11} Y_{t-1} + \cdots + \beta_{p1} Y_{t-p} + \varepsilon_t, q_t \leq \gamma \\ \alpha_{02} + \alpha_{12} I_0 + \beta_{12} Y_{t-1} + \cdots + \beta_{p2} Y_{t-p} + \varepsilon_t, q_t > \gamma \end{cases} \quad (1)$$

where Y_t is the variable of interest, and $\{Y_t = [Y_{L,t}, Y_{R,t}]\}$ indicates a stochastic interval procedure with the lower bound $Y_{L,t}$ and the higher bound $Y_{R,t}$. β_{ji} are the unknown scalar-valued coefficients with j=1,…, p and i=1, 2. $I_0 = [-\frac{1}{2}, \frac{1}{2}]$ is the unit interval so that $\alpha_{0i} + \alpha_{1i} I_0 = [\alpha_{0i} - \frac{1}{2}\alpha_{1i}, \alpha_{0i} + \frac{1}{2}\alpha_{1i}]$ is a constant interval intercept. q_t is the threshold variable which could be endogenous or exogenous and γ denotes an unknown scalar-valued threshold indicator. $\varepsilon_t = [\varepsilon_{L,t}, \varepsilon_{R,t}]$ is the interval innovation. Sun et al. (2018) assume the interval innovation item ε_t as an interval martingale difference sequence (IMDS) with respect to the information set I_{t-1} so that almost surely $\mathbb{E}(\varepsilon_t | I_{t-1}) = [0, 0]$.

Alternatively, the equivalent expression of equation (1) could be written as

$$Y_t = X_t'\beta_1 I(q_t \le \gamma) + X_t'\beta_2 I(q_t > \gamma) + \varepsilon_t \tag{2}$$

where $X_t = ([1,1], \left[-\frac{1}{2}, \frac{1}{2}\right], Y_{t-1}, \ldots, Y_{t-p})'$, $\beta_i = (\alpha_{0i}, \alpha_{1i}, \beta_{1i}, \beta_{2i}, \ldots, \beta_{pi})' \in \mathbb{R}^{p+2}$, i=1, 2.

To utilize interval information to estimate the parameters and whether these coefficients are significantly different, Sun et al. (2018) define a minimum D_K-distance estimator $\hat{\theta}$ in their model. Let $\delta = \beta_2 - \beta_1$ represent the threshold effect. The idea of their solution is letting $\delta \to 0$ as $T \to \infty$. The equivalent expression of the equation (1) is

$$Y_t = X_t'\beta + X_t(\gamma)'\delta + \varepsilon_t \tag{3}$$

By incorporating exogenous explanatory interval variables, Sun et al. (2018) extend their TARI model to a TARIX model and the generalized form could be expressed as

$$Y_t = [\alpha_{01} + \beta_{01} I_0 + \sum_{j=1}^{p} \beta_{j1} Y_{t-j} + \sum_{l=0}^{s} \delta_{l1}^{s} A_{t-j}] I(q_t \le \gamma) + [\alpha_{02} + \beta_{02} I_0 +$$

$$\sum_{j=1}^{p} \beta_{j2} Y_{t-j} + \sum_{l=0}^{s} \delta_{l2}^{s} A_{t-j}] I(q_t > \gamma) + u_t \tag{4}$$

where $A_t = (A_{1t}, \ldots, A_{qt})'$ is the exogenous strictly stationary interval vector procedure and $\delta_{ji} = (\delta_{l1i}, \ldots, \delta_{lqi})'$, $l =$ 0,…, s and i=1, 2, which denotes an unknown point-valued parameter vector. The asymptotic theory for the TARIX model is similar to the TARI model (Sun *et al.*, 2018).

In this study, we apply the TARIX model to investigate the ENSO-grain price relations, which may be asymmetric to the warm and cold shocks from the climatic conditions. Furthermore, the variability in ENSO can have important effects on agricultural commodity price variability as emphasized by Madramootoo and Fyles (2012). Sun et al. (2019) introduced an interval-based Wald test for the TARIX model, which allows us to consider climatic anomalies and test for asymmetry.

