Investigating Integration and Exchange Rate Pass-Through in World Maize Markets Using Post-Selection Inference

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Abstract

This paper investigates the extent of market integration and exchange rate pass-through but also those market factors that may be associated with deviations from perfect market integration and pass-through. To address the shortcomings of existing models of spatial market integration, we adopt an approach towards inference and model selection using the desparsified LASSO method for high-dimensional threshold regression. Our results support the integration of global corn markets, especially when the existence of thresholds is accounted for. We identify important relationships between several variables representing domestic and world economic conditions.

Keywords: Law of One Price, Threshold Regression Model, Exchange Rate

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Pass-Through

1 Introduction

Efficient markets are expected to eliminate any potential for riskless profits through arbitrage and trade, known as the "Law of One Price" (LOP). Economic arbitrage relies on the principle that prices of related goods should move together. The general implication here is that prices for homogeneous products at different geographic locations in otherwise freely functioning markets should differ by no more than transport and transactions costs. However, the existence of transactions costs can introduce a threshold effect, where deviations in prices above a certain threshold are necessary to trigger price movements. In recent years, studies analyzing this phenomenon have focused on developing nonlinear models that can better capture the effects of unobservable transaction costs in spatial price linkages. The motivation behind using such models is to better understand the dynamics of market integration and the role of transaction costs in the presence of regime changes. The use of nonlinear models has been largely driven by the application of threshold modeling techniques. These models are based on the idea that transaction costs and other barriers to spatial trade may lead to regime switching, with alternative regimes representing the trade and no-trade equilibria. This idea has been operationalized through various econometric techniques and model specifications.

Threshold autoregression (TAR) models have indeed had a significant impact on the analysis of asymmetric price transmission in agricultural economics. These models have been developed to capture the nonlinear dynamics of market integration and account for the effects of unobserved transaction costs that can affect spatial price linkages. A common approach to threshold modeling often involves an autoregressive model of the price differential. The study conducted by Goodwin and Piggott (2001) examined corn prices at local markets by combining a threshold structure with an error-correction model. Goodwin et al. (1990) noted that delivery lags that extend beyond a single time period may imply arbitrage conditions that involve noncontemporaneous price linkages. Based on this idea, Lence et al. (2018) examined the performance of the threshold cointegration approach, specifically Band-TVECM, in analyzing price transmission in an explicit context where trade decisions are made based on the expectation of final prices because trade takes time. In addition to the threshold model, Goodwin et al. (2021) applied generalized additive models to empirical considerations of price transmission and spatial market integration.

Although exchange-rate pass-through, i.e. the degree to which exchange rate movements are reflected in prices has long been a question of interest in international economics, there is limited literature that examines exchange-rate pass-through in global agricultural commodity markets. One study by Varangis and Duncan (1993) uses an econometric model of the wheat, corn, and soybean markets to investigate the dynamic effects of exchange rate fluctuations on U.S. commodity markets. The study finds that exchange rate fluctuations have a significant real impact on agricultural markets, particularly on the volume of exports and the relative split between exports and domestic use of these commodities. The econometric model developed in the study shows that agricultural prices are sensitive to movements in the exchange rate, with short-run adjustments being more dramatic than longer-run adjustments.Chambers and Just (1981) found that the extent to which changes in exchange rates affect import prices. The paper presents an imperfect competition model to estimate the impact of changes in the yen/dollar exchange rate and other factors on US and Japanese steel prices. The results show that such exchange rate changes have a less than fully passed-through effect on steel prices, as indicated by the imperfect competition model used in the study.

International trade in basic commodities is generally invoiced in US dollar terms. At first glance, this may seem to imply that exchange rates are irrelevant to market linkages. However, assuming that the commodities are valued in local currencies after being imported suggests that exchange rates may still be relevant to price linkages. We discuss this point in greater detail below.

Barrett and Li (2002) examine actual trade flows as a factor for assessing spatial market integration. They note that empirical tests should differentiate between the notions of spatial market integration and a competitive market equilibrium. The latter concept refers to market conditions where no trade occurs because arbitrage conditions do not provide opportunities for profitable trading. The authors highlight that prices in two segmented markets might react to exogenous factors like inflation or climatic conditions without representing a spatial equilibrium in markets. A recent overview from the World Bank Rebello (2020) addresses the factors influencing spatial market integration. The overview mentions the cooperation among policymakers on matters such as trade and investment policies, migration, transportation infrastructure, macroeconomic policy, natural resource policy, and others related to "shared sovereignty." Furthermore, the overview highlights the critical role of regional integration in policy reforms, contributing significantly to overall peace and security.

The integration of world markets for grains and oilseeds has been of interest for many years. In recent years, the global maize market has been dominated by major exporters such as the United States, Argentina, and Ukraine, which have consistently ranked among the top maize producers and exporters worldwide. The US, the largest producer, alone accounts for over one-third of global maize exports. Argentina and Ukraine collectively accounting for over one-fourth of global maize exports. The dominance of these countries in the global maize market is representative of the market and makes them candidates for studying price transmission and market integration. They play a crucial role in global maize prices and influencing maize markets worldwide. Likewise, the extent to which distortions arise due to incomplete pass-through of exchange rate shocks has been an important indicator of the overall functions of markets.

In addition to prices and exchange rates, other market factors can be conceptually related to market linkages, such as aggregate economic indicators like industrial production, trade policies, and exogenous shocks, such as the recent pandemic, interest rates, and nominal inflation rates in each market. These factors may be associated with deviations from perfect market integration, as they can affect the costs of transportation, communication, and transactions between markets, as well as the demand and supply conditions in each market. Understanding the effects of these market factors on price linkages is essential for policymakers and market participants to make informed decisions about trade, investment, and risk management.

In this paper, we discuss an approach that considers many potential market factors in representing the nonlinearities that may characterize price linkages over the regional distinct markets. Specifically, we apply a high dimensional threshold model to examine the effect of exchange rates and market factors on price linkages among spatially distinct world maize markets. Such an application is a natural methodological extension of existing empirical studies on spatial market integration models.

LASSO (least absolute shrinkage and selection operator) is a regression technique that uses shrinkage methods for variable selection. LASSO employs L1 regularization and shrinkage techniques to penalize the model based on the absolute value of parameter estimates. It is a valid approach for identifying an optimal model specification by selecting the variables that contribute the most to explaining a regression-type relationship. Although LASSO models have been widely used in economics studies, the shrinkage bias introduced due to the penalization in the LASSO loss function can affect the properly scaled limiting distribution of the LASSO estimator. Therefore, to conduct valid statistical inference, we need to remove this bias. This paper uses the desparsified (debaised) LASSO (least absolute shrinkage and selection operator) method for high dimensional threshold regression, recently developed by Yan and Caner (2022) to model the nonlinearity in the spatial price integration models.The fact is that existing literature on price transmission and exchange rate pass-through has developed from simple regression models to nonlinear specifications that allow differential impacts on price linkages. These differential effects are often identified using smooth or discrete threshold models.

2 Econometrics Models of Spatial Market Integration

Spatial market integration in agricultural product markets has been extensively studied in the literature. Consider a commodity traded in common currency in two regional or international markets represented by location indices j and k. The individual market prices are denoted by P^j and P^k, respectively. The arbitrage condition of perfect market integration reflects the equation $P_t^j/P_t^k = 1$, abstracting from trade and transportation costs. This condition has been adjusted to account for the wedge between prices due to transaction or transportation costs, which may differ significantly in regional markets. The general representation for this adjusted arbitrage condition is $1/(1-\kappa) \leq P_t^j/P_t^k \leq 1-\kappa$, where κ represents the proportional loss in commodity value due to transaction or transportation costs ($0 < \kappa < 1$). The greater the distance between locations j and k, the closer κ is to one. It should be noted that a number of factors may be relevant to price differences across markets. Most existing studies have only considered simple price relationships. An important distinction exists between transportation and transactions costs, which include transport costs as well as other factors that contribute to price differences. These factors could include variables associated with economic and trade policies, product characteristics, and risk.

Many spatial economic models utilize the iceberg trade cost proposed by Samuelson (1954), which assumes that part of the produced output representing the material costs of transportation melts away during transportation. That is, after taking natural logarithms and denoting $p_t^j = \ln P_t^j$, the inequality is often presented as

$$|p_t^j - p_t^k| \leq \ln(1-\kappa). \tag{2.1}$$

The inequality (2.1) is generally considered to reflect two distinct states of the market. The first state corresponds to a condition where there is no profitable trading, with $|p_t^1 - p_t^2| \leq \ln(1-\kappa)$. Under conditions of trade or profitable arbitrage opportunities, the condition holds as $|p_t^j - p_t^k| > \ln(1-\kappa)$. The speed at which the market adjusts to such deviations from the arbitrage equilibrium is often used as a measure of the degree of market integration. Typically, these discrete arbitrage and no-arbitrage conditions are represented using threshold models, where the threshold represents an empirical measure of the transaction cost, $\ln(1-\kappa)$. Bidirectional trade models may allow for different thresholds depending on which market price is higher.

Over time, log price differentials within the band limits are expected to follow a unit root process. Conversely, log price differences outside the band are expected to be mean-reverting, which suggests the existence of a transactions cost band, as assumed in the literature.

A wide literature has examined spatial market integration in world markets for agricultural commodities. Likewise, a large related literature has examined how shocks to exchange rates affect domestic and export prices, a phenomenon known as 'pass-through'. If a shock to exchange rates is fully reflected in adjustments to prices, the shock is considered to have been fully passed through. Most empirical studies of market integration and exchange rate pass-through assume a linear relationship, as represented by

$$p_t^j = \alpha + \beta p_t^k + \gamma_2 \pi_t^{jk} + \varepsilon_t, \tag{2.2}$$

where p_t^j is the price in market j in time period t and π_t^{jk} is the exchange rate between currencies in markets j and k, all in logarithmic terms.

