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, and exporter of maize, alone accounts for over one-third of global maize exports. Argentina and Ukraine follow, 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.

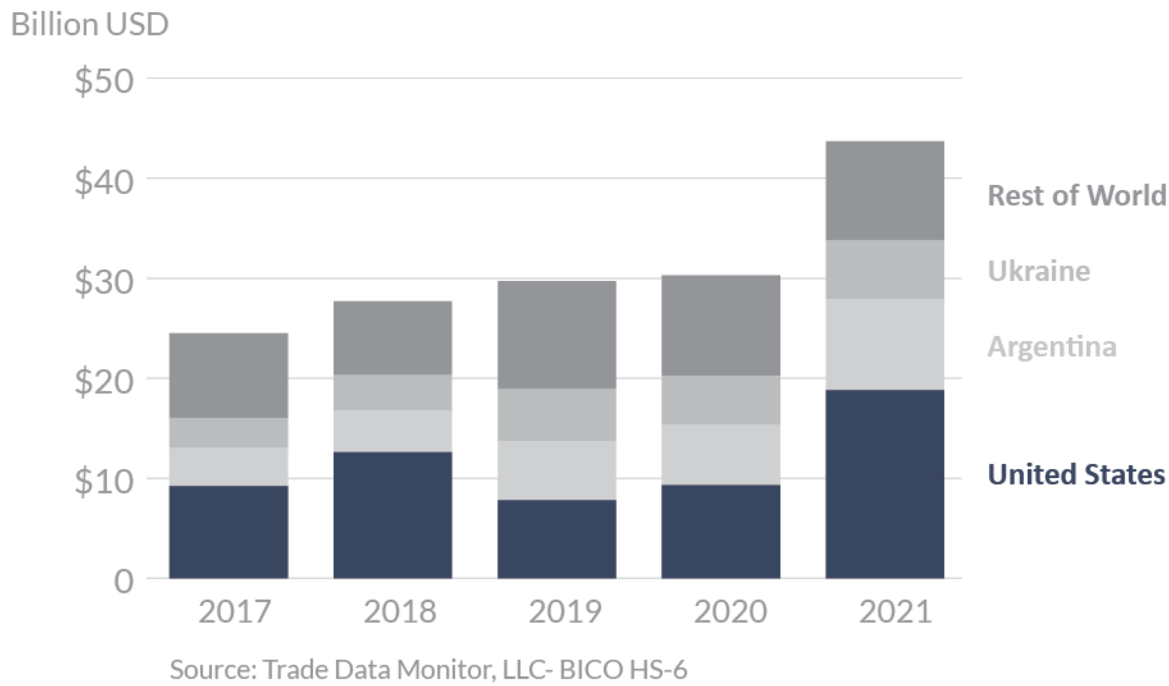

Figure 1: World Corn Exports by Country and Marketing Year, Source :U.S. Department of Agriculture (2022)

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 i and j. The individual market prices are denoted by P^i and P^j, respectively. The arbitrage condition of perfect market integration reflects the equation $P_t^1/P_t^2 = 1$, 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 $1/(1-\kappa) \leq P_t^1/P_t^2 \leq 1-\kappa$, where κ represents the proportional loss in commodity value due to transaction or transportation costs $(0 < \kappa < 1)$. The greater the distance between locations i and j, 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 $p_t^i = \ln P_t^i$, the inequality is often presented as

$$|p_t^1 - p_t^2| \leq \ln(1-\kappa). \tag{2.1}$$

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 $|p_t^1 - p_t^2| > \ln(1-\kappa)$. 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

$$p_t^1 = \alpha_0 + \beta_1 p_t^2 + \gamma_1 \pi_t^{12} + \varepsilon_t, \tag{2.2}$$

where p_t^i is the price in market i in time period t and π_t^{12} is the exchange rate between currencies in markets i and j, all in logarithmic terms.

Perfect integration is implied if $\alpha_0 = 0$ and $\beta_1 = 1$. In cases where prices are invoiced in different currencies, perfect integration also requires perfect exchange rate pass-through, which is implied if $\gamma_1 = 1$. 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. However, it is possible that exchange rate distortions may still affect price linkages, which is implied if $\gamma_1 \neq 0$, 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:

$$p_t^1 - p_t^2 = \gamma_1 \pi_t^{12} + \gamma_2 Z_t^{12} + \varepsilon_t, \tag{2.3}$$

where Z_t^{12} is a set of factors that may be conceptually relevant to market linkages, γ_2 is a vector of parameters corresponding to Z_t^{12}. 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 can evaluate the patterns of market price adjustments to isolated shocks that occur in distinct regional markets. In addition to the conventional specification of exchange rate pass-through, we propose an extension to this framework of spatial market integration that includes two regimes, where the regime switch depends on a forcing variable, usually a lagged price differential, that is expressed as:

(2.4)

$$\begin{aligned}
\Delta(p_t^1 - p_t^2) =& \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2) + \gamma_2 \Delta\pi_t^{12} + \gamma_3 \Delta Z_t^{12} \\
&+ \mathbf{1}\{p_{t-1}^1 - p_{t-1}^2 \geq c\}(\delta_0 + \delta_1(p_{t-1}^1 - p_{t-1}^2) + \delta_2 \Delta\pi_t^{12} + \delta_3 \Delta Z_t^{12}) + \varepsilon_t, \\
t =& \{1, \ldots, T\}
\end{aligned}$$

where γ_0 is a time trend coefficient if we add a linear time trend to equation (2.3). γ_0 and γ_1 are parameters that reflect the degree of market integration. In particular, γ_1 represents the degree of "error correction" that characterizes departures from price parity,which are reflected in large values of $p_{t-1}^1 - p_{t-1}^2$. 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)

$$
\begin{aligned}
\Delta(p_t^1 - p_t^2) =& \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2) + \sum_{l=0}^{L} \gamma_{2l} \Delta\pi_{t-l}^{12} + \sum_{l=0}^{L} \gamma_{3l} \Delta z_{t-l}^{12} \\
& + \mathbf{1}\{Q_t \geq c\} \left[\delta_0 + \delta_1(p_{t-1}^1 - p_{t-1}^2) + \sum_{l=0}^{L} \delta_{2l} \Delta\pi_{t-l}^{12} + \sum_{l=0}^{L} \delta_{3l} \Delta z_{t-l}^{12} \right] + \varepsilon_t \\
& t = \{1, \ldots, T\},
\end{aligned}
$$

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., $Q_t \in \{p_{t-1}^1 - p_{t-1}^2, \cdots, p_{t-L}^1 - p_{t-L}^2\}$. 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 $\frac{\partial\Delta(p_t^1 - p_t^2)}{\partial\Delta\pi_{t-s}} = \gamma_{1s}$. The dynamic marginal effect of $\Delta\pi_{t-s}$ on $\Delta(p_t^1 - p_t^2)$ at the s-th lag is given by $\frac{\partial\Delta(p_t^1 - p_t^2)}{\partial\Delta\pi_{t-s}} = \gamma_{1s}$. The dynamic marginal effect is essentially an effect of a temporary change in $\Delta\pi_{t-s}$ on $\Delta(p_t^1 - p_t^2)$, whereas the long-run cumulative effect $\sum_{s=1}^{L}\gamma_{1s}$ measures how much $\Delta(p_t^1 - p_t^2)$ will be changed in response to a permanent change in $\Delta\pi$ when both$\Delta\pi_t$ and $\Delta(p_t^1 - p_t^2)$ are stationary. The same derivation can be applied to any element of the vector Δz_{t-s}. 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} and δ_{2s} 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)

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

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 scale normalizing factor.

Step 2.

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), the first two steps involve LASSO estimates that can achieve threshold selection consistency under specific regularity conditions. Threshold selection consistency entails correctly identifying the estimates of differences between the two regimes, denoted as $(\delta_0, \delta_{10}, \cdots, \delta_{1L}, \delta_{20}, \cdots, \delta_{2L})$, as equal to zero if the model is linear. 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.