Using the econometric framework of the TARIX model as shown by equation (4), we analyze the relationship between grain prices and the two ENSO extreme phases, El Niño and La Niña, respectively. Accordingly, the two-regime TARIX model in this study is constructed as follows:

$$P_t = \alpha_0 + \delta_0 I_0 + \delta_1 P_{t-1} + \delta_2 E_{t-1} I(O_{t-1} \leq -0.5) + \delta_3 E_{t-1} I(O_{t-1} \geq 0.5) + v_t \tag{5}$$

where $P_t = [P_{L,t}, P_{R,t}]$ is the quarterly logarithmic interval-valued agricultural commodity prices; $E_t = [E_{L,t}, E_{R,t}]$ is the interval-valued ENSO index (SST anomalies); and O_{t-1} is the seasonal point-valued ONI, chosen to rank the strength of the ENSO. In our model, ONI serves as the threshold parameter to recognize the climate pattern of the ENSO. If $O_t \leq -0.5$, this indicates La Niña conditions, whereas $O_t \geq 0.5$ indicates El Niño conditions; and if the value of ONI falls into the interval $[-0.5, 0.5]$ then it denotes a neutral episode (Royce et al., 2011).The unit interval is given as $I_0 = [-\frac{1}{2}, \frac{1}{2}]$ and $\alpha_0 + \delta_0 I_0 = [\alpha_0 - \frac{1}{2}\delta_0, \alpha_0 + \frac{1}{2}\delta_0]$ is a constant interval intercept. Here, the α_0 and δ_0 measures for the constant mark-up in the trend and volatility, respectively. In equation (5), $v_t = [v_{L,t}, v_{R,t}]$ is an interval innovation. Following Sun et al. (2018) it is assumed $\{v_t\}$ is an interval martingale difference sequence (IMDS) with respect to the information set I_{t-1}, and that $E(v_t \mid I_{t-1}) = [0,0]'$. The parameter δ_1 measures the lagged grain prices; δ_2 estimates the effect of La Niña conditions on the prices and δ_3 estimates the influence of El Niño on the prices. The interval is divided into two regimes in response to the La Niña phase, (i.e.$O_t \leq -0.5$) and El Niño phase, (i.e. $O_t \geq 0.5$) to capture asymmetric effects (if any) in both mean and range of prices. Note, as the entries of the ENSO index for La Niña events are negative and below -0.5, a negative coefficient estimate would suggest that La Niña conditions has a positive impact on grain prices.

The econometric framework employed allows us to test whether La Niña and El Niño events would affect grains prices. It is expected that warmer and cooler temperatures cause corn and soybean production to fall, and past studies suggest that both El Niño and La Niña events may increase grain prices through decreasing the grain yield. Therefore, we would expect $\delta_2 < 0$ and $\delta_3 > 0$, which implies that both the La Niña and El Niño events would increase soybean and corn prices. Conditional on finding evidence that both El Niño and La Niña events affect grain prices, we can make a further test to determine whether La Niña and El Niño events have an asymmetric effect on grain prices. It is plausible that corn price response can be different from soybean price response when faced with extreme weather anomalies. As discussed earlier, corn planting can be delayed in spring due to excess precipitation leading to increased soybean acreage, that could potentially depress soybean prices more relative to corn. Therefore, price adjustment in El Niño events could be different from the La Niña events. To test this type of asymmetry implies rejecting the null hypothesis, $H_0: |\delta_2| = |\delta_3|$.

5. Data and preliminary analysis

In this study, we choose the *Niño 3.4* index to represent ENSO, and to facilitate comparison, we employ the two different *Niño 3.4* SST anomalies, which are OISST and ERSST, in the empirical analysis for the comparison[6]. To delineate the warm (El Niño) and cold (La Niña) range of the ENSO cycle separately, we select the ONI has to serve as the threshold. The grain prices are the U.S. farm-gate prices of corn and soybean. We choose farm prices because of the direct impact climatic anomalies have on production and therefore the price received by growers. The farm-gate price data for soybean and corn are obtained from the online publications of the National Agricultural Statistical Service (NASS) of the United States Department of Agriculture (USDA). These are cash prices and represent the sales from producers to first buyers, including all grades and qualities. Considering the inflation effects, the nominal spot and cash prices are deflated applying the U.S. producer price index (PPI), which is reported by the U.S. Bureau of Labor Statistics. All the prices used in this study are quoted in U.S. dollars, and hereafter the analysis of data is carried out on logarithm of real grain prices.

To investigate the linkage between ENSO and agricultural commodity prices, we construct interval-valued quarterly prices from monthly data[7]. Considering the ENSO influences on rainfall take more time than at a monthly frequency, we choose quarterly frequency data to be appropriate, as it aligns with the climatic changes across seasons in a year. The quarterly interval-valued prices are formed by using the minimum and maximum monthly point-valued prices within a quarter. Thus, for each price series, the minimum and maximum monthly point-valued data form the lower and upper bounds, respectively. Due to the presence of negative values in ENSO indices, the quarterly interval-valued ENSO variables are constructed in the same way but using the minimum and maximum monthly point-valued data without taking logarithms.