Perfect integration is implied if $\alpha = 0$ and $\beta = 1$. In cases where prices are invoiced in different currencies, perfect integration also requires perfect exchange rate pass-through, which is implied if $\gamma_2 = 1$. If prices are invoiced in a common currency, as is often the case when trade is conducted in US dollar terms, the exchange rate is 1 and thus the logarithmic value of zero eliminates the exchange rate effect[1]. However, it is possible that exchange rate distortions may still affect price linkages, which is implied if $\gamma_2 \neq 0$, even if prices are quoted in a common currency.

It is also essential to consider the market factors associated with deviations from perfect integration. To this end, we consider an alternative version of equation (2.2) that is expressed as:

$$p_t^j - p_t^k = \gamma_2 \pi_t^{jk} + \gamma_3 Z_t^{jk} + \varepsilon_t, \tag{2.3}$$

where Z_t^{jk} is a set of factors that may be conceptually relevant to price linkage, γ_3 is a vector of parameters corresponding to Z_t^{jk}. These factors include exogenous shocks such as exchange rates, interest rates, unemployment rates, and nominal inflation rates in each of the markets.

To further analyze spatial price linkages, we evaluate deviations from a price parity condition, considering threshold effects of price differentials and isolated shocks in spatially distinct markets. In addition to the conventional specification, we propose an extension to this framework of spatial market integration that includes two regimes. One regime represents a case of no trade, while another represents conditions of profitable trade and arbitrage. The regime switch depends on a forcing variable,

[1] If we define π_t^{jk} as the exchange rate of 1 unit of currency in market j to the currency in market k, a value of $\gamma_2 = -1$ represents perfect exchange rate pass-through.

usually a lagged price differential, expressed as:

(2.4)

$$\begin{aligned}\Delta(p_t^j - p_t^k) =& \gamma_0 + \gamma_1(p_{t-1}^k - p_{t-1}^k) + \gamma_2\Delta\pi_t^{jk} + \gamma_3\Delta Z_t^{jk} \\ &+ \mathbf{1}\{|p_{t-1}^j - p_{t-1}^k| \geq c\}(\delta_0 + \delta_1(p_{t-1}^j - p_{t-1}^k) + \delta_2\Delta\pi_t^{jk} + \delta_3\Delta Z_t^{jk}) + \varepsilon_t,\end{aligned}$$

where γ_0 and δ_0 are time trend coefficients if we add a time trend to equation (2.3). γ_0, γ_1, δ_0, and δ_1 are parameters reflecting the degree of market integration. In particular, γ_1 and δ_1 represent the degree of 'error correction' characterizing departures from price parity, which are reflected in large values of $p_{t-1}^j - p_{t-1}^k$. The threshold parameter c represents the amount of proportional transaction costs that a price differential must exceed to cross the threshold and trigger the "trade" regime adjustments. We allow δ_0, δ_1,δ_2 and δ_3 to nonzero according to whether $|p_{t-1}^j - p_{t-1}^k|$ is within (i.e., $|p_{t-1}^j - p_{t-1}^k| < c$) or outside (i.e., $|p_{t-1}^j - p_{t-1}^k| \geq c$) of a symmetric band

Differencing is employed in this study to measure short-run relationships between variables. The first-difference model is utilized to avoid nonstationary variables, allowing a focus on immediate changes between variables. While differencing proves invaluable in capturing short-run dynamics, it is essential to recognize its limitation in terms of potentially losing long-run information.

To assess the potential presence of transaction costs, we consider a multivariate threshold distributed lag model that includes the price differential, exchange rate, and exogenous shocks as well as their lagged (past period) values, as follows:

(2.5)

$$\begin{aligned}\Delta(p_t^j - p_t^k) =& \gamma_0 + \gamma_1(p_{t-1}^j - p_{t-1}^k) + \sum_{l=0}^{L}\gamma_{2l}\Delta\pi_{t-l}^{jk} + \sum_{l=0}^{L}\gamma_{3l}\Delta z_{t-l}^{jk} \\ &+ \mathbf{1}\{Q_t \geq c\}\left[\delta_0 + \delta_1(p_{t-1}^j - p_{t-1}^k) + \sum_{l=0}^{L}\delta_{2l}\Delta\pi_{t-l}^{jk} + \sum_{l=0}^{L}\delta_{3l}\Delta z_{t-l}^{jk}\right] + \varepsilon_t \\ & t = \{1, \ldots, T\},\end{aligned}$$

where L is the maximum possible lag, which may increase with the sample size (i.e., slowly grow to infinity), and Q_t is the lagged price differential used as the forcing variable to identify the thresholds, i.e., $Q_t \in \{p_{t-1}^j - p_{t-1}^k, \cdots, p_{t-L}^j - p_{t-L}^k\}$. We assume that the maximal lag order L is known. A distributed lag model (Almon (1965)) is utilized to reveal both short- and long-run dynamic effects between explanatory variables and response variables. Additionally, we employ LASSO, a flexible and supervised learning method. When dealing with time-lagged relationships, selecting the appropriate lag length is crucial in time series modeling. Typically, a well-defined lag length is chosen, and all lags up to that period are included in the model. However, in contexts like ours, where we investigate the dynamic relationship between price linkages, exchange rates, and market factors in agricultural commodities, the delivery time from one market to another spans several weeks to months. Consequently, not all lags are considered equally important in capturing price linkages in response to market shocks. In such scenarios, a distributed lag model (DLM) with lag selection, facilitated by LASSO, proves to be more suitable. LASSO's ability to determine distributed lags through a data-driven search enables a more precise representation of dynamic relationships in agricultural commodity markets. This framework offers a richer evaluation of price dynamics and patterns of adjustment.

Economic agents adjust their expectations of price differentials based on the level of transaction costs observed in previous periods. If the transaction costs (i.e., price differentials) exceed certain thresholds, agents anticipate larger effects when transaction costs are high. This implies that agents perceive an increase in transaction costs beyond the threshold to have a more prominent impact in the presence of high price differentials. The specified model offers the advantage of capturing simultaneous relationships between exchange rates and other variables. Linear modeling techniques may not accurately capture the nonlinearities present in the model. Therefore, it is essential to investigate the impact of transaction costs on the market's response to an exchange rate shock or other market shocks nonlinearly. The existence of different levels of transaction costs can influence how price differentials respond to exchange rates or other shocks, as it determines the presence or absence of arbitrage opportunities. The proposed model recognizes that the movements in the exchange rate can adjust how markets respond to changes, leading to different regimes based on transaction costs. By considering the effects of transaction costs, we can gain a more comprehensive understanding of the dynamics of the exchange rate pass-through mechanism and the effect of market factors.

The lag coefficients γ_s for $s = 1, \cdots L$ represent the lag distribution and define the pattern of how $\Delta\pi_{t-s}$ or Δz_{t-s} affects $\Delta(p_t^1 - p_t^2)$over time. The dynamic marginal effect of $\Delta\pi_t$ at the s-th lag is $\frac{\partial\Delta(p_t^j - p_t^k)}{\partial\Delta\pi_{t-s}} = \gamma_{1s}$. The dynamic marginal effect of $\Delta\pi_{t-s}^{jk}$ on $\Delta(p_t^j - p_t^k)$ at the s-th lag is given by $\frac{\partial\Delta(p_t^j - p_t^k)}{\partial\Delta\pi_{t-s}^{jk}} = \gamma_{1s}$. The dynamic marginal effect is essentially an effect of a temporary change in $\Delta\pi_{t-s}^{jk}$ on $\Delta(p_t^j - p_t^k)$, whereas the long-run cumulative effect $\sum_{s=1}^{L}\gamma_{1s}$ measures how much $\Delta(p_t^j - p_t^k)$ will be changed in response to a permanent change in $\Delta\pi$ when both$\Delta\pi_t$ and $\Delta(p_t^j - p_t^k)$ are stationary. The same derivation can be applied to any element of the vector Δz_{t-s}^{jk}. In the context of the threshold regression model considered here, γ_{1s} and γ_{2s} represent the effect regardless of the status of the forcing variable Q_t, termed the structural effect. On the other hand, δ_{1s}^{jk} and δ_{2s}^{jk} represent the effect when $Q_t > c$, referred to as the threshold effect.

To obtain a specification that incorporates a broad range of variables in (2.5), we utilize a novel approach to inference and model selection: the desparsified LASSO (least absolute shrinkage and selection operator) method for high-dimensional threshold regression, which was recently developed by Yan and Caner (2022). This method allows us to fit the threshold regression models using the threshold LASSO estimator of Lee et al. (2016) in conjunction with the work of van de Geer et al. (2014). Compared to other estimators, this approach can construct asymptotically valid confidence bands for a low-dimensional subset of a high-dimensional parameter vector. Understanding the significance of the estimators can provide insights into the changes in transaction costs and threshold effects over time. However, standard approaches to inference are not applicable to such models.

To simplify, let

$$\alpha = (\gamma_0, \gamma_1, \gamma_{20}\cdots, \gamma_{2L}, \gamma_{30}\cdots, \gamma_{3L}, \delta_0, \delta_1, \delta_{20}\cdots, \delta_{2L}, \delta_{30}\cdots, \delta_{3L})'$$

be slope parameter vector, The dimension of α is $4 + 2(1+p)(L+1)$, where p is number of other exogenous shocks. Let $\mathbf{X}$ be a $T \times [2 + (1+p)(L+1)]$ matrix of all regressors. To provide a more precise description of our estimation procedures, we propose a three-step estimation approach for the model. The three-step procedure can be outlined as follows:

Step 1.

For each $c \in \mathbb{C}$, $\widehat{\alpha}(c)$ is defined as

(2.6)

$$\widehat{\alpha}(c) := \text{argmin}_{\alpha} \left\{ T^{-1} \sum_{t=1}^{T} \left(\Delta(p_t^j - p_t^k) - [X_t', X_t' \mathbf{1}\{Q_t \geq c\}]' \alpha \right)^2 + \lambda \left\| \mathbf{D}(c)\alpha \right\|_1 \right\},$$

where we can rewrite the ℓ_1 penalty as

$$\lambda \left| \mathbf{D}(c)\alpha \right| 1 = \lambda \sum j = 1^{2+(1+p)(L+1)} \left[\left\| X^{(j)} \right\|_n \left| \alpha^{(j)} \right| + \left\| X^{(j)}(\tau) \right\|_n \left| \alpha^{(1+(1+p)(L+1)+j)} \right| \right],$$

in order to adjust the penalty differently for each coefficient, depending on the scale normalizing factor.