As the shrinkage bias introduced due to the penalization in LASSO loss function will show up in the properly scaled limiting distribution of LASSO estimator. Therefore, to conduct statistical inference, we need to remove this bias. However, when modeling threshold regression with a rich set of variables, a challenge arises. Threshold models involve splitting the sample based on a continuously-distributed variable. With a rich set of regressors, there is a risk that the number of observations in any split sample may be less than the number of variables which causes the sample covariance matrix to be of reduced rank. However, standard approaches are invalid in such a situation. So in order to desparsify (debias) our LASSO estimator, we need an approximate inverse of a certain singular sample covariance matrix in the sense of van de Geer et al. (2014). We refer toYan and Caner (2022) for details in the case of the Lasso applied to the high-dimensional threshold regression model and do not pursue these extensions further here.

Step 3

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

$$\hat{a}(\widehat{c}) \;=\; \hat{\alpha}(\hat{c}) + \widehat{\boldsymbol{\Theta}}(\widehat{c})\mathbf{X}'(\widehat{c})(\Delta(p^1 - p^2) - \mathbf{X}(\widehat{c})\widehat{\alpha}(\widehat{c}))/n, \tag{2.8}$$

where

$$\widehat{\mathbf{\Theta}}(\widehat{c}) = \begin{bmatrix} \widehat{\mathbf{B}}(\widehat{c}) & -\widehat{\mathbf{B}}(\widehat{c}) \\ -\widehat{\mathbf{B}}(\widehat{c}) & \widehat{\mathbf{A}}(\widehat{c}) + \widehat{\mathbf{B}}(\widehat{c}) \end{bmatrix}, \tag{2.9}$$

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) to select the optimal lag structure for the forcing variables. As the BIC applies a stronger penalty on the degree of freedom, it is more conservative in variable selection compared to AIC.

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. Additionally, we investigate two regional markets in the US as a comparison. 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 66.2% of the global corn trade by value in 2021. 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 study also utilized the US Feed Grain Yearbook's corn price dataset, which provides data on Yellow Corn No. 2 from nine regional markets across the United States, which are Gulf ports, Louisiana; St. Louis, Missouri; Omaha, Nebraska; Central Illinois; Chicago, Illinois; Kansas City, Missouri; Toledo, Ohio; Memphis, Tennessee; and Minneapolis, Minnesota.

According to the National Park Service, the agricultural products and agribusiness industry in the Mississippi basin are responsible for producing 92% of the nation's agricultural exports. Moreover, it accounts for 78% of the world's exports in feed grains and soybeans. The Mississippi River serves as a vital transportation route for this agricultural trade. Approximately 60% of all grain exported from the US is shipped through the Port of New Orleans and the Port of South Louisiana, both of which are situated along the river. In terms of corn exports, the Mississippi River connects various markets along its route. Gulf ports in Louisiana, such as the Port of New Orleans and the Port of South Louisiana, serve as the main locations for corn exports in the region. Additionally, other locations along the Mississippi River also play a role in corn export activities.

Our dataset spans from January 2000 to January 2023, comprising 277 monthly observations for each series. However, there were some missing values in the series, which we addressed by replacing them using spline interpolation during the selected period. Due to limitations in data availability, the time span for US market factors is limited to January 2000 to January 2023, resulting in a total of 277 observations. The available market factors data for Ukraine covers the period from March 2002 to January 2002, comprising 239 observations. The market factors data for Argentina spans from August 2003 to June 2020, encompassing 203 observations.[1].

In addition, we obtained the exchange rates for Ukraine (USD to Ukrainian Hryvnia) and Argentina (USD to Argentina Peso). To capture market factors related to the US market, we sourced data from the Federal Reserve Economic Data (FRED), which included interest rates, nominal inflation rates, unemployment rates, industrial production monthly percent change, and US gas prices. For US corn stock data, we utilized quarterly data from the US Feed Grain Yearbook and converted it into monthly data for our analysis[2]. Market factors for Argentina and Ukraine were sourced from the National Summary Data Pages (NSDPs). Furthermore, we collected the Baltic Exchange Dry Index, which measures the cost of shipping dry goods, such as maize, worldwide.

[1]We employed cubic spline interpolation to address missing price data within selected continuous periods.

[2]To align the data frequencies for our econometric analysis, we employed cubic spline interpolation to convert the quarterly US corn stock data, Argentina unemployment rate, and Ukraine employment rate into the same frequency as all other monthly variables.

The basic unit of analysis used throughout is the natural logarithm of the price ratio, denoted as $p_t^i - p_t^j (= \ln(P_t^i/P_t^j))$, where i and j indicate locations (i.e., $i, j = 1, \cdots, 11$), and t is a time index such that $i, j = 1, \cdots, T$, where $T = 277$. The international price data and each pair of markets price are shown in logarithmic form in Figure 2, 3 4, 5 in appendix. The price data for Ukraine covers the period from January 2000 to April 2022, comprising a total of 267 monthly observations.

Figure 7 illustrates the logarithmic prices in Kansas City, MO, and the Gulf ports. The spatial linkages of the corn market within the United States are particularly noteworthy. The Gulf ports play a crucial role as the main location for US corn exports, while Kansas City is traversed by the Missouri River, a tributary of the Mississippi River. Consequently, our objective is to examine and compare the spatial linkages in the corn market between the United States and Ukraine or Argentina, as well as distinct regions in the United States.

Figure 8 displays a graphical representation of logarithmic pairs of prices plotted against each other, providing insight into the relationship between price levels and price differentials, as indicated by deviations from the 45-degree line in each plot. The plots reveal distinct basis patterns where one price tends to be higher or lower than the other. These patterns likely reflect the presence of transaction costs associated with regionally distinct market trades. With the exception of the 4th panel, the plots show that the points are evenly distributed on both sides of the 45-degree line. However, in the 4th panel representing Kansas City, MO, and Gulf ports, LA, all the points fall below the 45-degree line. This observation is consistent with reality, as the primary shipping route for most US corn exports involves transporting goods down the Mississippi River, leading to transportation occurring predominantly from Kansas City, MO, to Gulf ports, LA. Therefore, it is expected that the market price in Kansas City, MO would consistently be lower than that in Gulf ports, LA.

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 tests for the stationarity of the price differentials are presented in Table 2 in the appendix, which indicates that the null hypothesis of nonstationarity of the price differentials is strongly rejected in every case. Transmission elasticities($\frac{\partial P_t^1}{\partial P_t^2}$) close to one provide support for market integration, with 1.0 corresponding to perfect market integration. Additionally, we performed ADF tests on the first difference of the logarithmic exchange rate and other exogenous shocks in Table 3 in the appendix and found that they were all significant in rejecting nonstationary series. Our augmented Dickey-Fuller test on the first difference of the logarithm of all variables strongly rejects the null hypothesis of nonstationarity. Thus, we can implement equation (2.5) for estimating the model with the available data.

Prior to a consideration of semi-parametric 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. A standard 'self-exciting' threshold autoregressive (SETAR) model of the form applied to prices in spatially distinct markets by Goodwin and Piggott (2001) was considered for each of the market pairs. This specification is given by:

$$\begin{aligned}\Delta(p_t^1 - p_t^2) =& \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2) + \mathbf{1}\{Q_t \geq c\}\left[\delta_0 + \delta_1(p_{t-1}^1 - p_{t-1}^2)\right] + \varepsilon_t \\ & t = \{1, \dots, T\},\end{aligned} \tag{3.1}$$

where c is a threshold value, 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.[3] The tests for each international market pair are not rejected, suggesting insufficient evidence for nonlinearity in the estimation of price parity among the three maize export markets. However tests of US regional market pair are rejected by at least 2 of the alternative linearity tests at 5% significant level. These results suggest the potential of nonlinearity in the estimation of price parity among the US maize markets.The tests strongly reject linearity among the price linkages and thus motivate a consideration of alternative, flexible specifications that can accommodate nonlinearities.

Based on a standard autoregressive model of the form:

$$\begin{aligned}\Delta(p_t^1 - p_t^2) =& \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2) \\ & t = \{1, \dots, T\},\end{aligned} \tag{3.2}$$

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

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.

Additionally, we consider the exchange rate with a specification:

$$\Delta(p_t^1 - p_t^2) = \gamma_0 + \gamma_1(p_{t-1}^1 - p_{t-1}^2) + \gamma_2 \Delta\pi_{t-l}^{12}, \quad t = \{1, \ldots, T\}, \tag{3.3}$$

We estimate model (3.1) with the data of Kansas City, MO, to Gulf ports, LA. Table 5, 6, 7 contains OLS and TAR estimates of a simple price transmission model.