Descriptive statistics of the soybean and corn prices are shown in Table 1 for two time periods where comparable data is available. The first sample data set starts from 1964 to 2019 and the second sample starts from 1982 to 2019. In Table 1, the descriptive statistics of the point-valued quarterly soybean and corn prices, including the quarterly prices, are denoted by $\text{Soybean}_{C,t}$ and $\text{Corn}_{C,t}$, respectively, and the interval-valued quarterly range is denoted $\text{Soybean}_{r,t}$ defined as ($\text{Soybean}_{r,t} = \text{Soybean}_{U,t} - \text{Soybean}_{L,t}$); similarly, $\text{Corn}_{r,t}$ defined as $(\text{Corn}_{r,t} = \text{Corn}_{U,t} - \text{Corn}_{L,t})$, where

[6] A complete list and detailed descriptions of ENSO indicators, ONI, along with the farm received commodity prices, are shown in Table A1 in the Appendix.

[7] The original data on *Niño 3.4* index from the NOAA and soybean and corn data from USDA are reported at a monthly frequency.

$\text{Soybean}_{U,t}$ (or $\text{Corn}_{U,t}$) and $\text{Soybean}_{L,t}$ (or $\text{Corn}_{L,t}$) are the monthly maximum and minimum prices within a quarter. Further, $\Delta\text{Soybean}_{L,t} = \text{Soybean}_{L,t} - \text{Soybean}_{C,t-1}$ (or $\Delta\text{Corn}_{L,t} = \text{Corn}_{L,t} - \text{Corn}_{C,t-1}$) and $\Delta\text{Soybean}_{U,t} = \text{Soybean}_{U,t} - \text{Soybean}_{C,t-1}$ (or $\Delta\text{Corn}_{U,t} = \text{Corn}_{U,t} - \text{Corn}_{C,t-1}$) denote the minimum and maximum quarter-to-quarter changes, respectively. The construction of these variables allows us to exploit the informational gain of the interval-valued methods over the point-valued methods, as underscored by Sun et al. (2018; 2019; 2021), by obtaining lower standard deviations for interval value estimates and therefore more precise estimates. Let us consider the case of the sample period 1964–2019 as an example. First, the intra-quarter fluctuation measured by the sample mean of the quarterly range $\text{Soybean}_{r,t}$ is about two and three times larger than the minimum and maximum quarter-to-quarter changes (that is, the sample average of $\Delta\text{Soybean}_{L,t}$ and $\Delta\text{Soybean}_{U,t}$), respectively. The same can be said for $\text{Corn}_{r,t}$. This implies interval-valued data captures the significant changes in both trend and volatility of the price process in a given quarter, thereby giving the interval-based estimates obtain a measure of information gain (Sun et al., 2018; 2019; 2021). Secondly, from Table 1, we see that the standard deviations of point-valued prices ranges are more than five times their ranges, which provides further evidence that interval-based values are likely to be more stable than point-based quarterly prices (Sun et al., 2021). Thirdly, the distributions of $\text{Soybean}_{r,t}$ and $\text{Corn}_{r,t}$ are significantly left-skewed with the skewness of 2.772 and 1.671, respectively, and the kurtosis of $\text{Soybean}_{r,t}$ and $\text{Corn}_{r,t}$ are high with values 13.017 and 6.665, respectively, showing that the interval time series have relatively higher skewness and being more leptokurtic than the point-valued processes. The series with excess kurtosis indicates that the increase in variance is caused by the extreme values, which are extremely higher or lower than the average values. The upshot is that the point-valued processes contain partial information in comparison to interval-valued processes which could capture the information about the extreme values, trend and volatility. Therefore, the interval-based model with an interval observation treated as an inseparable unit, is expected to exploit the information more efficiently than the point-based models (Sun et al., 2018; 2019; 2021).

In addition, greater absolute values of skewness and kurtosis imply that more extreme values exist in the sample period. In comparison to $\text{Corn}_{r,t}$, we find $\text{Soybean}_{r,t}$ is more skewed and leptokurtic. This suggests the soybean prices are more sensitive to an increase in variance caused by the more extreme values than corn prices. As an example, the value of the coefficient of variation (C.V.) for soybean prices is 1.014, while it is only 0.841 for corn prices, implying that variability is relatively higher in the case of soybean prices. As such, we may expect to obtain contrary results in the case of interval-based models when comparing soybean against corn. The descriptive statistics for the sample period 1982 – 2019 are similar and lead us to the same a priori expectations.