Define $\widehat{c}$ as the estimate of c_0 such that:

(2.7)

$$\widehat{c} := \text{argmin}_{c \in \mathbb{C} \subset \mathbb{R}} \left\{ T^{-1} \sum_{t=1}^{T} \left(\Delta(p_t^1 - p_t^2) - [X_t', X_t' \mathbf{1}\{Q_t \geq c\}]' \widehat{\alpha}(c) \right)^2 + \lambda \left\| \widehat{\alpha}(c) \right\|_1 \right\}.$$

In accordance with Yan and Caner (2022), we next turn to variable selection by means of thresholding. We follow sharp threshold detection techniques provided by Callot et al. (2017) to finding out whether there is a threshold or not, that is, whether

$$(\delta_0, \delta_1, \delta_{20} \cdots, \delta_{2L}, \delta_{30} \cdots, \delta_{3L})'$$

is nonzero or not.

Step 2. We define the thresholded Lasso estimator as

$$\tilde{\delta}_{(j)}(\widehat{c}) = \begin{cases} \widehat{\delta}_{(j)}(\widehat{c}), & \text{if } |\widehat{\delta}_{(j)}(\widehat{c})| \geq H, \\ 0, & \text{if } |\widehat{\delta}_{(j)}(\widehat{c})| < H. \end{cases} \tag{2.8}$$

where H is the threshold determining whether a coefficient should be classified as zero or nonzero and $\widehat{\delta}^{(j)}(\widehat{c})$ are elements of the Lasso estimator defined by (2.6) and (2.7) jointly. In particular, we shall see that choosing $H = 2D\lambda$ yields consistent model selection. The thresholding parameter D can be selected using the Bayesian Information Criterion (BIC) through grid search. This ensures that parameters smaller (in absolute value) than $\widehat{D}\widehat{\lambda}$ are set to zero by the thresholded Lasso.

The thresholded Lasso in (2.8) can achieve threshold selection consistency. The consistency of the LASSO estimator implies that if the underlying true model is nonlinear, then the LASSO estimator will correctly estimate any of the non-zero parameters, including $(\delta_0, \delta_1, \delta_{20}, \cdots, \delta_{2L}, \delta_{30}, \cdots, \delta_{3L})$. In other words, if any of these parameters are non-zero, the LASSO estimator will consistently estimate them as non-zero, indicating the presence of a nonlinear relationship between the variables. This is in contrast to the conventional 'self-exciting' threshold autoregressive (SETAR) model, where nonlinear tests such as Hansen's modification of standard Chow-type tests, Tsay (1989) linearity test, or neural network tests of linearity are utilized to detect nonlinearity. Therefore, if we misspecify a linear model and use the LASSO method for the threshold model described here, we may estimate all threshold effects as zero for a sufficiently large sample size. To put it another way, if our estimates of $(\delta_0, \delta_1, \delta_{20}, \cdots, \delta_{2L}, \delta_{30}, \cdots, \delta_{3L})$ after steps 1 and 2 have at least one non-zero, it indicates that the probability of the model being linear approaches 0.

Once variables are selected through LASSO estimation and the presence of threshold effects is confirmed, the shrinkage bias induced by penalization in the LASSO loss function becomes evident in the properly scaled limiting distribution of the LASSO estimator. Therefore, to enable statistical inference, an estimation strategy must be employed to eliminate this bias. However, when modeling threshold regression with a rich set of variables, a challenge emerges. Threshold models entail splitting the sample based on a continuously-distributed variable. With a rich set of regressors, there's a risk that the number of observations in any split sample may be less than the number of variables, leading to a reduced-rank sample covariance matrix. Standard approaches are inadequate in such a situation. To desparsify (debias) our LASSO estimator, an approximate inverse of a certain singular sample covariance matrix is needed, as discussed by van de Geer et al. (2014). For a more in-depth exploration and extensions in the case of the LASSO applied to the high-dimensional threshold regression model, detailed information can be found in Yan and Caner (2022). However, we do not delve further into these extensions here.

Step 3

Finally, we can obtain desparsified LASSO estimates for the threshold model, which is given by:

$$\hat{a}(\widehat{c}) \;=\; \hat{\alpha}(\hat{c}) + \widehat{\mathbf{\Theta}}(\widehat{c})\mathbf{X}'(\widehat{c})(\Delta(p^1 - p^2) - \mathbf{X}(\widehat{c})\widehat{\alpha}(\widehat{c}))/n, \tag{2.9}$$

where

$$\widehat{\mathbf{\Theta}}(\widehat{c}) = \begin{bmatrix} \widehat{\mathbf{B}}(\widehat{c}) & -\widehat{\mathbf{B}}(\widehat{c}) \\ -\widehat{\mathbf{B}}(\widehat{c}) & \widehat{\mathbf{A}}(\widehat{c}) + \widehat{\mathbf{B}}(\widehat{c}) \end{bmatrix}, \tag{2.10}$$

and $\widehat{\mathbf{B}}(\widehat{c})$ and $\widehat{\mathbf{A}}(\widehat{c})$ are the inverse or approximate (if the sample covariance matrix is singular) inverse of the split sample covariance matrices.

For model selection i.e. to determine the optimal lag structure on forcing variable Q_t, we use selection criteria such as the Akaike information criterion (AIC) or Bayesian information criterion (BIC), and generalized information criterion (GIC)(Konishi and Kitagawa (1996)) to select the optimal lag structure for the forcing variables. As the GIC applies a stronger penalty on the degree of freedom, it is more conservative in variable selection compared to BIC or AIC. In the next section, we use GIC to select the optimal lag structure.

3 Empirical Application

The empirical analyses in our study focus on international corn markets, specifically on three major exporting markets: the US, Argentina, and Ukraine. Despite its widespread consumption and spatial dispersion, corn production is typically concentrated in specific regions. To gain a comprehensive understanding of its behavior, we focus our study on the corn markets in the US, Argentina, and Ukraine. These three markets collectively accounted for 66.5% of the world corn trade by volume in 21/22 market year. Given the intricate spatial dynamics of the corn market, analyzing spatial linkages is crucial.

We collected monthly maize price data from multiple sources which are discussed below. As noted above, the main dependent variable of interest in this study is the maize price in international markets. We collected the yellow corn export price of the US, Ukraine, and Argentina. Price data for the main three export markets were obtained from the FAO Food Price Monitoring and Analysis (FPMA) Tool, reporting prices in US dollars per metric ton.

Our dataset spans from April 2002 to December 2022, providing 243 monthly observations for each series. However, due to data availability constraints, market factors data for Ukraine is only accessible from April 2002 to February 2022, comprising 239 observations. Similarly, market factors data for Argentina is available from July 2003 to December 2022, encompassing 234 observations. To address missing values, we applied spline interpolation during the selected period*[2]

We obtained exchange rates for Ukraine (USD to Ukrainian Hryvnia) and Argentina (USD to Argentine Peso). Additionally, we collected the Baltic Exchange Dry Index, measuring the cost of shipping dry goods like maize worldwide. To capture US market factors, we sourced data from the Federal Reserve Economic Data (FRED), including unemployment rates, consumer price index, industrial production index, interest rates, and gas prices. For US corn stock data, we utilized quarterly information from the US Feed Grain Yearbook, converting it into monthly data for analysis[3]. Market factors for Ukraine, such as unemployment rates, consumer price index, and industrial production index, along with those for Argentina, such as unemployment rates, consumer price index, and inflation rate, were sourced from the National Summary Data Pages (NSDPs)[4]

The basic unit of analysis used throughout is the natural logarithm of the price ratio, denoted as $p_t^j - p_t^k (= \ln(P_t^j / P_t^k))$, where i and j indicate locations (i.e., $j, k = 1, 2, 3$ denote the US, Ukraine, and Argentina respectively), and t is a time index such that $t = 1, \cdots, T$. The international price data and each pair of market prices are

[2]Cubic spline interpolation was employed to handle missing price data within continuous periods. There are 20 observations missing during April 2002 to February 2022 for Ukraine Maize export price.

[3]To align the data frequencies for our econometric analysis, cubic spline interpolation was applied to convert the quarterly US corn beginning stock data into the same frequency as all other monthly variables. US corn beginning stock data is from 2001 Q2 (Dec-Feb) to 2021 Q3 (Mar-May), totaling 82 observations and converted to 246 monthly data.

[4]To align the data frequencies for our econometric analysis, cubic spline interpolation was applied to convert the quarterly Argentina unemployment rate and Ukraine employment rate into the same frequency as all other monthly variables. The data for Ukraine unemployment ranges from 2022 Q1 to 2021 Q4 (standard calendar quarters), totaling 80 observations and converted to 240-month observations. The data for Argentinian unemployment spans from 2002 Q4 to 2022 Q4, comprising 81 observations and converted to 243-month observations. Given that the variables, including the consumer price index of Ukraine, industrial production index of Ukraine, and industrial production index of Argentina, are segmented into multiple partitions over the selected period, and each partition is calculated using different units in the data sources, we employ cubic spline interpolation to estimate the data for the months where unit changes occur.

shown in logarithmic form in Figure 2, 3, 4, 5 in the appendix.

Figure 6 presents a graphical representation of logarithmic pairs of prices plotted against each other, offering insights into the relationship between price levels and price differentials. Deviations from the 45-degree line in each plot reveal distinct basis patterns, where one price tends to be higher or lower than the other. These patterns likely reveal the influence of transaction costs associated with regionally distinct market trades. Maize flows between markets often occur primarily in two directions, implying that the three markets are typically both exporters and importers. In such a scenario, thresholds may be symmetric, as shipments in one direction are similar to shipments in the opposite direction.