As mentioned earlier, the LASSO for threshold regression offers the advantage of variable selection and selection consistency, 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, inflation, unemployment rate, and industrial production index for each market. Additionally, we included US interest rate, US Corn Stock, and US gas price as control variables. It is important to note that for the model focusing on Kansas City, MO and Gulf ports, LA, the exchange rate variable was not included in the model. A comprehensive list of the covariates used in each LASSO estimation for the four paired markets is provided in Table 1.

To determine the optimal lag structure for the forcing variable, we select the lag order with the lowest AIC value for each model. Table 8 presents the BIC values for the threshold Lasso estimation, which is used to select the lag structure for the forcing variable Q_t. In this context, the lagged price differential $|p_{t-d}^1 - p_{t-d}^2|$ undergoes a transformation into $Q_t = \widehat{F}(p_{t-d}^1 - p_{t-d}^2)$, where $\widehat{F}$ denotes the empirical distribution function of the data $\{p_1^1 - p_1^2, \cdots p_{T-d}^1 - p_{T-d}^2\}$.An assumption is imposed that all $|p_{t-d}^1 - p_{t-d}^2|$ values are distinct, a convenient condition ensuring that the transformation by $\widehat{F}$ is a one-to-one function without loss of generality. This assumption holds under the assumption of continuous distribution for $|p_{t-d}^1 - p_{t-d}^2|$. Consequently, the estimates of lagged price differential can be inverted using the function $\widehat{F}^{-1}$ with threshold estimates.

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 investigate

Market	Variable
US/Argentina	Exchange rate(USD to Argentine Peso), Baltic Exchange Dry Index, US Unemployment Rate, US Monthly Inflation, US Interest Rate, US Industrial Production Index, US Gas Price, US Corn Stock, Argentina Unemployment Rate, Argentina Monthly Inflation, Argentina Industrial Production Index
US/Ukraine	Exchange rate(USD to Ukrainian hryvnia), Baltic Exchange Dry Index, US Unemployment Rate, US Monthly Inflation, US Interest Rate, US Industrial Production Index, US Gas Price, US Corn Stock, Argentina Unemployment Rate, Argentina Monthly Inflation, Argentina Industrial Production Index
Argentina/Ukraine	Exchange rate(Argentine Peso to Ukrainian hryvnia), Baltic Exchange Dry Index, Argentina Unemployment Rate, Argentina Monthly Inflation, Argentina Industrial Production Index Ukraine Unemployment Rate, Ukraine Monthly Inflation, Ukraine Industrial Production Index
Gulfs/KCMO	Baltic Exchange Dry Index, US Unemployment Rate, US Monthly Inflation, US Interest Rate, US Industrial Production Index, US Gas Price, US Corn Stock

Table 1: Covariates in Each pair of markets

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 and the global financial/economic crisis of 2008-09. Specifically, the breakpoints for these events are set in February 2014 and October 2008, respectively. The corresponding parameter estimates are detailed in Table 9, 10,11 and 12 [4].

The quantile estimates, as shown in Table 9, 10, 11, and 12, provide insights into whether, during the selected periods, monthly observations more frequently fall into trade regimes with lower quantile estimates. In all situations, entry into trade regimes is less frequent, as indicated by quantile estimates of the forcing variable greater than 0.5, based on the optimal lag structure we selected using BIC. Additionally, time delay structures are evident in all cases, except for the pair of the US and Ukraine during the selected periods, such as pre-2008 financial/economic crisis, pre- and post-2014 Crimea, and post-2008 financial/economic crisis for US regional markets.

Next, we remove the shrinkage bias introduced due to the penalization in Equation (2.6) using Equation (2.8) before conducting statistical inference.

Our estimation setup considers a richer examination of price linkage among global

[4]Here,"break 2008" refers to the breakpoint of the 2008-2009 world financial/economic crisis, while "break 2014" represents the breakpoint of the 2014 Crimean crisis.

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 perfect market integration 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). The ranges of estimates vary from market-pair to market-pair in our results.[5] Tables 13, 14, 15, and 16 provide a summary of the estimates of the degree of error correction based on (2.5).

Tables 17, 18, 19, and 20 present the signs of statistically significant estimates at the 5% significance level. Notably, the desparsified LASSO estimates are statistically insignificant when the slope coefficient estimates by Equations (2.6) and (2.7) are zero. Therefore, we only present non-zero estimates by the LASSO method.

If we set aside the consideration of structural breaks and focus solely on estimating the entire period's data, the findings reveal no significant estimates among the market pairs of Argentina/Ukraine, US/Argentina, and Gulf/KCMO—except for the US/Ukraine pair. The United States, holding a prominent global position in maize production and exportation, assumes a pivotal role. Meanwhile, Ukraine contends with a challenging and unstable economic and market environment. Consequently, the sensitivity of price linkages between the two markets is more clearly estimated, with several significant impact factors. Interestingly, we do not observe a significantly imperfect exchange rate pass-through effect in either US/Argentina, US/Ukraine, or Argentina/Ukraine.

[5]The detailed desparsified LASSO estimates for all models are not included here due to space constraints but are presented in the "Appendix".

Next, we examine the estimation results using the desparsified LASSO method for each case under the structural breaks specification we imposed.

In Table 17, it is evident that the 5-month lag in Argentina's inflation rate consistently exhibits significant effects in both the no-trade and trade regimes. Moreover, notable additional significant factors emerge in the trade regime, including the 3-month lag in Argentina's unemployment rate and the 4-month lag in Ukraine's unemployment rate. These findings suggest nonlinearity in the Argentina/Ukraine case before the 2014 Crimean crisis. After the break, several factors achieve statistical significance. The Baltic index change at the second lag, Ukraine's inflation at the second lag, Argentina's inflation at the first lag, and Argentina's unemployment rate show statistical significance only in the trade regime. Argentina's unemployment at the sixth lag is positive and statistically significant in both trade and no-trade regimes. Consequently, the overall effects of Argentina's unemployment rate remain uncertain in the trade regime. Additionally, the current month's Argentina unemployment has a positive effect, particularly in the trade regime. The exchange rate pass-through is negative and statistically significant in both trade and no-trade regimes at the fourth lag. Generally, we identify more significant factors in the trade regime and more after the break.

The analysis of Table 18 reveals several significant factors during the partition periods in the case of the US/Ukraine, except for the period preceding the 2008/09 financial crisis break. When considering the structural break during the 2014 Crimea crisis in the pre-break situation, it is evident that the US inflation rate dynamically affects both the trade and no-trade regimes. The US unemployment rate at several lags, the Baltic Freight Index, the US Industrial Production Index, and the Ukraine Industrial Production Index exhibit significant effects on the price differentials, displaying nonlinearity. Notably, certain estimates of the threshold effect (the difference between the two regimes) are significant. The consistent sign of estimates for different lagged periods in both the structural and threshold effect estimates implies a larger magnitude and a prominent effect of these factors in the trade regime. Regarding the US corn stock, the long-run propensity effects are significant and observed in both the trade and no-trade regimes, but the direction of its cumulative effect is uncertain. For Ukraine's employment, the cumulative effect is only significant in the trade regime, with an uncertain direction. In the post-break scenario, accounting for the structural break during the 2014 Crimea crisis, we observe positive and nonlinear cumulative effects of the Baltic Freight Index and US inflation on price differentials. The US corn stock exhibits cumulative effects, though the overall impact in the trade regime is uncertain. Meanwhile, the Ukraine Industrial Production Index shows negative cumulative effects but follows a linear pattern. In the estimation corresponding to the selected data period before the 2008/09 financial crisis, only the US Monthly Inflation at the third lag and Ukraine's Monthly Industrial Production Index at the sixth lag exhibit effects in the trade regime. It's worth noting that no significant factors are found in the no-trade regime for this sub-period. However, for the selected data period after the 2008/09 financial crisis, we find that the cumulative effect of US gas prices is positive and nonlinear. Additionally, the cumulative effect of the US Unemployment Rate is negative and nonlinear. The effect of Ukraine inflation is cumulatively negative in both trade and no-trade regimes. Furthermore, the effect of US interest rates is nonlinear, with US interest rates at the fifth lag being only significant in the trade regime.