Table 1: Basic statistical analysis on interval-valued soybean and corn prices

	1964-2019								1982-2019							
	$\mathbf{Soybean}_{C,t}$	$\mathbf{Soybean}_{r,t}$	$\mathbf{DSoybean}_{L,t}$	$\mathbf{DSoybean}_{U,t}$	$\mathbf{Corn}_{C,t}$	$\mathbf{Corn}_{r,t}$	$\mathbf{DCorn}_{L,t}$	$\mathbf{DCorn}_{U,t}$	$\mathbf{Soybean}_{C,t}$	$\mathbf{Soybean}_{r,t}$	$\mathbf{DSoybean}_{L,t}$	$\mathbf{DSoybean}_{U,t}$	$\mathbf{Corn}_{C,t}$	$\mathbf{Corn}_{r,t}$	$\mathbf{DCorn}_{L,t}$	$\mathbf{DCorn}_{U,t}$
Mean	1.787	0.068	-0.038	0.029	0.868	0.063	-0.034	0.029	1.616	0.060	-0.034	0.026	0.688	0.062	-0.033	0.029
Median	1.761	0.044	-0.021	0.017	0.836	0.047	-0.011	0.029	1.761	0.044	-0.021	0.017	0.836	0.047	-0.011	0.029
Maximum	2.902	0.445	0.149	0.584	1.766	0.321	0.210	0.408	2.037	0.427	0.133	0.306	1.271	0.321	0.210	0.346
Minimum	1.157	0.001	-0.542	-0.301	0.111	0.000	-0.472	-0.351	1.157	0.001	-0.542	-0.237	0.111	0.002	-0.472	-0.351
Std. Dev.	0.324	0.069	0.100	0.106	0.350	0.053	0.105	0.100	0.212	0.056	0.088	0.086	0.252	0.052	0.108	0.103
Skewness	0.385	2.772	-1.631	1.046	0.180	1.671	-1.057	0.169	-0.207	2.794	-1.714	0.403	0.259	1.641	-1.119	-0.116
Kurtosis	3.133	13.017	8.232	7.479	2.331	6.665	5.011	4.744	2.556	15.022	9.448	3.882	2.675	6.788	5.500	4.360
C.V.		1.014				0.841				0.933				0.838		

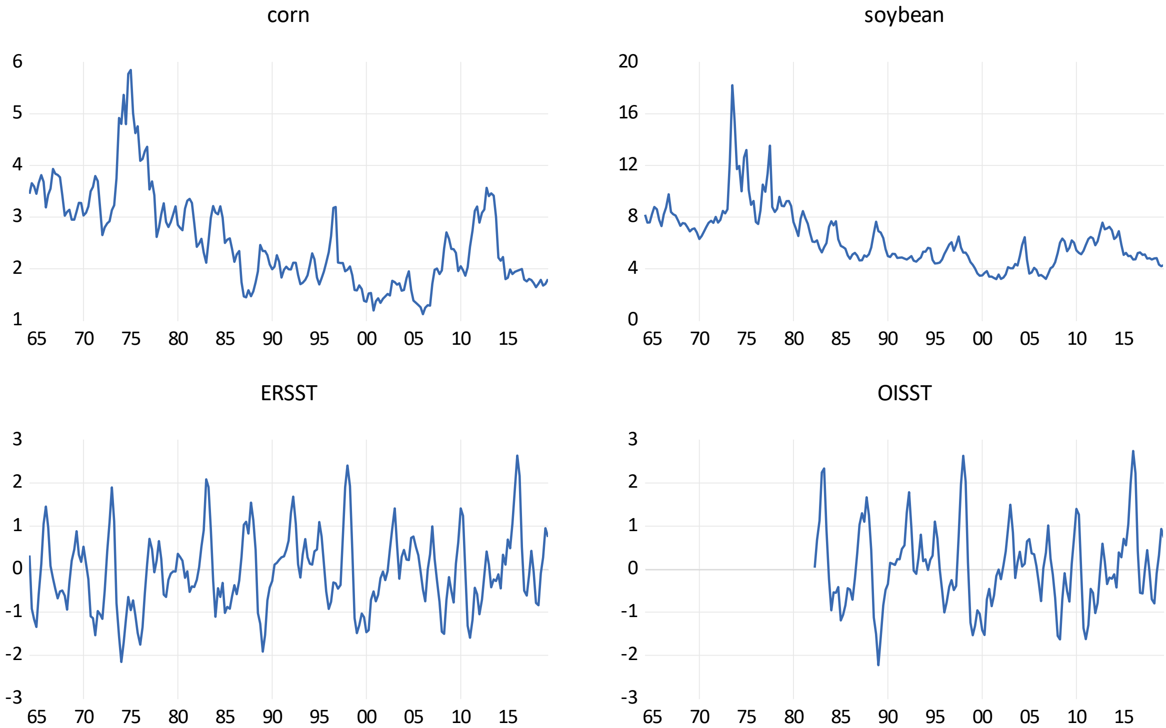
Notes: Since the data for OISST starts from 1982 and ERSST data starts from 1964, we carry out the basic statistics for corn and soybean prices using two different samples; from 1964 to 2019 and 1982 to 2019.