In order to examine the characteristics of time series prices and identify the most appropriate model for evaluating spatial price linkages, we conducted augmented Dickey-Fuller tests for each pair of price differentials. The results of the Augmented Dickey-Fuller (ADF) tests for the stationarity of the price differentials are presented in Table 1 in the appendix, which indicates that the null hypothesis of nonstationarity of the price differentials is strongly rejected in every case. Transmission elasticities($\frac{\partial P_t^j}{\partial P_t^k}$) close to one provide support for market integration, with 1.0 corresponding to perfect market integration. Additionally, we performed ADF tests on the first differences of the logarithms of variables (all variables are logarithmic except for the unemployment rates of three countries and Argentina's inflation rate), exchange rates, and other exogenous shocks. The results, presented in Table 2 in the appendix, indicate that all these variables significantly differ from nonstationary series. Our Augmented Dickey-Fuller (ADF) test on the first differences of all variables strongly rejects the null hypothesis of nonstationarity. Therefore, we can confidently implement Equation (2.5) for estimating the model with the available data.

Prior to a consideration of two-regime switch models, we consider a suite of tests intended to detect departures from linearity in conventional time-series models. A range of (non) linearity tests were conducted for the price data. We applied a standard Self-Exciting Threshold AutoRegressive (SETAR) model, as formulated by Goodwin and Piggott (2001), to prices in spatially distinct markets for each of the market pairs. The specification is given by:

$$\Delta(p_t^j - p_t^k) = \gamma_0 + \gamma_1(p_{t-1}^j - p_{t-1}^k) + \mathbf{1}\{Q_t \geq c\} \left[\delta_0 + \delta_1(p_{t-1}^j - p_{t-1}^k)\right] + \varepsilon_t \tag{3.1}$$

where c is a threshold parameter, and $\gamma_1 + \delta_1$ is the parameter for trade regime. Each of the linearity tests was applied to the collection of prices. Tests on pairs of prices were conducted on the differential between logarithmic prices. Linearity testing results are contained in Table 4.[5] The tests for all international market pairs are rejected by at least one of the alternative linearity tests at a 10% significance level. These tests robustly reject linearity among the price linkages, prompting the exploration of alternative, flexible specifications capable of accommodating nonlinearities.

We shall estimate the the 3 pair-market using a standard autoregressive model of the form:

$$\Delta(p_t^1 - p_t^2) = \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2), \tag{3.2}$$

where γ_0 and γ_1 are parameters reflecting the degree of market integration. A value of γ_1 closer to zero implies a slower adjustment to shocks.

Moreover, we extend our analysis to include the exchange rate, considering the following specification:

$$\Delta(p_t^1 - p_t^2) = \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2) + \gamma_2 \Delta\pi_t^{12}, \tag{3.3}$$

where $(j,k) = (1,2)$, $(j,k) = (1,3)$, and $(j,k) = (3,2)$. Besides model (3.2) and (3.3), estimations are conducted based on model (3.1). In addition, we use exchange rates as covariates and estimate threshold models of the form:

$$\Delta(p_t^j - p_t^k) = \gamma_0 + \gamma_1(p_{t-1}^j - p_{t-1}^k) + \gamma_2\Delta\pi_t^{jk} + \mathbf{1}\{Q_t \geq c\}\left[\delta_0 + \delta_1(p_{t-1}^j - p_{t-1}^k) + \delta_2\Delta\pi_t^{jk}\right] + \varepsilon_t. \tag{3.4}$$

Table 6, 7, 8 presents estimates of standard autoregressive price parity models and threshold autoregressive price parity models. When threshold behavior is disregarded in the linear model, in every case, models incorporating exchange rates suggest adjustments in response to deviations from equilibrium that are at least as fast as the

[5] Hansen's modification of standard Chow-type tests of the bootstrapping results presented in this paper utilized 1000 replications.

models when exchange rates are ignored. However, when considering the threshold models, the estimations for the “no-trade” regime are inconsistent with the theory. This inconsistency is evident as the estimates of the degree of error correction are positively close to zero in every case except for US/Ukraine with exchange rate. The theoretical expectation is for these estimates to be negatively approaching zero. Nevertheless, except for the model of Ukraine/Argentina with exchange rate, we obtain negative estimates for δ_1, indicating much faster adjustments in response to deviations from equilibrium in the “trade” regime than the “no-trade” regime. This is concluded if the estimates of structural effects γ_1 are negative. It's interesting to note that when we consider the exchange rate effect in the models, the exchange rates for models of US/Ukraine and Ukraine/Argentina, with or without a threshold, exhibit undershooting. Specifically, the exchange rate effect is a perfect pass-through in the model of US/Argentina without a threshold, while there is no significant effect in the model of US/Argentina with a threshold.

As mentioned earlier, our estimation procedures for threshold regression offer the advantage of variable selection and threshold detection, eliminating the need for conventional nonlinear tests commonly used in threshold models. In our study, the covariates included in the analysis are the exchange rate, Baltic Exchange Dry Index, unemployment rate, consumer price index(or inflation), and industrial production index for each market. Additionally, we included US interest rate, US Corn Stock, and US gas price as control variables. A comprehensive list of the covariates used in each LASSO estimation for the three paired markets is provided in Table 3.

To determine the optimal lag structure for the forcing variable, we select the lag order with the lowest GIC value for each model. The candidates for lag orders range from 1 to 6, considering the price differentials for pairs of market prices. Table 9 presents the GIC values for the threshold Lasso estimation, which is used to select the lag structure for the forcing variable Q_t. In this context, the symmetric lagged price differential $|p^j_{t-d} - p^k_{t-d}|$ transforms into Q_t, representing the quantile of $|p^j_{t-d} - p^k_{t-d}|$ in selected samples. The estimation of thresholds is conducted using a grid search. An assumption is made that all $|p^j_{t-d} - p^k_{t-d}|$ values are distinct. This is a convenient condition, ensuring that the transformation into quantiles is a one-to-one function without any loss of generality. This assumption holds under the assumption of continuous distribution for $|p^j_{t-d} - p^k_{t-d}|$.

As shown in Table 9, the forcing variables for pairs of market prices of the US/Ukraine and US/Argentina are selected as the 4-month lagged price differentials, while a 3-month lag is chosen for Ukraine/Argentina. The threshold estimates offer insights into transaction costs. Simultaneously, the quantile estimates (refer to the same tables) illuminate whether, during the selected periods, monthly observations more frequently align with trade regimes characterized by lower quantile estimates. Based on the optimal lag structure determined by minimum GIC values, in the scenarios of US/Ukraine and Ukraine/Argentina, price differentials within the bands occur more frequently, as quantile estimates of the threshold parameters exceed 0.5. However, for US/Argentina, arbitrage activities are triggered more frequently, leading to the "trade" regime. When examining the magnitude of the price differential estimates, the width of the band representing "no trade", as implied by the thresholds, is widest for the Ukraine/Argentina markets and narrowest for the US/Argentina markets.

The standard threshold model assumes a fixed threshold, a potentially limiting assumption. It is reasonable to consider that relationships may evolve over time, signaling structural changes in the underlying economic dynamics. To explore this possibility, we introduce partitions that reflect changes in market environments. The data is segmented into two periods corresponding to two significant economic shocks: the 2014 Crimean crisis (e.g., Korovkin and Makarin (2023)) and the global financial/economic crisis of 2008-09 (e.g., Liefert et al. (2021)). Specifically, the breakpoints for these events are defined as February 2014 and October 2008, respectively, in our monthly dataset. The corresponding LASSO estimation results are provided in Table 10, 11, and 12. Introducing a break in the dataset corresponding to October 2008 for the global financial/economic crisis and February 2014 for the 2014 Crimean crisis reveals that, in most cases, the selected optimal lagged forcing variables differ across the entire period, pre-breakpoint, and post-breakpoint. Profitable arbitrage opportunities are more frequent only in the Post-February 2014 period for the US/Ukraine markets, while in every other case, such opportunities are fewer. When examining the magnitude of the price differential estimates, post-break threshold bands are narrower in all comparisons except for US/Argentina pre/post-October 2008. Subsequently, we remove the shrinkage bias introduced by the penalization in Equation (2.6) using Equation (2.9) for post-selection statistical inference. Our estimation setup considers a richer examination of price linkage among global maize markets. The fundamental framework of the threshold model illustrates that if any of the estimates of the slope coefficients (exchange rate pass-through or exogenous shock) are regime-specific, the effects of certain lagged exchange rate or exogenous shock on price differentials (which could be lagged variables) between two distinct markets differs depending on the magnitude of a certain forcing variable representing unobserved transaction costs. Estimates of non-zero differences between the two regimes imply nonlinear relationships. The slope coefficient directly corresponds to elasticity, measuring the responsiveness of the dependent variable (the price linkages in time t) to changes in the explanatory factors (lagged exchange rate between the two markets or any market factor). A straightforward way to illustrate the effects of exchange rates, market factors, or exogenous shocks on potential deviations from price parity is by analyzing the coefficient estimates obtained from our estimations. All lagged variables are allowed to have a dynamic linear effect or a dynamic nonlinear effect depending on the existence of a regime switch (threshold).

Tables 13, 14, and 15 offer a comprehensive summary of the estimates for the degree of error correction and exchange rate effects based on (2.5) using the LASSO method[6]. These tables provide valuable insights into the adjustments and effects in each market pair, shedding light on the interdependence between different markets. In almost every case, encompassing entire periods and structural breaks, the estimates of the degree of "error correction" adjustments are negatively approaching zero, except for the Post-February 2014 period in the US/Ukraine markets. The threshold models suggest adjustments in response to deviations from equilibrium in the "trade" regime that are at least as fast as those in the "no-trade" regime, except for Pre-February 2014 in the US/Ukraine markets and Pre-February 2014 in the Ukraine/Argentina markets. The results regarding whether pre-break adjustments or post-break adjustments are faster are mixed.

The threshold models indicate that exchange rates exhibit perfect pass-through to markets during the Pre-February 2014 period in the US/Ukraine pair and throughout the entire period in the US/Argentina pair. However, during the Pre-February

[6] If γ_1, γ_2, δ_1, or δ_2 is not selected by the LASSO step, their estimates and standard errors are left blank in the table. The detailed desparsified LASSO estimates for all variables are not included here due to space constraints but are presented in the Appendix.