Turning to Table 19, we observe that the US corn stock demonstrates a negative cumulative effect pre-break but a positive cumulative effect post-break in both the trade and no-trade regimes. Moreover, there is a positive cumulative effect of the US unemployment rate and a negative cumulative effect of the Baltic Freight Index in both the trade and no-trade regimes after the break. Additionally, we note a nonlinear cumulative effect of the exchange rate of the US Dollar to the Argentine Peso, with the magnitude of the cumulative exchange rate pass-through effect being larger in the trade regime. What this means is that with a US dollar appreciation, the ratio of real prices in the US to real prices in Argentina will decrease by a smaller change than the actual change in the exchange rate. As a further illustration, we attempted to apply the method developed for the three international markets to the US domestic market. However, the results vary significantly compared to the previous three export market pairs. Despite the threshold estimates selected through the scaled LASSO method in Table 8, it's worth noting the absence of significant factor estimates that differ between trade and no-trade regimes. Consequently, there are no significant factors indicating nonlinear relationships in either of the selected periods. Given that maize transportation within the US heavily relies on the Mississippi River system, and the movements of corn are one-directional, barge freight costs emerge as the most pertinent factor influencing the price linkages of the US domestic corn market. While we didn't discover any significant factors in the entire period or post-2008 break, in the model of the pre-2008 financial crisis, we observed several significant factors. Notably, only US inflation rates at several lags have a negative overall effect on the pre-break markets. However, for the Baltic Freight Index, the US Industrial Production Index, and US gas prices, the cumulative effects don't have patterns, displaying uncertainty with varied (positive or negative) effects across different lagged periods.

In the four cases, we observe that the results of partition periods reveal more significant factors influencing price linkages, considering that the threshold is not fixed throughout the entire period. Additionally, trade regimes appear to be influenced by a greater number of market factors, and the magnitudes of these factors affecting price linkages tend to be larger compared to the no-trade regime. In essence, market factors have a more lasting and prominent impact on price linkages within the trade regime.

4 Summary and Concluding Remarks

We develop a model of price linkages in spatially distinct international export markets for maize under perfect integration to investigate 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 results are consistent with the presence of imperfect pass-through, which distorts international price linkages. The markets appear to be strongly linked in most cases, and nonlinear adjustments are confirmed in most cases. Consistent with existing research, the results indicate that distortions from market equilibrium caused by exchange rate or market factors are generally larger in response to large price differences, which reflect more substantial disequilibrium conditions and therefore larger arbitrage opportunities.