Table 2 reports the descriptive statistics of the *Niño 3.4* SST data used in this study. The ENSO measures include the OISST and ERSST. For both ENSO measures, the mean and standard deviation appear to be similar, as well as the coefficient of variation. The coefficient of variation for both ENSO measures is approximately around 67% which shows that variability is prominent. A plot of the variables is shown in Figure 2. It is clear that both corn and soybean prices tend to show a declining trend with a fair amount of variability. The large range in climate measures such as OISST and ERSST do not go unnoticed. It should be noted that the OISST measure starts from 1982, whereas the ERSST measure starts from 1964. The data endpoint is the second quarter of 2019.

Table 2: Basic statistics for lower-upper interval ranges of *Niño 3.4* SST anomalies index

	Mean	Min	Max	Std. Dev.	C.V.
OISST	0.411	0.020	1.710	0.275	0.669
ERSST	0.393	0.040	1.470	0.264	0.671

Figure 2: Time series plots of soybean prices, corn prices and ENSO measures



As a prelude to the TARIX estimation, we first determine the order of integration of the ENSO intensity measures and the price series examined in the study. To this end, we employ unit root tests which include the standard augmented Dickey-Fuller (ADF) test along with the relatively more powerful GLS detrended test due to Elliott et al. (1996) and the M-based tests of Ng and Perron (2001). Table 3 summarizes the unit root test results for all the variables.

Based on the battery of unit root tests, we can conclude that all ENSO indices reject the null hypothesis of a unit root, thus denoting that the ENSO indicators are integrated of order zero, or I(0). The unit root test results for the farm received corn and soybean prices show that using the standard ADF tests we cannot reject the unit root null for the lower bound soybean prices and the upper bound corn prices. However, some of these results are borderline non-rejections of the null. Bearing in mind that unit root tests are known to suffer from low power, we find that the more powerful unit root tests, due to Elliot et al. (1996) and Ng and Perron (2001) soundly reject for the upper and lower bound soybean and corn prices. Accordingly, the subsequent TARI modeling is carried out on the price levels of corn and soybean prices. The TARIX interval-based analysis is followed by the TAR point-based model to facilitate comparison between the two models.

Table 3: Unit root test on interval-valued variables

	ADF		ERS		MZa		MZt	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
OISST	-6.876***	-7.446***	-6.800***	-7.464***	-84.681***	-98.432***	-6.498***	-7.007***
ERSST	-8.256***	-8.511***	-8.261***	-6.969***	-122.281***	-84.102***	-7.805***	-6.484***
ONI	-9.137***		-7.637***		-103.185***		-7.182***	
Soybean (1982-2019)	-2.655*	-3.326**	-1.981**	-2.723**	-8.248**	-15.902**	-1.923*	-2.736***
Corn (1982-2019)	-3.304**	-3.195**	-2.145**	-2.578**	-9.034**	-13.306**	-2.079**	-2.560**
Soybean (1964-2019)	-3.165*	-3.134	-3.178**	-3.115**	-18.560**	-19.598**	-3.046**	-3.129**
Corn (1964-2019)	-2.834	-3.286*	-2.849*	-3.308**	-16.443*	-21.662**	-2.863*	-3.281**

Notes: This table presents a set of unit root test results for two ENSO indicators and the two grain prices, based on the interval time series sample information. The unit root test for the Oceanic Niño Index is based on the point time series sample information over two different time periods. ***, ** and * denote rejection of the null hypothesis of unit root process at the 1%, 5% and 10% significance level, respectively.