2014 period in the Ukraine/Argentina pair and throughout the entire period in the US/Ukraine pair, the directions of the exchange rate pass-through effect in the two regimes are different. In every other case, the exchange rate pass-through effect in response to deviations from equilibrium in the "trade" regime is at least as large as that in the "no-trade" regime.

In every case, some other market factors and their past period values are selected and tested as statistically significant.

4 Summary and Concluding Remarks

We develop a model of price parity in spatially distinct international export markets for maize to investigate the degree of "error correction", the exchange rate pass-through, and other market factor effects. The models are developed within the framework of high-dimensional threshold models. We consider such nonlinear models, that has developed an increasingly rich set of factors in models of spatial market integration, as extensions to existing literature. The desparsified LASSO estimation procedures are used to specify the models.

In summary, our findings consistently indicate faster adjustments in response to deviations from equilibrium in conditions of profitable trade and arbitrage compared to the case of no trade. The markets exhibit strong linkages in most cases, with confirmed nonlinear adjustments. Aligned with existing research, the results suggest that distortions from market equilibrium, induced by exchange rates or market factors, are generally more pronounced in response to large price differences. These differences signify more substantial disequilibrium conditions, thereby presenting larger arbitrage opportunities.

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5 Appendix

Augmented Dickey-Fuller test Results		
Variable		ADF
Unit Root		
ln_US_Ukraine_diff		-4.446
ln_US_Argentina_diff		-3.860
ln_Ukraine_Argentina_diff		-4.877
Alternative hypothesis: stationary	Lag order = 6	
Significant level	Critical value	
1%	-3.96	
5%	-3.41	
10%	-3.12	

*The critical values are interpolated from Table 4.2 of Banerjee et al. (1993).

Table 1: Augmented Dickey-Fuller Test Results of Price Differentials

Augmented Dickey-Fuller Test		
Variable (1st diff)		Dickey-Fuller
ln_US_Ukraine_diff		-5.403
ln_US_Argentina_diff		-8.379
ln_Ukraine_Argentina_diff		-6.283
ln_USD_UAH_Exchange		-5.207
ln_USD_Peso_Exchange		-5.222
ln_Peso_UAH_Exchange		-4.650
ln_Baltic_Freight		-8.028
US Unemployment Rate		-7.146
Ukraine Unemployment Rate		-6.261
Argentina Unemployment Rate		-5.148
ln_US Industrial Production Index		-5.794
ln_Ukraine Industrial Production Index		-6.467
ln_Argentina Industrial Production Index		-7.630
ln_US Consumer price index		-6.301
ln_Ukraine Consumer price index		-4.290
Argentina Monthly Inflation		-6.374
US Interest Rate		-3.055
ln_US Monthly Gas Price		-7.502
ln_US Corn Stock		-11.561
Alternative hypothesis: stationary	Lag order = 6	
Significant level	Critical value	
1%	-3.96	
5%	-3.41	
10%	-3.12	

*The critical values are interpolated from Table 4.2 of Banerjee et al. (1993).

Table 2: Augmented Dickey-Fuller Test Results of First Difference of Time Series

Market pair	All	US/Argentina	US/Ukraine	Argentina/Ukraine
Variable	Exchange rate Baltic Exchange Dry Index Unemployment Rate Industrial Production Index	US Interest Rate US Gas Price US Corn Stock US Consumer price index Argentina Monthly Inflation	US Interest Rate US Gas Price US Corn Stock US Consumer price index Ukraine Consumer price index	Argentina Monthly Inflation Ukraine Consumer price index

Table 3: Variables in Each pair of markets

Nonlinearity test	US/ Ukraine		US/Argentina	
	Test Statistics	p-value	Test Statistics	p-value
Teraesvirta's neural network test χ^2	2.596	0.273	2.541	0.281
White neural network test χ^2	2.898	0.235	6.587	0.037
Keenan's one-degree test for nonlinearity F-test	1.639	0.202	0.115	0.735
Tsay's Test for nonlinearity F-test	1.360	0.099	1.125	0.340
Likelihood ratio test for threshold nonlinearity χ^2	22.777	0.077	10.476	0.132
(SETAR) models: Linear AR versus 1 threshold TAR F-test	5.882	0.515	8.795	0.202
	Ukraine/Argentina			
	Test Statistics	p-value		
Teraesvirta's neural network test χ^2	3.005	0.223		
White neural network test χ^2	3.529	0.171		
Keenan's one-degree test for nonlinearity F-test	2.181	0.141		
Tsay's Test for nonlinearity F-test	2.166	0.048		
Likelihood ratio test for threshold nonlinearity χ^2	10.573	0.207		
(SETAR) models: Linear AR versus 1 threshold TAR F-test	6.216	0.479		

Table 4: Nonlinearity specification testing results

	US/ Ukraine $\Delta(p_t^1 - p_t^2)$	US/ Ukraine $\Delta(p_t^1 - p_t^2)$
(Intercept) γ_0	-0.008*	-0.010**
	(0.005)	(0.005)
degree of "error correction" γ_1	-0.137 ***	-0.142 ***
	(0.032)	(0.032)
exchange rate effect γ_2		0.234**
		(0.100)
Observations	233	233
R^2	0.074	0.095
Adjusted R^2	0.070	0.087
F-statistic	18.44	12.12
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 5: OLS Estimates of Auto-regressive Error Correction Price Parity Model US/ Ukraine: $\Delta(p_t^1 - p_t^2) = \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2) + \gamma_2\Delta\pi_t^{12}$

	US/ Ukraine $\Delta(p_t^1 - p_t^2)$	US/ Ukraine $\Delta(p_t^1 - p_t^2)$	US/ Ukraine $\Delta(p_t^1 - p_t^2)$	US/ Ukraine $\Delta(p_t^1 - p_t^2)$
(Intercept) γ_0	-0.008*	-0.010**	-0.006	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)
degree of "error correction" γ_1 γ_1	-0.137 ***	-0.142 ***	0.040	-0.091
	(0.032)	(0.032)	(0.071)	(0.086)
exchange rate effect γ_2		0.234**		0.083
		(0.100)		(0.112)
(Intercept) δ_0			-0.009	-0.021 **
			(0.011)	(0.010)
degree of "error correction" δ_1			-0.230**	-0.108
			(0.082)	(0.094)
exchange rate effect δ_2				0.787***
				(0.242)
threshold estimate			0.130	0.111
threshold quantile			0.73	0.65
Observations	233	233	233	233
R^2	0.074	0.095	0.105	0.142
Adjusted R^2	0.070	0.087	0.089	0.120
F-statistic	18.44	12.12	6.71	6.28
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: OLS Estimates of Auto-regressive Error Correction Price Parity Model US/ Ukraine: $\Delta(p_t^1 - p_t^2) = \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2) + \gamma_2\Delta\pi_t^{12}$

	US/ Argentina $\Delta(p_t^1 - p_t^3)$	US/ Argentina $\Delta(p_t^1 - p_t^3)$	US/ Argentina $\Delta(p_t^1 - p_t^3)$	US/ Argentina $\Delta(p_t^1 - p_t^3)$
(Intercept) γ_0	0.001	0.001	0.003	0.002
	(0.002)	(0.003)	(0.004)	(0.005)
degree of "error correction" γ_1	-0.136 ***	-0.136 ***	0.278	0.274
	(0.033)	(0.034)	(0.221)	(0.222)
exchange rate effect γ_2		0.000		0.048
		(0.071)		(0.130)
(Intercept) δ_0			-0.001	-0.000
			(0.005)	(0.006)
degree of "error correction" δ_1			-0.424	-0.420*
			(0.223)	(0.225)
exchange rate effect δ_2				-0.076
				(0.155)
threshold estimate			0.033	0.033
threshold quantile			0.36	0.36
Observations	228	228	228	228
R^2	0.068	0.068	0.083	0.052
Adjusted R^2	0.064	0.060	0.067	0.025
F-statistic	16.57	8.249	5.079	1.936
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 7: OLS Estimates of Auto-regressive Error Correction Price Parity Model US/ Argentina: $\Delta(p_t^1 - p_t^3) = \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^3) + \gamma_2\Delta\pi_t^{13} + \mathbf{1}\{p_{t-1}^1 - p_{t-1}^3 \geq c\}\left[\delta_0 + \delta_1(p_{t-1}^1 - p_{t-1}^3) + \delta_2\Delta\pi_t^{13}\right] + \varepsilon_t$

	Ukraine/ Argentina $\Delta(p_t^3 - p_t^2)$	Ukraine/ Argentina $\Delta(p_t^3 - p_t^2)$	Ukraine/ Argentina $\Delta(p_t^3 - p_t^2)$	Ukraine/ Argentina $\Delta(p_t^3 - p_t^2)$
(Intercept) γ_0	-0.009 *	-0.008	0.002	-0.003
	(0.005)	(0.005)	(0.008)	(0.005)
degree of "error correction" γ_1	-0.147 ***	-0.152 ***	0.131	0.093
	(0.035)	(0.034)	(0.275)	(0.076)
exchange rate effect γ_2		0.178 **		0.197**
		(0.082)		(0.093)
(Intercept) δ_0			-0.019 *	0.012
			(0.010)	(0.011)
degree of "error correction" δ_1			-0.305	0.052
			(0.278))	(0.142)
exchange rate effect δ_2				-0.242
				(0.220)
threshold estimate			0.046	0.113
threshold quantile			0.40	0.71
Observations	218	218	218	218
R^2	0.074	0.094	0.089	0.052
Adjusted R^2	0.069	0.085	0.072	0.025
F-statistic	17.2	11.1	5.252	1.936
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 8: OLS Estimates of Auto-regressive Error Correction Price Parity Model Ukraine/ Argentina: $\Delta(p_t^3 - p_t^2) = \gamma_0 + \gamma_1(p_{t-1}^3 - p_{t-1}^2) + \gamma_2\Delta\pi_t^{32} + \mathbf{1}\{p_{t-1}^3 - p_{t-1}^2 \geq c\}\left[\delta_0 + \delta_1(p_{t-1}^3 - p_{t-1}^2) + \delta_2\Delta\pi_t^{32}\right] + \varepsilon_t$

time delay for the threshold variable	1	2	3	4	5	6
US/ Ukraine						
GIC	4.16	0.19	3.25	-0.62	2.99	1.56
Threshold estimate	0.11	0.15	0.07	0.09	0.05	0.11
Threshold estimate(quantile)	0.64	0.77	0.42	0.55	0.27	0.67
US/Argentina						
GIC	1.37	1.17	1.15	-2.48	-2.36	-2.46
Threshold estimate	0.06	0.05	0.07	0.04	0.07	0.07
Threshold estimate(quantile)	0.58	0.52	0.68	0.46	0.70	0.70
Ukraine/Argentina						
GIC	-0.11	-0.08	-0.61	0.39	1.48	0.57
Threshold estimate	0.11	0.12	0.13	0.12	0.13	0.11
Threshold estimate(quantile)	0.70	0.73	0.77	0.74	0.77	0.69