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5 Appendix

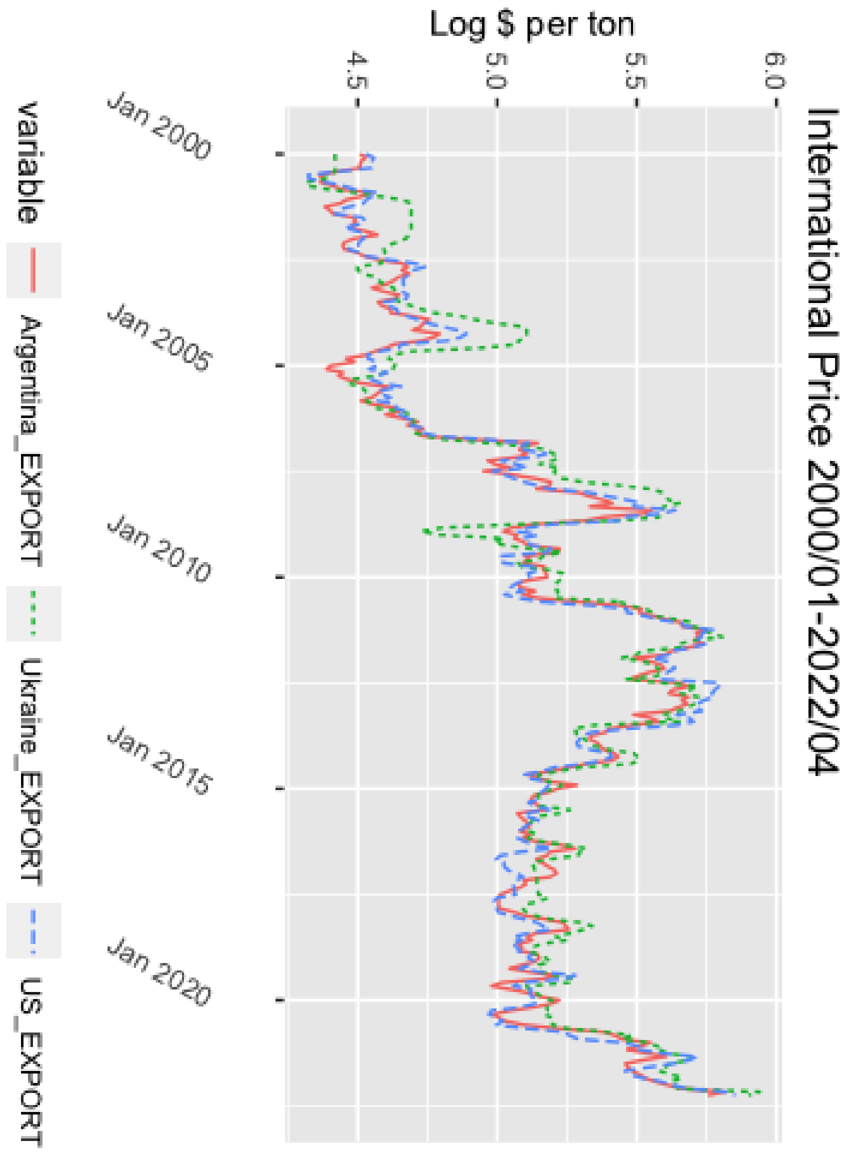

Figure 2: World Corn Export price by Country

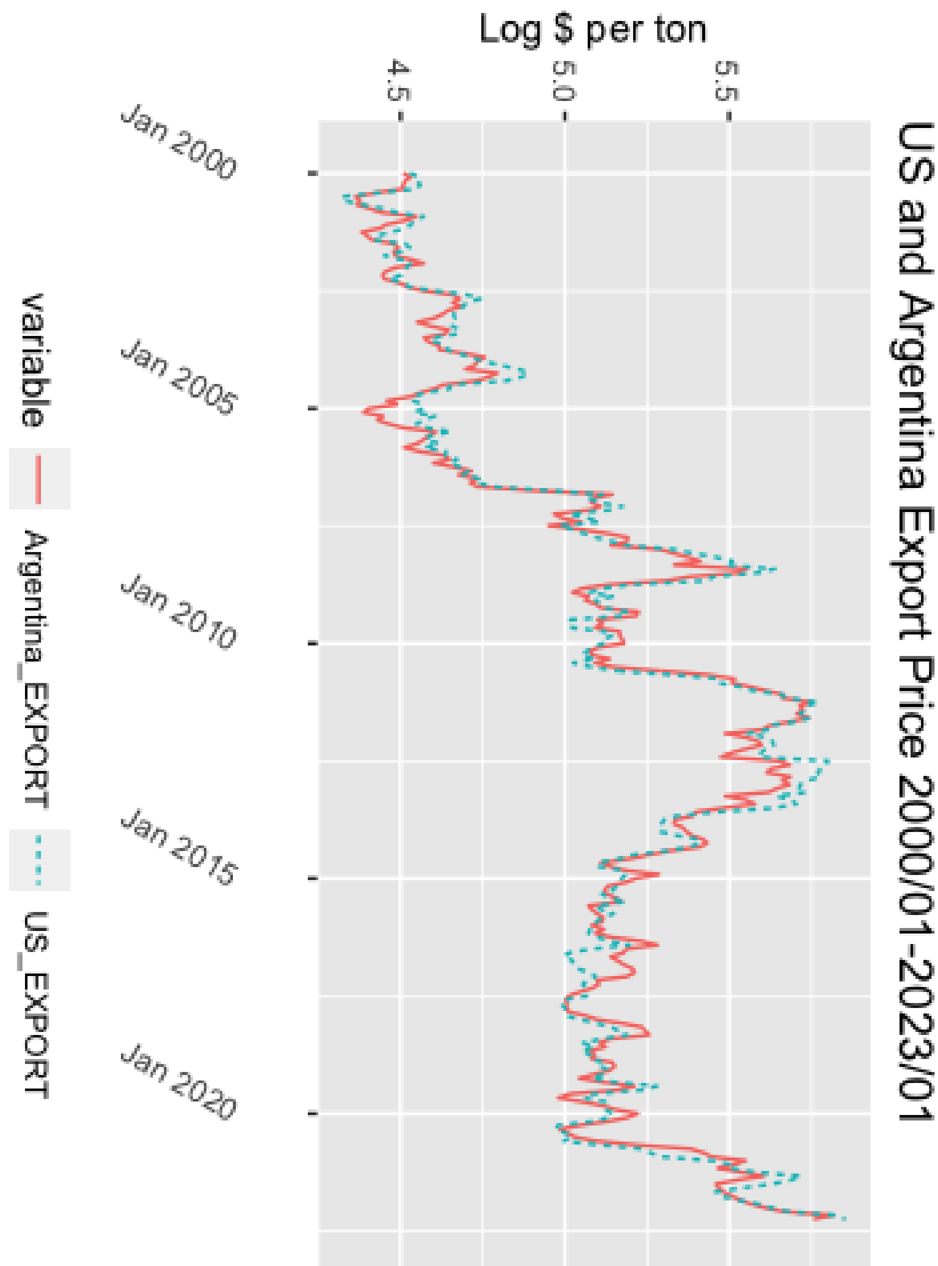

Figure 3: the U.S. and Argentina Corn Market Price

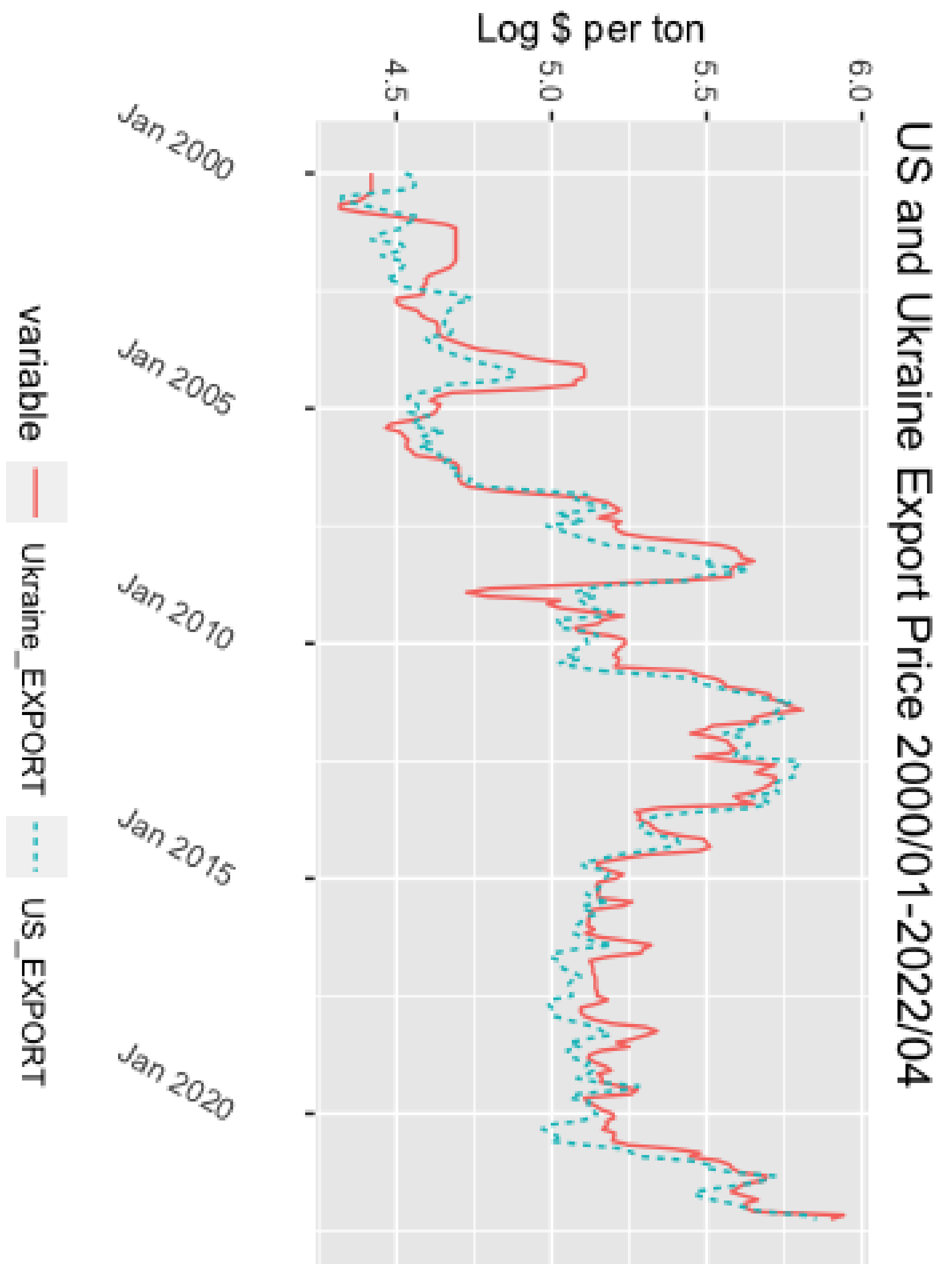

Figure 4: the U.S. and Ukraine Corn Market Price

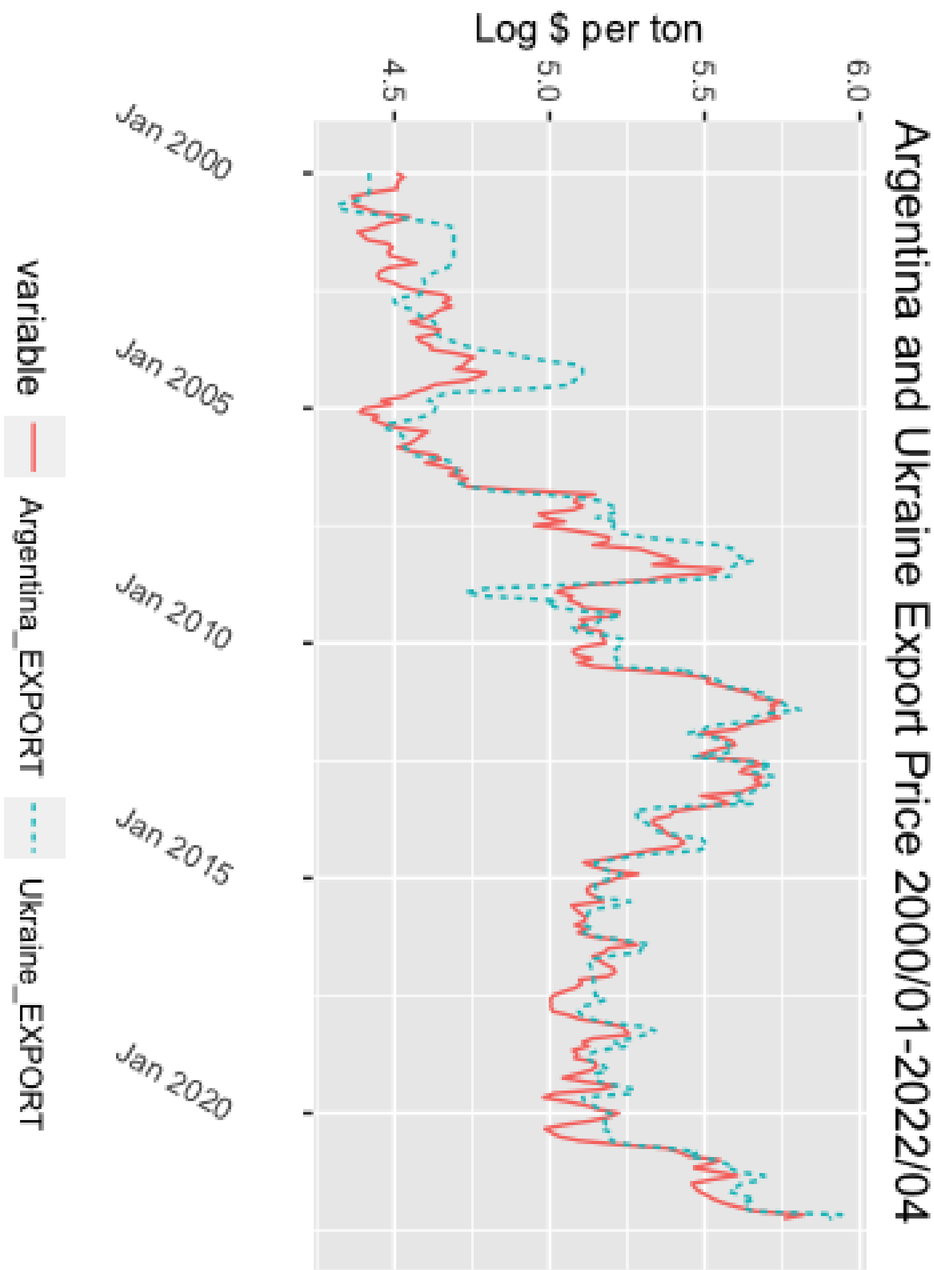

Figure 5: Argentina and Ukraine Corn Market Price

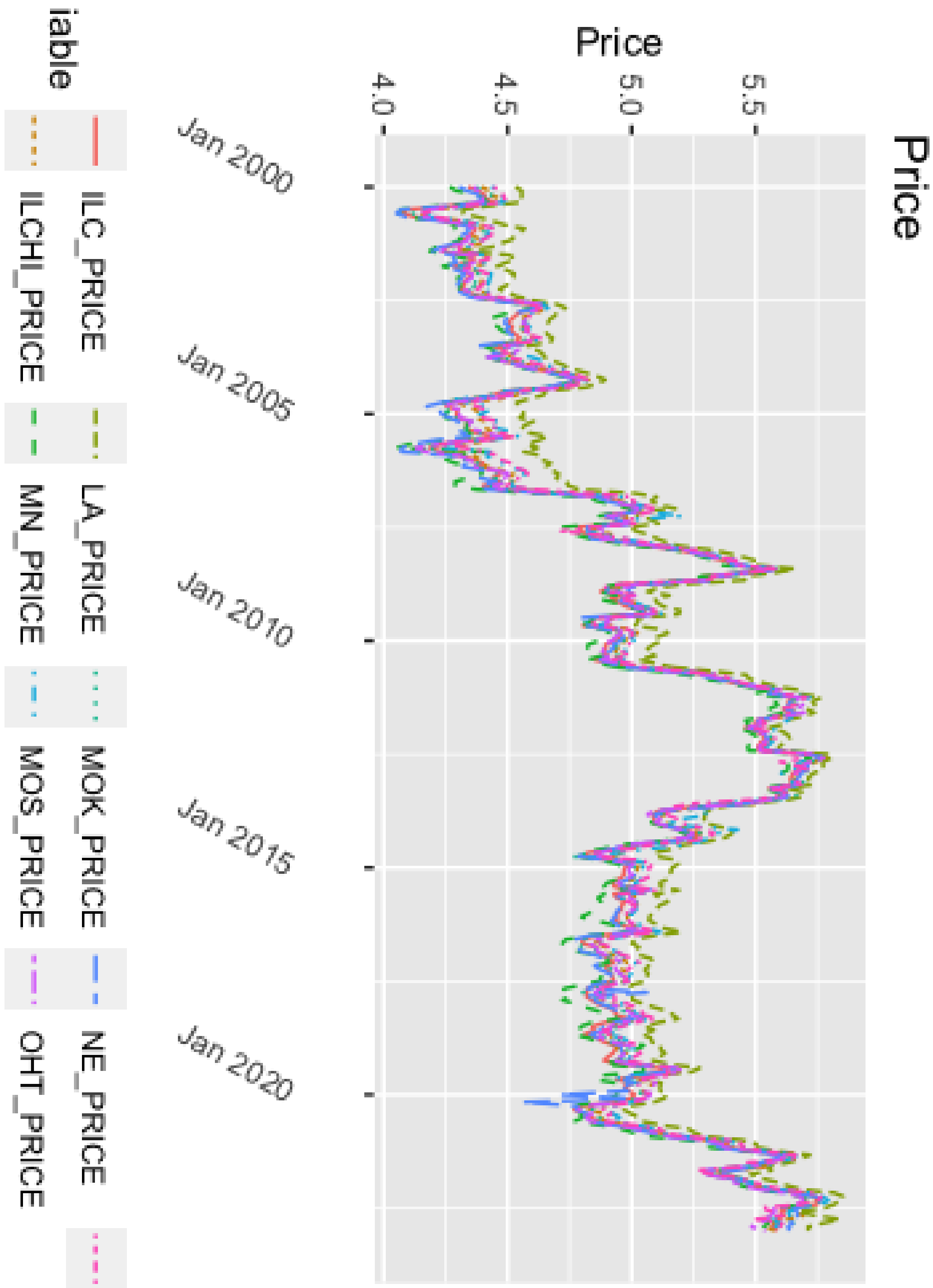

Figure 6: the U.S. Corn Market Price by Location

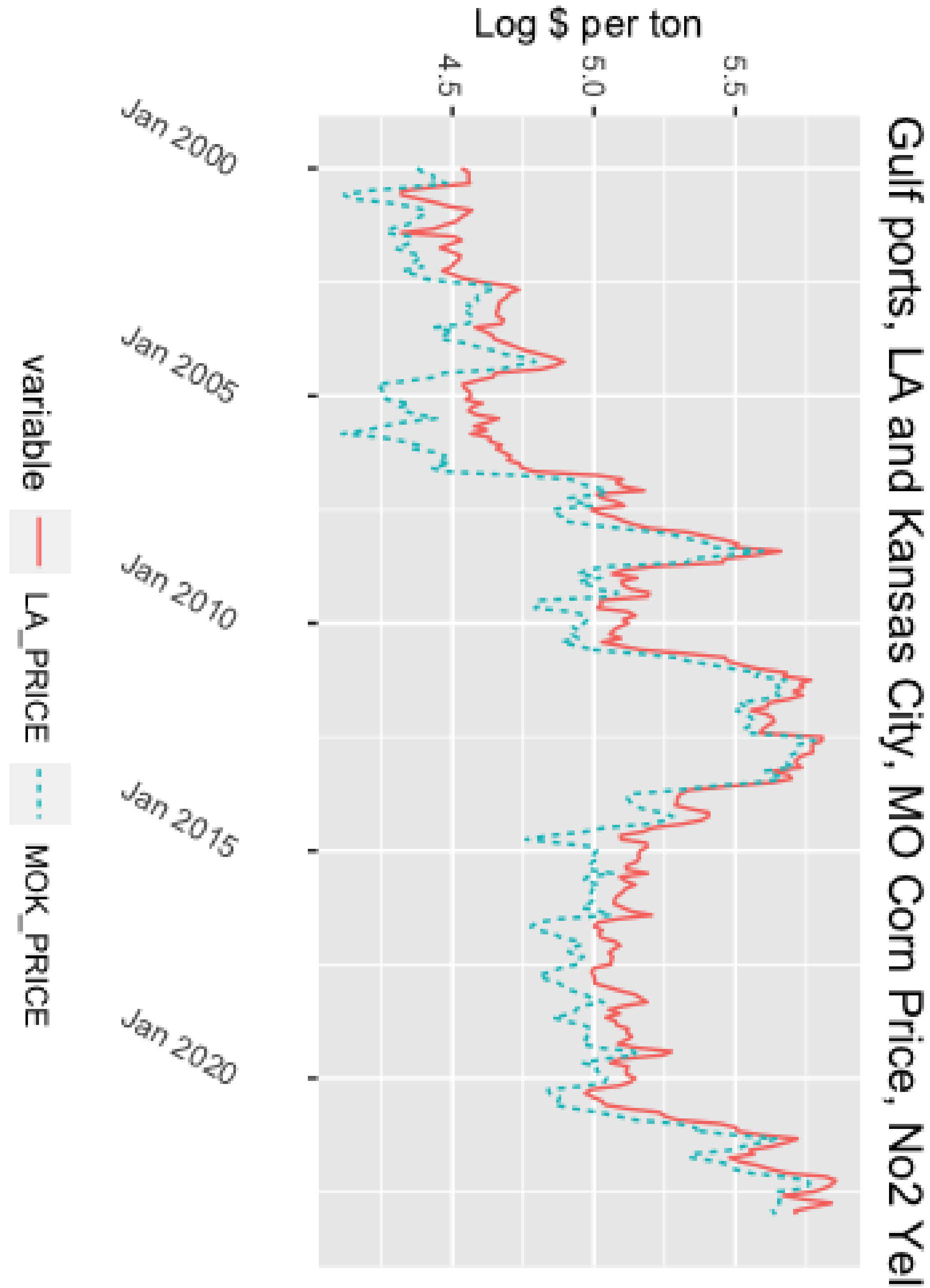

Figure 7: the U.S. Corn Market Price-Kansas City, MO&Gulf ports, LA

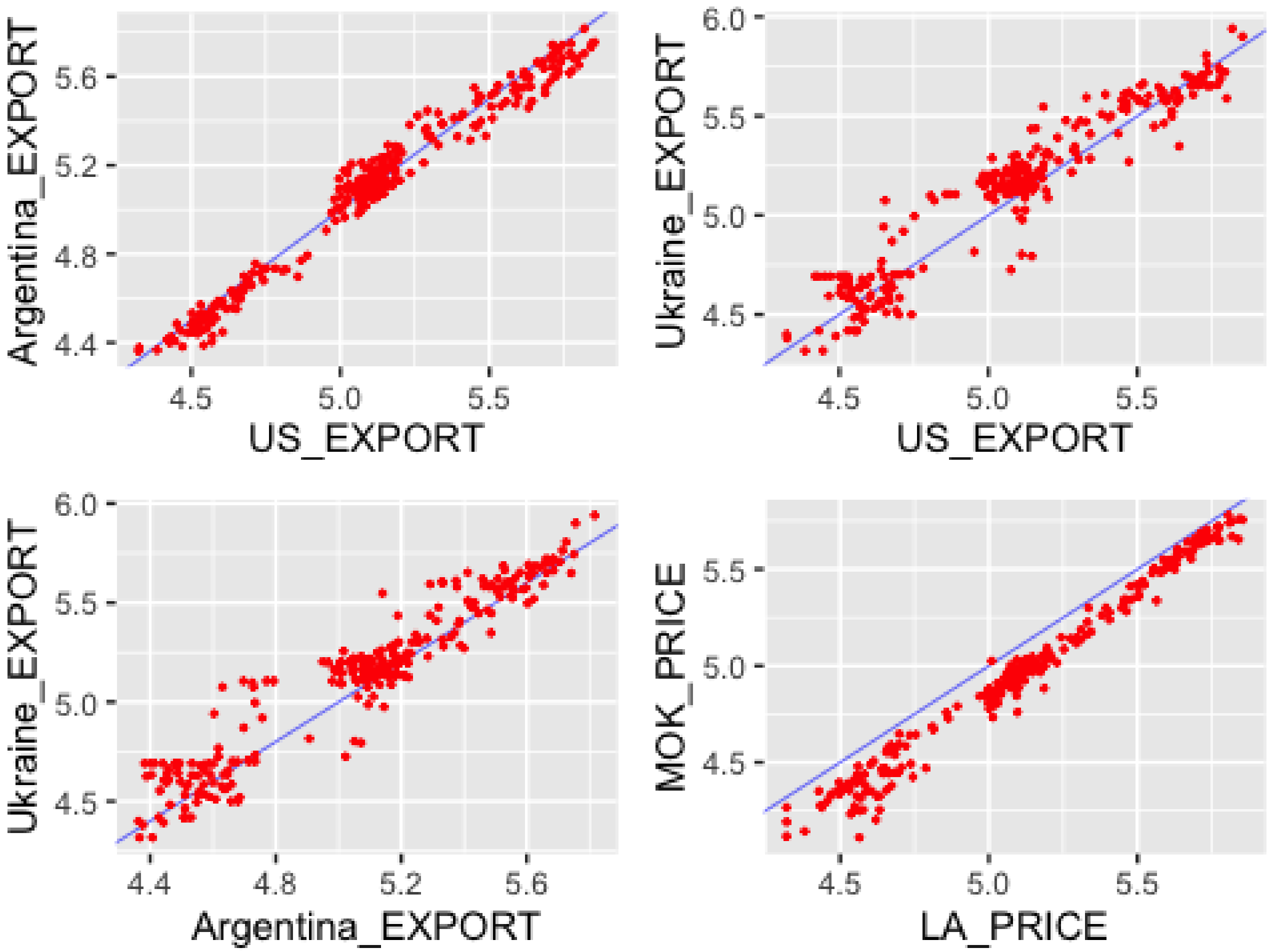

Figure 8: Corn Market Logarithmic Prices pairs

Augmented Dickey-Fuller test Results		
Variable		ADF
Unit Root		
price_diff_US_Argentina		-4.473
price_diff_US_Ukraine		-4.7348
price_diff_Argentina_Ukraine		-4.6487
price_diff_Gulf_KCMO		-3.1602
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 Price Differentials

Augmented Dickey-Fuller Test	
Variable (1st diff)	Dickey-Fuller
price_diff_US_Argentina	-9.068
price_diff_US_Ukraine	-5.9761
price_diff_Argentina_Ukraine	-6.7176
price_diff_Gulf_KCMO	-8.7288
UAH_USDollar	-5.652
Peso_USDollar	-5.7734
Peso_UAH	-5.5003
Baltic_Freight	-7.8916