6. Empirical results and discussion

In this section, we employ both the *Niño 3.4* SST, that is, OISST and ERSST, to individually analyze the impact of climate anomalies on U.S. corn and soybean farm-gate prices. The results are displayed in Table 4 for the TARIX model. First, in the case of the OISST-soybean price relationship, we find we find no effect of La Niña on soybean prices as shown by the insignificant coefficient of δ_2 in the threshold regression (see the first column of results) but we do find El Niño effects on soybean prices given by the significant estimate of the δ_3 parameter. The results are consistent for the alternative ENSO measure, ERSST. Thus, we obtain a consistent result that La Niña has effects on soybean prices whereas we find no El Niño effects. We obtain the expected signs of the parameter estimates; that is, the sign of the δ_3 parameter is positive, indicating that warmer conditions would cause soybean prices to increase. The results also show that there is persistence in the prices as the parameter δ_1 is significant, and this is not unusual as it is well known that agricultural prices tend to be autocorrelated (Deaton, 1999). In the case of corn prices, the results are different. This time we find both El Niño and La Niña conditions have an effect on corn prices. The signs are as expected, that is, $\delta_2 < 0$, and $\delta_3 > 0$, in the sense they support the hypothesis that both warmer and cooler conditions have a positive impact on corn prices. The magnitudes of the parameter estimates look reasonably close and accordingly, we test to see if there is any asymmetry in the ENSO-corn price relationship. Given that both the parameters are significant, we test for asymmetry by using the null: $H_0: |\delta_2| = |\delta_3|$. Our results show that we cannot reject the null of symmetry given the high p-values, that is, $p > 0.10$, thereby concluding that these warmer and cooler climatic changes do not have a significantly different impact on corn prices.

Table 4: Estimation results of interval-based regression for soybean and corn cases

	ENSO-soybean prices		**ENSO-corn prices**	
	OISST	ERSST	OISST	ERSST
$\boldsymbol{\alpha_0}$	0.2317***	0.1342***	0.0859***	0.0516***
	(0.0000)	(0.0067)	(0.0007)	(0.0059)
$\boldsymbol{\delta_0}$	0.0083	0.0018	0.0123*	0.0060
	(0.2266)	(0.7618)	(0.0717)	(0.2666)
$\boldsymbol{\delta_1}$	0.8501***	0.9187***	0.8438***	0.9188***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{\delta_2}$	**-0.0108**	**-0.0007**	**-0.0432*** **	**-0.0313** **
	(0.4296)	**(0.9572)**	**(0.0098)**	**(0.0148)**
$\boldsymbol{\delta_3}$	**0.0142***	**0.0282** **	**0.0215***	**0.0237** **
	(0.0866)	**(0.0479)**	**(0.0768)**	**(0.0344)**
H0: $\boldsymbol{|\delta_2| = |\delta_3|}$	**0.0339**	**1.7084**	**0.8275**	**0.1516**
	(0.8539)	**(0.1912)**	**(0.3630)**	**(0.6970)**

Notes: This table reports the estimated results of the TARIX regression on *Niño 3.4* SST anomalies measures from OISST.v2 (1981-2010 base period) and ERSST.v5 (1981-2010 base period) dataset. The last row of results reports the asymmetry test statistics. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Values in brackets denote the corresponding p-values.

We can draw inferences from the empirical results that we obtain from the TARIX model. In the case of corn, La Niña conditions cause high temperatures and low precipitations that affect the moisture balance and thereby negatively impacts production (Phillips et al., 1999; Wannebo and Rosenzweig, 2003; Tack and Ubilava, 2013), which in turn exerts upward pressure on corn prices. During El Niño conditions, the excessive rainfalls lead to the delay of the corn planting and therefore impair the corn yields (Handler and Handler, 1983), and drive up corn prices. Our results show that we cannot find any asymmetry in relation to how corn prices respond separately to El Niño and La Niña phases, thereby concluding that these warmer and cooler climatic changes have no difference in terms of their impact on corn prices. Using the different climate anomaly measures, we find that our results are consistently leading to the same conclusions in general. The considerable range in climate anomalies have important implications for corn and soybean production because the ENSO-driven extremes could simultaneously create large-scale grain losses across a wide production area (e.g., Phillips et al., 1999, Adams et al., 1999, Tack and Ubilava, 2013) and the contraction of corn production can explain the increased corn prices[8]. In the case of soybean prices, we find they are only affected by El Niño events. The explanation of this finding can be drawn from the weather conditions or substitution demand due to Keppenne (1995) and Letson and McCullough (2001). For example, drier weather over the soybean plant area results in poor harvest, which reduces the supply and raises the prices (Letson and McCullough, 2001). Besides, warm conditions associated with the El Niño events hurt the fishing industry by decreasing the harvests of anchovy and tuna, thereby triggering a higher demand for fish-protein substitutes. This increasing demand exerts a positive impact on soybean prices which can be a fish-protein substitute for livestock feed (Keppenne, 1995). During the La Niña years, we do not find any effect on soybean prices and this could be attributed to the fishing conditions over the equatorial Pacific not being negatively affected by the La Niña shocks (Keppenne, 1995). Therefore, soybean prices are only responsive to El Niño events. Our use of interval estimates highlights the fact that the variability of the ENSO conditions as well as prices captures causal relations that depart from studies by Hansen et al. (1998) and Ubilava (2017a), who fail to find evidence of ENSO effects on cereal grain prices in general.