Table 9: Lasso Estimation with GIC

time delay for the threshold variable	1	2	3	4	5	6
US/ Ukraine						
GIC	4.16	0.19	3.25	-0.62	2.99	1.56
Threshold estimate	0.11	0.15	0.07	0.09	0.05	0.11
Threshold estimate(quantile)	0.64	0.77	0.42	0.55	0.27	0.67
Pre-October 2008						
GIC	4.93	5.81	5.20	4.71	5.08	4.37
Threshold estimate	0.11	0.09	0.12	0.13	0.21	0.24
Threshold estimate(quantile)	0.58	0.44	0.62	0.66	0.76	0.79
Post-October 2008						
GIC	0.28	3.56	4.48	4.13	4.44	4.29
Threshold estimate	0.11	0.08	0.08	0.06	0.06	0.06
Threshold estimate(quantile)	0.68	0.53	0.49	0.36	0.36	0.36
Pre-February 2014						
GIC	4.42	5.49	4.59	5.17	4.92	1.14
Threshold estimate	0.10	0.08	0.12	0.09	0.07	0.14
Threshold estimate(quantile)	0.58	0.48	0.68	0.49	0.39	0.73
Post-February 2014						
GIC	4.04	4.54	3.63	4.53	4.62	5.05
Threshold estimate	0.09	0.07	0.06	0.06	0.06	0.05
Threshold estimate(quantile)	0.56	0.44	0.39	0.37	0.45	0.32

Table 10: Lasso Estimation with GIC

time delay for the threshold variable	1	2	3	4	5	6
US/Argentina						
GIC	1.37	1.17	1.15	-2.48	-2.36	-2.46
Threshold estimate	0.06	0.05	0.07	0.04	0.07	0.07
Threshold estimate(quantile)	0.58	0.52	0.68	0.46	0.70	0.70
Pre-October 2008						
GIC	4.16	4.37	3.96	4.19	4.63	4.66
Threshold estimate	0.06	0.06	0.06	0.04	0.05	0.05
Threshold estimate(quantile)	0.56	0.52	0.54	0.38	0.45	0.45
Post-October 2008						
GIC	4.33	3.47	3.61	4.20	3.36	4.27
Threshold estimate	0.05	0.05	0.06	0.06	0.07	0.05
Threshold estimate(quantile)	0.52	0.55	0.59	0.59	0.62	0.55

Table 11: Lasso Estimation with GIC

time delay for the threshold variable	1	2	3	4	5	6
Ukraine/Argentina						
GIC	-0.11	-0.08	-0.61	0.39	1.48	0.57
Threshold estimate	0.11	0.12	0.13	0.12	0.13	0.11
Threshold estimate(quantile)	0.70	0.73	0.77	0.74	0.77	0.69
Pre-February 2014						
GIC	4.42	4.96	3.62	4.44	4.83	5.54
Threshold estimate	0.10	0.09	0.13	0.11	0.08	0.08
Threshold estimate(quantile)	0.62	0.56	0.67	0.61	0.51	0.46
Post-February 2014						
GIC	2.91	3.10	3.51	3.12	3.38	3.81
Threshold estimate	0.09	0.05	0.06	0.07	0.09	0.06
Threshold estimate(quantile)	0.70	0.48	0.58	0.63	0.69	0.58

Table 12: Lasso Estimation with GIC

	US/Ukraine $\Delta(p_t^1 - p_t^2)$	Pre-October 2008 $\Delta(p_t^1 - p_t^2)$	Post-October 2008 $\Delta(p_t^1 - p_t^2)$	Pre-February 2014 $\Delta(p_t^1 - p_t^2)$	Post-February 2014
(Intercept) γ_0	–0.012***	-0.026***	-0.008 **	-0.001	-0.002***
	(0.001)	(0.000)	(0.003)	(0.005)	(0.000)
degree of "error correction" γ_1	-0.070***		-0.090 ***	-0.061***	0.177***
	(0.003)		(0.006)	(0.009)	(0.054)
exchange rate effect $\gamma_{2,0}$	-0.101 ***	-0.589***	0.065**		0.129***
	(0.031)	(0.179)	(0.027)		(0.000)
(Intercept) δ_0					-0.045***
					(0.000)
degree of "error correction" δ_1	-0.068 *	-0.264***	-0.161 ***	0.004	-0.437***
	(0,039)	(0.031)	(0.044)	(0.089)	(0.048)
exchange rate effect $\delta_{2,0}$	0.229	-0.590 ***			0.070 ***
	(0.156)	(0.194)			(0.011)
other variables omitted	...	...	...	...	...
	...	...	...	...	...
threshold estimate	0.089	0.237	0.111	0.143	0.060
threshold quantile	0.55	0.79	0.68	0.73	0.39
optimal threshold time delay	4	6	1	6	3
Observations	233	73	160	137	96

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: Threshold Estimates of Price Parity Model US/ Ukraine: $\Delta(p_t^1 - p_t^2) = \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2) + \sum_{l=0}^{L} \gamma_{2l}\Delta\pi_{t-l}^{12} + \sum_{l=0}^{L} \gamma_{3l}\Delta z_{t-l}^{12} + \mathbf{1}\{Q_t \geq c\} \left[\delta_0 + \delta_1(p_{t-1}^1 - p_{t-1}^2) + \sum_{l=0}^{L} \delta_{2l}\Delta\pi_{t-l}^{12} + \sum_{l=0}^{L} \delta_{3l}\Delta z_{t-l}^{12}\right] + \varepsilon_t$

	US/Argentina $\Delta(p_t^1 - p_t^3)$	Pre-October 2008 $\Delta(p_t^1 - p_t^3)$	Post-October 2008 $\Delta(p_t^1 - p_t^3)$
(Intercept) γ_0	-0.004	0.003***	0.017 ***
	(0.005)	(0.000)	(0.000)
degree of "error correction" γ_1		-0.221 ***	-0.006
		(0.022)	(0.015)
exchange rate effect $\gamma_{2,0}$			0.317*
			(0.190)
(Intercept) δ_0			-0.014***
			(0.000)
degree of "error correction" δ_1	-0.193***	-0.025	0.533
	(0.056)	(0.019)	(0.583)
exchange rate effect $\delta_{2,0}$		0.476***	
		(0.025)	
	...	...	...
	...	...	...
threshold estimate	0.043	0.058	0.066
threshold quantile	0.46	0.54	0.62
optimal threshold time delay	4	3	5
Observations	228	58	170
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 14: Threshold Estimates of Price Parity Model US/Argentina: $\Delta(p_t^1 - p_t^3) = \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^3) + \sum_{l=0}^{L} \gamma_{2l} \Delta\pi_{t-l}^{13} + \sum_{l=0}^{L} \gamma_{3l} \Delta z_{t-l}^{13} + \mathbf{1}\{Q_t \geq c\} \left[\delta_0 + \delta_1(p_{t-1}^1 - p_{t-1}^3) + \sum_{l=0}^{L} \delta_{2l} \Delta\pi_{t-l}^{13} + \sum_{l=0}^{L} \delta_{3l} \Delta z_{t-l}^{13}\right] + \varepsilon_t$

	Ukraine/Argentina $\Delta(p_t^3 - p_t^2)$	Pre-February 2014 $\Delta(p_t^3 - p_t^2)$	Post-February 2014 $\Delta(p_t^3 - p_t^2)$
(Intercept) γ_0	-0.012*	-0.0004***	-0.011 ***
	(0.006)	(0.000)	(0.000)
degree of "error correction" γ_1	-0.177 ***	-0.379***	-0.112
	(0.058)	(0.001)	(0.118)
exchange rate effect $\gamma_{2,0}$	0.138*	-1.247 ***	0.131***
	(0.075)	(0.001)	(0.011)
(Intercept) δ_0		0.016***	
		(0.000)	
degree of "error correction" δ_1		0.324***	
		(0.004)	
exchange rate effect $\delta_{2,0}$	5.507	1.480***	0.192***
	(4.899)	(0.001)	(0.029)
	...	...	...
	...	...	...
threshold estimate	0.134	0.128	0.093
threshold quantile	0.77	0.67	0.70
optimal threshold time delay	3	3	1
Observations	218	122	96
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 15: Threshold Estimates of Price Parity Model Ukraine/Argentina: $\Delta(p_t^3 - p_t^2) = \gamma_0 + \gamma_1(p_{t-1}^3 - p_{t-1}^2) + \sum_{l=0}^{L} \gamma_{2l} \Delta\pi_{t-l}^{32} + \sum_{l=0}^{L} \gamma_{3l} \Delta z_{t-l}^{32} + \mathbf{1}\{Q_t \geq c\} \left[\delta_0 + \delta_1(p_{t-1}^3 - p_{t-1}^2) + \sum_{l=0}^{L} \delta_{2l} \Delta\pi_{t-l}^{32} + \sum_{l=0}^{L} \delta_{3l} \Delta z_{t-l}^{32}\right] + \varepsilon_t$