US Unemployment Rate	-7.4513
US Industrial Production Index	-9.9739
US Monthly Inflation	-9.3708
US Interest Rate	-3.2288
US Monthly Gas Price	-7.6682
US Corn Stock	-11.708
Argentina Unemployment Rate	-4.5384
Argentina Monthly Industrial Production Index	-12.332
Argentina Monthly Inflation	-7.2783
Ukraine Unemployment Rate	-6.3418
Ukraine Monthly Industrial Production Index	-9.3515
Ukraine Monthly Inflation	-8.6679

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

Nonlinearity test				
	US/Argentina		US/ Ukraine	
	Test Statistics	p-value	Test Statistics	p-value
Teraesvirta's neural network test χ^2	2.249	0.325	2.564	0.278
White neural network test χ^2	1.278	0.528	1.066	0.587
Keenan's one-degree test for nonlinearity F-stat	2.030	0.155	0.990	0.321
Tsay's Test for nonlinearity F-stat	0.895	0.444	1.381	0.058
Likelihood ratio test for threshold nonlinearity χ^2	7.970	0.250	29.653	0.028
(SETAR) models: Linear AR versus 1 threshold TAR F-stat	7.824	0.318	6.203	0.426
	Gulf ports/Kansas City		Ukraine/Argentina	
	Test Statistics	p-value	Test Statistics	p-value
Teraesvirta's neural network test χ^2	3.082	0.214	2.481	0.289
White neural network test χ^2	3.225	0.199	2.558	0.278
Keenan's one-degree test for nonlinearity F-stat	2.176	0.141	2.237	0.136