To facilitate a comparison with point-based data analysis, we compare and contrast the TARIX results with a TAR model, using point-valued data. As a prelude to the TAR model estimation, we carry out the necessary unit root tests on point-valued variables, which are shown in Table 5. We draw the same conclusion about the order of integration of the variables; all variables are found to reject the unit root null. Therefore, the following TAR analysis is conducted on the price levels of corn and soybean prices.

[8] The magnitude of the point estimates are slightly different, and this is not unusual as the sample size for OISST-corn/soybean price relationships is smaller than those of the ERSST-corn/soybean relations.

Table 5: Unit root test on point-valued variables

	ADF	ERS	MZa	MZt
OISST	-7.547***	-7.568***	-103.940***	-7.200***
ERSST	-8.933***	-8.221***	-117.652***	-7.666***
ONI	-9.137***	-7.637***	-103.185***	-7.182***
Soybean (1982-2019)	-2.529	-1.965**	-9.122**	-2.032**
Corn (1982-2019)	-3.103**	-2.498**	-14.890***	-2.700***
Soybean (1964-2019)	-2.920	-2.913**	-17.061*	-2.919**
Corn (1964-2019)	-3.236*	-3.253**	-24.165***	-3.470***

Notes: This table presents the unit root test results for ENSO indicators and selected cereal grain farm received prices, based on the point time series sample information. ***, ** and * denote rejection of the null hypothesis of unit root process at the 1%, 5% and 10% significance level, respectively.

Table 6 reports the results of the point-based regression. For all cases, the estimated coefficients δ_1 are significant, indicating the prices are autocorrelated, which is expected. In the case of soybean, there are no linkages found with ENSO as shown by the insignificant estimates of δ_2 and δ_3 implying that neither El Niño nor La Niña affects soybean prices. This result is in sharp contrast to the TARIX model where we find El Niño events to affect soybean prices.

Table 6: Estimation results of point-based regression for soybean and corn cases

	ENSO-soybean prices		**ENSO-corn prices**	
	OISST	ERSST	OISST	ERSST
$\boldsymbol{\alpha_0}$	0.1189 **	0.0619	0.0336	0.0195
	(0.0382)	(0.1643)	(0.2233)	(0.3067)
$\boldsymbol{\delta_1}$	0.9198 ***	0.9575 ***	0.9150 ***	0.9535 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{\delta_2}$	**-0.0150**	**-0.0086**	**-0.0524 ****	**-0.0347 ****
	(0.3516)	**(0.5076)**	**(0.0117)**	**(0.0159)**
$\boldsymbol{\delta_3}$	**0.0109**	**0.0297**	**0.0273 ****	**0.0277 ****
	(0.2399)	**(0.1119)**	**(0.0360)**	**(0.0291)**

Notes: This table reports the estimated results of the TAR regression on *Niño 3.4* SST anomalies measures ERSST.v5 (1981-2010 base period) and ERSSTv5 (centered base period) datasets. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Values in brackets denote the corresponding p-values.

However, in the case of corn, we find both El Niño and La Niña are found to affect the corn prices given the significant estimates of δ_2 and δ_3 which also have the correct signs. Therefore, in the case of corn, we get similar results, but a different result for soybean. The difference in results for soybean underscores the observation we made earlier that the relatively more extreme values and higher variances in soybean prices compared to corn, could affect the relationship the prices have with climate anomalies.

We find evidence that the interval-based model utilizes the information contained in the interval time series and delivers a more accurate inference than point-valued models. The presence of extreme values and higher variances in soybean prices compared to corn prices can inform us that interval-based time-series estimations are necessary to obtain the correct inference when analyzing climate-induced grain price fluctuations, especially when it is known that agricultural prices are known to be variable. This information would be of use to farmers, policymakers and investors when anticipating the effect of climate anomalies on grains that compete for acreage and are therefore strongly linked.