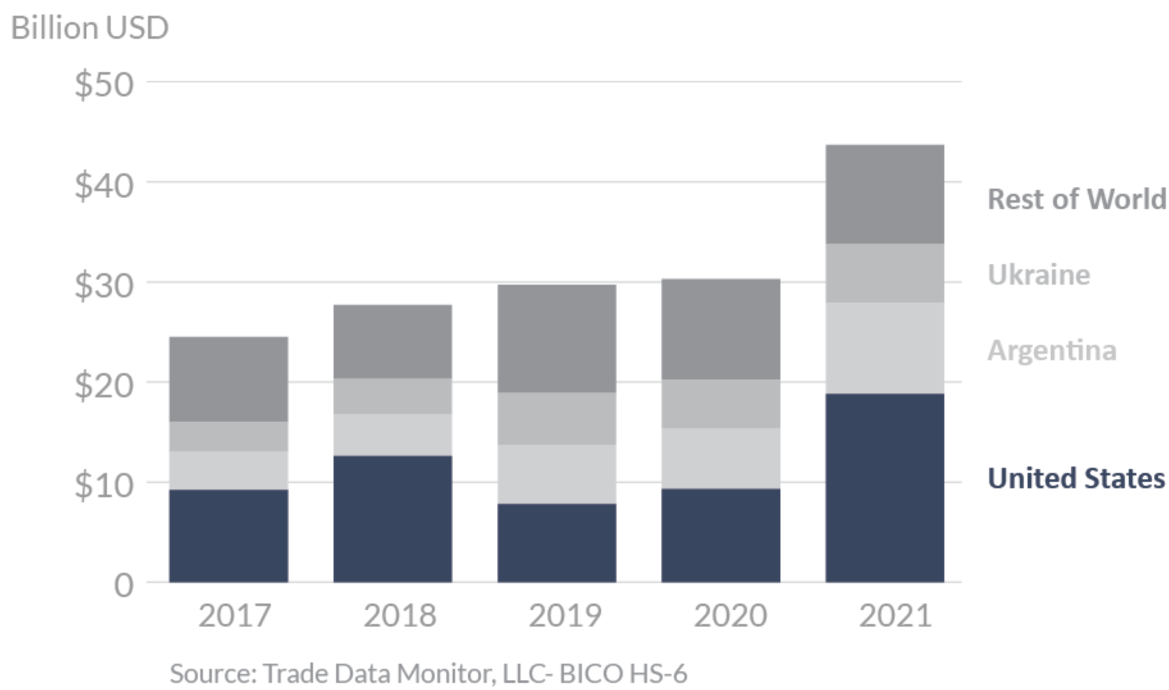

Figure 1: World Corn Exports by Country and Marketing Year, Source :U.S. Department of Agriculture (2022)