Tsay's Test for nonlinearity F-stat	3.047	0.007	1.401	0.215
Likelihood ratio test for threshold nonlinearity χ^2	14.840	0.061	12.280	0.133
(SETAR) models: Linear AR versus 1 threshold TAR [6] F-stat	13.592	0.032	3.983	0.824

Table 4: Nonlinearity specification testing results

	US/Argentina	US/ Ukraine	Ukraine/Argentina
(Intercept)	−0.001974	0.006311	0.007981*
	(0.002159)	(0.004282)	(0.004364)
degree of "error correction"	0.144412 ***	0.124143 ***	0.133380 ***
	(0.031209)	(0.030017)	(0.030916)
Observations	276	267	267
R^2	0.07248	0.06063	0.06563
Adjusted R^2	0.0691	0.05709	0.0621
F-statistic	21.41	17.1	18.61
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: OLS estimates of autoregressive error correction price parity model (3.2)

	US/Argentina	US/ Ukraine	Ukraine/Argentina
(Intercept)	−0.002904	0.005144	0.008365 *
	(0.002257)	(0.0107)	(0.004368)
degree of "error correction"	0.146185 ***	0.118960 ***	0.127017 ***
	(0.031182)	(0.0107)	(0.0124)
exchange rate	0.047907	0.138564	-0.070481
	(0.034486)	(0.101927)	(0.053817)
Observations	276	267	267
R^2	0.07899	0.06716	0.07166
Adjusted R^2	0.07224	0.06009	0.06463
F-statistic	11.71	9.503	10.19
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: OLS estimates of autoregressive error correction price parity model (3.3)