7. Conclusion

Climate change has been dominating the headlines and, in this light, a great deal of attention has been paid to the issues of global climate variability on grain prices. We exploit this variability, not just climatic anomalies but also the variability in grain prices. We argue that using global climate anomalies, the extreme episodes of the ENSO strongly affect the temperature and precipitation, which motivates and the need to understand its effect on agricultural prices by examining interval time series data – a concept that, to our knowledge, is the first to study the link between climate anomalies and agricultural prices. To this end, the newly proposed interval-based threshold method is employed to examine the ENSO-grain price relationship. Following the extant literature, we allow for nonlinearities, and we exploit the interval-based estimation to examine the relation using both the mean and volatility of the variables simultaneously. The TARIX model delivers an appropriate modeling procedure that allows us to compare two different ENSO measures and their relation with two grain prices - soybean and corn. The key findings are that only La Niña has an effect on soybean prices, whereas both El Niño and La Niña is found to affect the corn prices; further, there is no significantly different response of corn prices from El Niño and La Niña conditions.

The results have important policy implications in the context of corn and soybeans. The results are useful as they help inform in relation to farm risk management and planning crop plantation. The rotation strategy for corn and soybean can be adjusted in light of the information we obtain on climate change (Tack and Ubilava, 2013). Given that our results report that soybean prices are affected by El Niño events only, strategies of land allocation to the preferable crops could be planned in advance to hedge against climate risks and improve the economic returns during different phases of ENSO. Unfortunately, the ability to forecast prices is limited. Future work on the predictions based on interval-valued forecasts could be an avenue for added research an area for future research. Furthermore, it is helpful to investigate the interaction between ENSO shocks and cereal grain prices from the regional perspective because of the spatial heterogeneity of ENSO effects following Phillips et al. (1999) and Tack and Ubilava (2013).

It has been argued that as food demand increases with a growing population and changing dietary preferences, an increase in the demand for water usage will occur placing a strain on global freshwater resources (Mekonnen et al. 2020). Irrigation consumes vast amounts of water and farmers of soybean and corn are likely to face tougher constraints in water usage. Since climate anomalies can affect corn and soybean yield and therefore prices, the results we obtain can inform policymakers about water usage. For example, rain-fed and irrigated crop yields can both be affected by climate change, however, there would be more impact on the rainfed crop, especially in the case of drought, as water availability is more stable in the case of irrigation (Mekonnen et al. 2020). Corn has become more drought-tolerant since the 1980s compared to soybeans in terms of the absolute number of loss of corn in bushels (Yu and Babcock, 2010). A policy recommendation may be that the crop insurance and Risk Management Agency of the USDA may want to factor in the variability of climate change on corn and soybean prices noting the different impact that climate anomalies can have on the two competing crops. In addition, our findings also have interesting implications in relation to the prioritizing of R&D investments to adapt to future climate anomalies. As climate anomalies lead to reduced production and increased prices, adaptation strategies including changing planting dates and designing rotation plans, along with R&D investments in seed developments should be understood. For example, as further understanding between the ENSO-grain price linkages is uncovered, farmers can adjust the cultivar selection to reduce the risks or take advantage of favorable conditions (Hansen et al., 1998). In the U.S., the predominance of subsidized crop insurance partly leads to the recent efforts on seed breeding are not focus on reducing heat and drought sensitivity (Cui, 2020). By documenting the increased prices due to the nationwide reductions in corn and soybean productions under the extreme ENSO conditions, we suggest the seed development should be focused on maintaining the productions and prices under the extreme climate variations.

Although this study offers important insights in disentangling supply and demand-side channels through which ENSO may affect price movements, there are limitations to this study that can be overcome with further research. Our analysis concentrates on the reduced-form relationship between climate anomalies on soybean and corn prices, while other economic and technological factors that can affect agricultural commodity prices are excluded to keep the model simple. As climate anomalies are becoming prominent over time (McCarl and Hertel, 2018) and farmers are already adapting to changing conditions, such as crop mix and planting dates, further research needs to take into account the variability of climate on grain prices and the results of this paper would help broaden the avenues of future research into this area.

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Appendix

Table A1: Description of the ENSO indicators, threshold variable and commodity prices

Variable		Description	Time range
ENSO indicators	OISST.v2	(1981-2010 base period) *Niño 3.4* (5°North-5°South) (170-120°West)	1982:01-2019:06
	ERSST.v5	(1981-2010 base period) *Niño 3.4* (5°North-5°South) (170-120°West)	1964:01-2019:06
Threshold variable	Oceanic Niño Index	3-month running average in *Niño 3.4* (5°North-5°South) (170-120°West)	1964:01-2019:06
Farm received prices	Soybean Corn	national-level season-average price received by farmers($/bu)	1964:01-2019:06

Notes: This table lists the description and time range of the raw data collected from the Climate Prediction Center (CPC) at the National Oceanic and Atmospheric Administration (NOAA) and National Agricultural Statistical Service (NASS) of the United States Department of Agriculture (USDA).