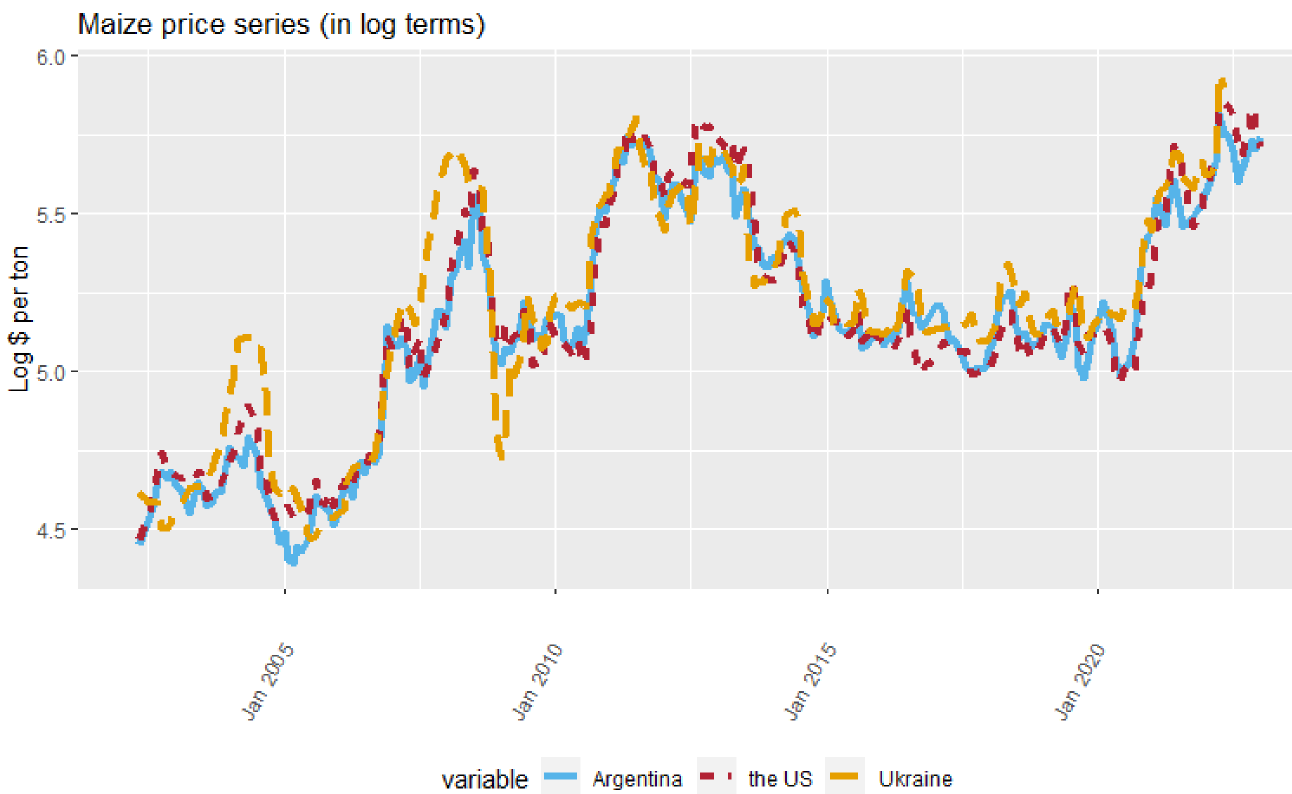

Figure 2: Maize Export price by Country

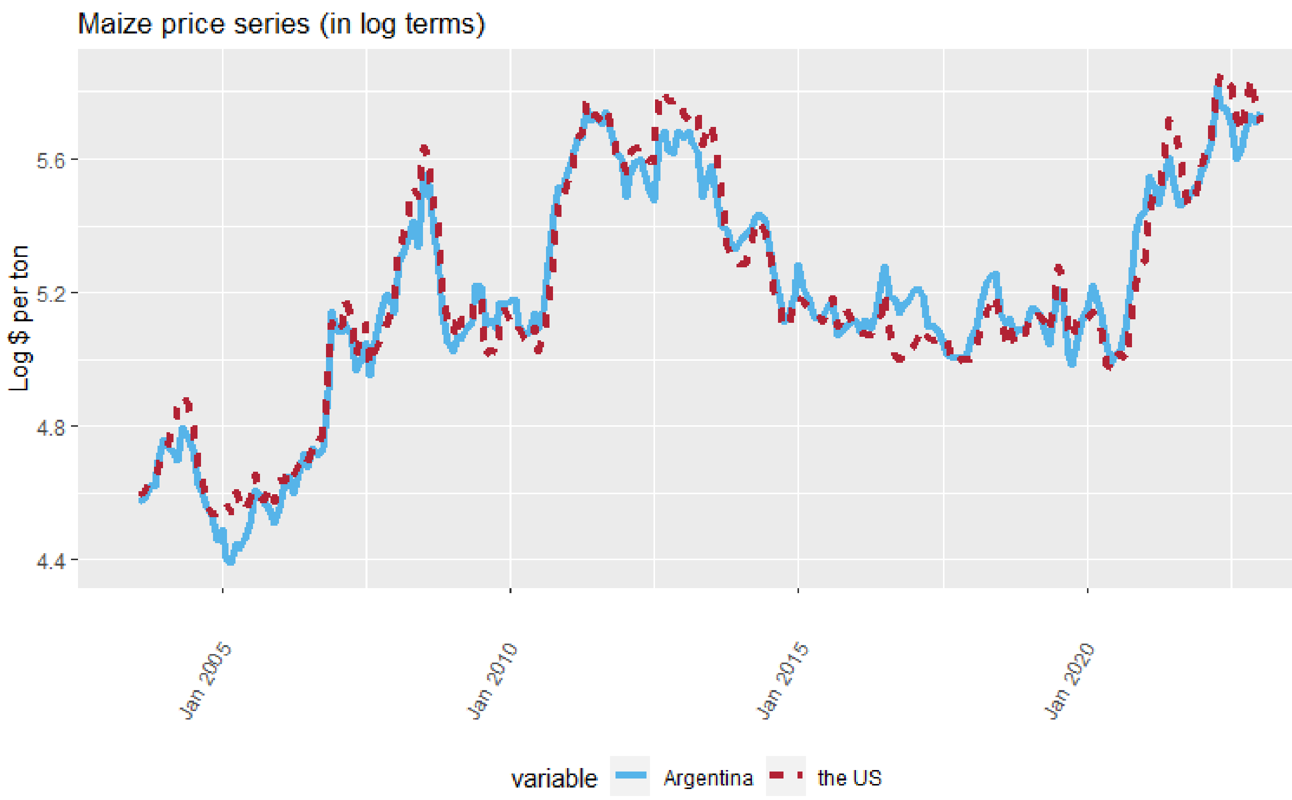

Figure 3: the U.S. and Argentina Corn Market Price

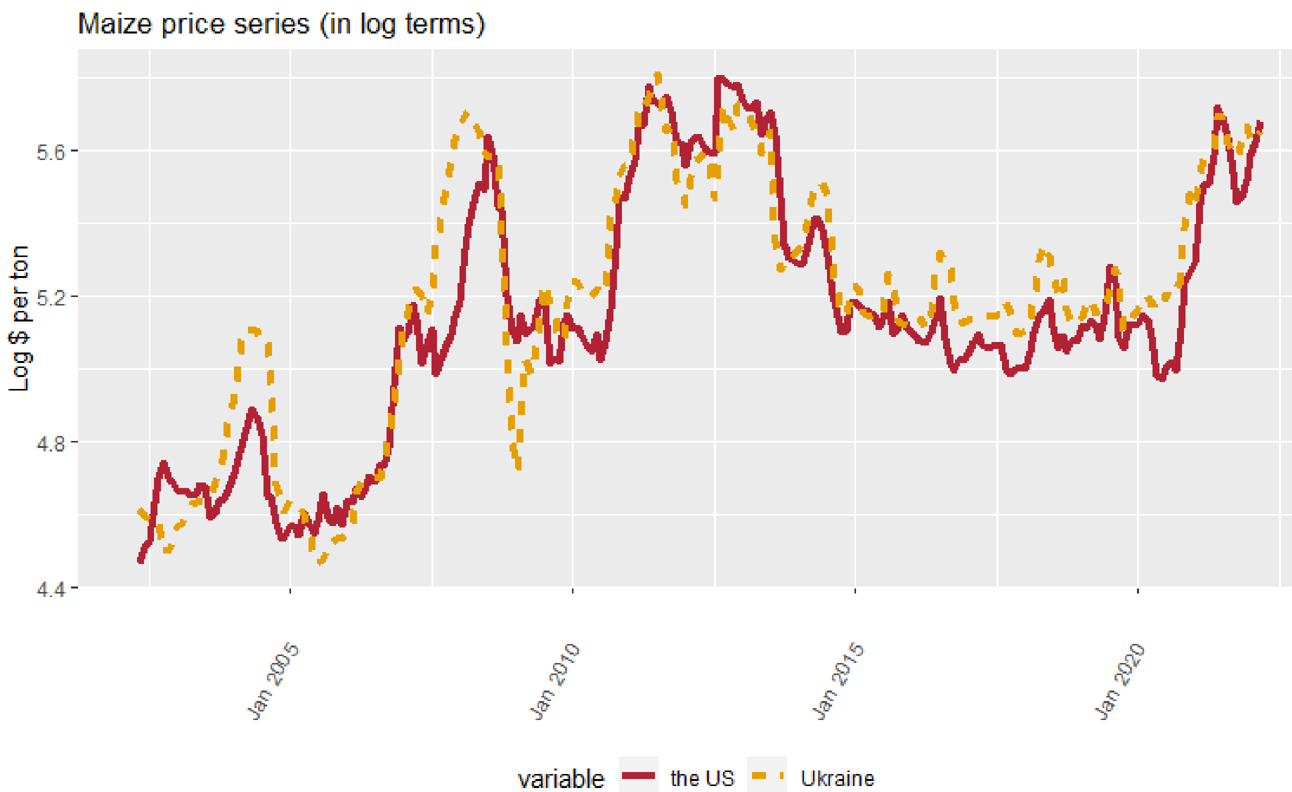

Figure 4: the U.S. and Ukraine Corn Market Price

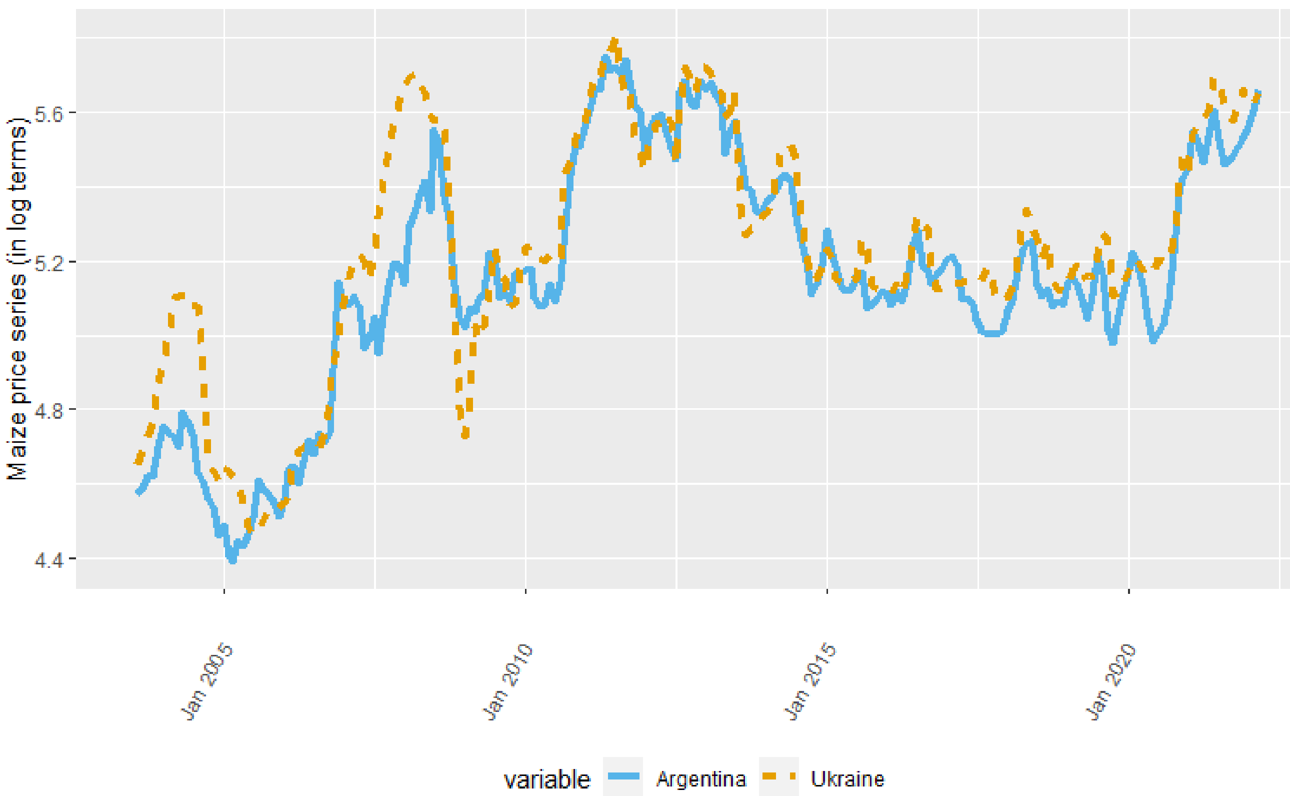

Figure 5: Argentina and Ukraine Corn Market Price

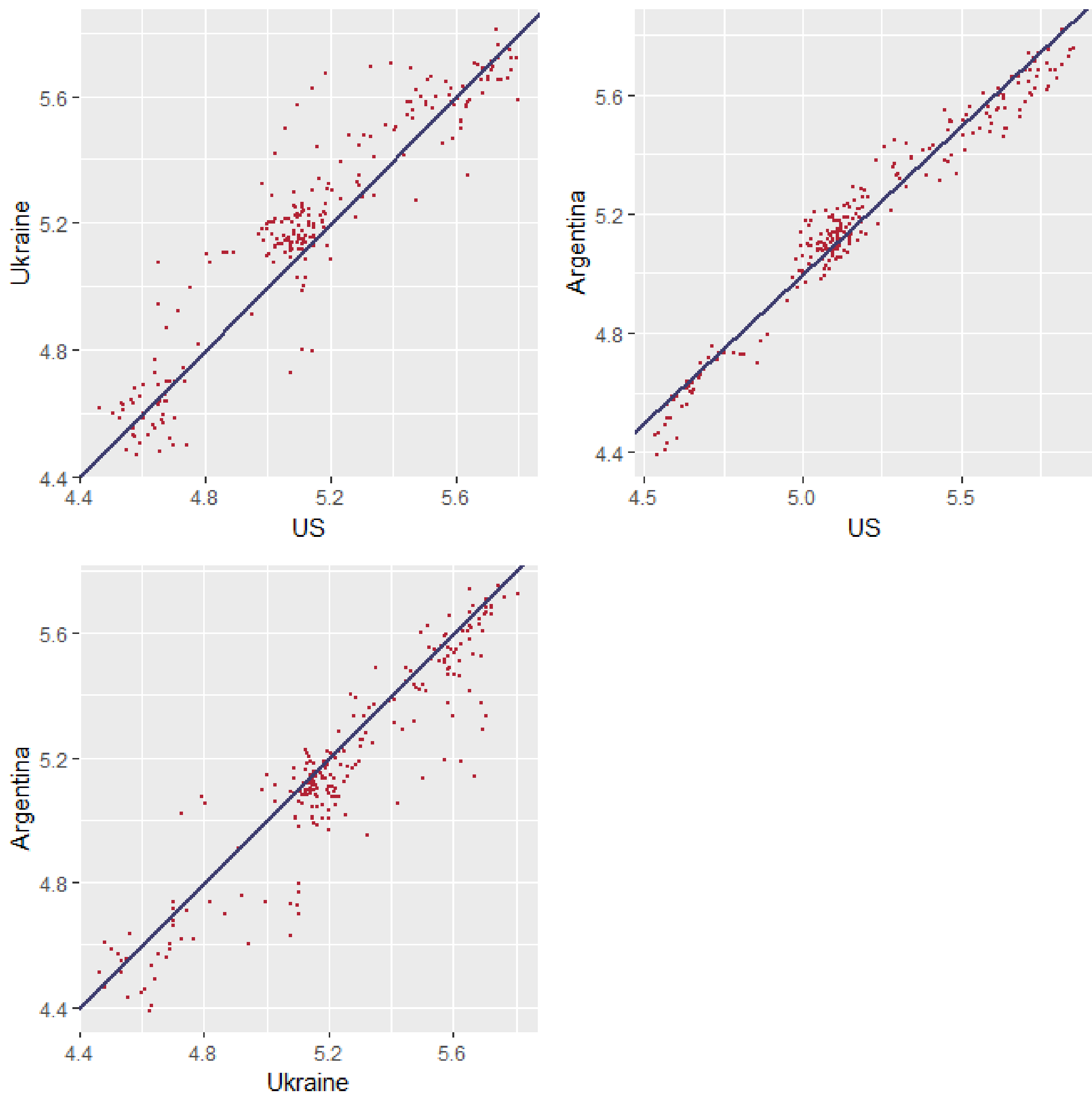

Figure 6: Corn Market Logarithmic Prices pairs