	Gulf ports/Kansas City		
	structural effect	threshold effect	Linear without threshold
(Intercept)	-0.04609592^{***}	-0.00753288	-0.017931 ***
	(0.006287735)	(0.009523180)	(0.004539)
degree of "error correction"	0.49574257 ***	-0.26337144 ***	0.124237 ***
	(0.055176968)	(0.065753137)	(0.028919)
estimated threshold quantile	0.57		
Observations	276		276
R^2			0.06311
Adjusted R^2			0.05969
F-statistic			18.46
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: TAR estimates of autoregressive error correction price parity model (3.1)

US/ Ukraine						
time delay for the threshold variable	1	2	3	4	5	6
BIC	1.52	1.72	-0.15	1.71	1.72	1.79
Threshold estimate(quantile)	0.62	0.60	0.75	0.63	0.35	0.46
US/Argentina						
time delay for the threshold variable	1	2	3	4	5	6
BIC	0.91	0.63	0.34	0.88	0.56	1.10
Threshold estimate(quantile)	0.48	0.65	0.52	0.59	0.67	0.59
Ukraine/Argentina						
time delay for the threshold variable	1	2	3	4	5	6
BIC	-0.31	0.37	-0.23	-0.38	-0.27	0.45
Threshold estimate(quantile)	0.80	0.66	0.71	0.78	0.65	0.64
Gulf ports/Kansas City						
time delay for the threshold variable	1	2	3	4	5	6
BIC	-2.55	-2.10	-2.53	-2.56	-2.55	-2.36
Threshold estimate(quantile)	0.79	0.83	0.83	0.75	0.72	0.76

Table 8: Lasso Estimation with BIC

US/ Ukraine						
time delay for the threshold variable	1	2	3	4	5	6
BIC	1.52	1.72	-0.15	1.71	1.72	1.79
Threshold estimate(quantile)	0.62	0.60	0.75	0.63	0.35	0.46
pre break 2014						
time delay for the threshold variable	1	2	3	4	5	6
BIC	2.13	2.66	2.54	2.51	2.58	2.12
Threshold estimate(quantile)	0.73	0.63	0.56	0.67	0.37	0.74
post break 2014						
time delay for the threshold variable	1	2	3	4	5	6
BIC	1.11	1.58	1.58	1.92	1.73	1.96
Threshold estimate(quantile)	0.62	0.58	0.43	0.43	0.48	0.39
pre break 2008						
time delay for the threshold variable	1	2	3	4	5	6
BIC	2.21	2.78	2.48	2.67	2.28	2.51
Threshold estimate(quantile)	0.58	0.46	0.65	0.64	0.53	0.57
post break 2008						
time delay for the threshold variable	1	2	3	4	5	6
BIC	2.47	2.76	2.68	2.42	1.74	2.23
Threshold estimate(quantile)	0.48	0.49	0.51	0.47	0.36	0.37

Table 9: Lasso Estimation with BIC

US/Argentina						
time delay for the threshold variable	1	2	3	4	5	6
BIC	0.91	0.63	0.34	0.88	0.56	1.10
Threshold estimate(quantile)	0.48	0.65	0.52	0.59	0.67	0.59
pre break 2008						
time delay for the threshold variable	1	2	3	4	5	6
BIC	0.77	0.52	1.11	0.95	0.89	0.67
Threshold estimate(quantile)	0.36	0.52	0.65	0.31	0.34	0.33
post break 2008						
time delay for the threshold variable	1	2	3	4	5	6
BIC	0.69	0.65	0.95	0.93	0.90	1.09
Threshold estimate(quantile)	0.69	0.61	0.61	0.38	0.63	0.47

Table 10: Lasso Estimation with BIC

Ukraine/Argentina						
time delay for the threshold variable	1	2	3	4	5	6
BIC	-0.31	0.37	-0.23	-0.38	-0.27	0.45
Threshold estimate(quantile)	0.80	0.66	0.71	0.78	0.65	0.64
pre break 2014						
time delay for the threshold variable	1	2	3	4	5	6
BIC	2.49	2.47	2.35	2.88	2.50	2.89
Threshold estimate(quantile)	0.61	0.57	0.64	0.49	0.59	0.54
post break 2014						
time delay for the threshold variable	1	2	3	4	5	6
BIC	1.11	1.00	1.01	1.07	1.19	0.87
Threshold estimate(quantile)	0.52	0.54	0.54	0.69	0.34	0.63

Table 11: Lasso Estimation with BIC

Gulf ports/Kansas City						
time delay for the threshold variable	1	2	3	4	5	6
BIC	-2.55	-2.10	-2.53	-2.56	-2.55	-2.36
Threshold estimate(quantile)	0.79	0.83	0.83	0.75	0.72	0.76
pre break 2008						
time delay for the threshold variable	1	2	3	4	5	6
BIC	-0.76	-1.16	-0.15	-2.09	0.60	0.64
Threshold estimate(quantile)	0.76	0.77	0.78	0.77	0.61	0.57
post break 2008						
time delay for the threshold variable	1	2	3	4	5	6
BIC	-3.00	-1.67	-1.01	-2.80	-2.72	-2.76
Threshold estimate(quantile)	0.64	0.45	0.49	0.52	0.42	0.39

Table 12: Lasso Estimation with BIC

	entire period	pre 2008	post 2008	pre2014	post2014
Structural Effect	0.170 ***	0.019 *	-0.558	0.152***	0.125
	(0.016)	(0.010)	(0.813)	(0.005)	(0.573)
Threshold Effect	-0.258		0.202	-0.290***	-0.189
	(0.167)		(0.366)	(0.010)	(0.409)

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

Table 13: Estimates of degree of "error correction" using Lasso Estimation for US/Ukraine

	entire period	pre 2008	post 2008
Structural Effect	0.332 ***	0.102	0.322 ***
	(0.009)	(0.191)	(0.008)
Threshold Effect	-0.319 ***		-0.296 ***
	(0.007)		(0.004)

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

Table 14: Estimates of degree of "error correction" using Lasso Estimation for US/Argentina

	entire period	pre 2014	post 2014
Structural Effect	0.256 ***	0.367 ***	0.419 ***
	(0.022)	(0.001)	(0.135)
Threshold Effect	-0.577	-0.390 ***	-0.550 ***
	(0.362)	(0.022)	(0.107)
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 15: Estimates of degree of "error correction" using Lasso Estimation for UKraine/Argentina

	entire period	pre 2014	post 2014
Structural Effect	0.039	-1.182	-1.802
	(0.109)	(1.360)	(2.186)
Threshold Effect	-0.176		0.123
	(0.116)		(0.337)
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 16: Estimates of degree of "error correction" using Lasso Estimation for Gulfs/KC

Model	Argentina/Ukraine	pre break 2014	post break 2014
lag_5_FD_Argentina Monthly Inflation		-	
trade_lag_3_FD_Argentina Unemployment Rate		-	
trade_lag_4_FD_Ukraine Unemployment Rate		+	
lag_4_FD_Argentina Monthly I.P.I % Change			-
lag_4_FD_Ukraine Monthly Inflation			-
lag_4_Peso_UAH % Change			-
FD_Ukraine Unemployment Rate			-
lag_1_FD_Ukraine Monthly I.P.I % Change			-
trade_lag_2_Baltic_Freight % Change			-
trade_lag_2_FD_Ukraine Monthly Inflation			-
trade_FD_Argentina Unemployment Rate			-
trade_lag_1_FD_Argentina Monthly Inflation			+
lag_6_FD_Argentina Unemployment Rate			+
cos			+

Table 17: Argentina Ukraine Signs of Significant Estimates

Model	US/Ukraine	pre break 2014	post break 2014	pre break 2008	post break 2008
Baltic_Freight Percent Change	-		+		
lag_1_Baltic_Freight Percent Change	-				
lag_5_Baltic_Freight Percent Change	-				
trade_lag_3_FD_US Monthly Industrial Production Index	-				
trade_lag_4_FD_US Monthly Industrial Production Index	+				
lag_3_FD_US Monthly Inflation	+				
lag_4_FD_LN_US Corn Stock	+				
trade_lag_1_FD_US Unemployment Rate	+				-
lag_1_FD_Ukraine Monthly Inflation		-			
lag_2_FD_US Unemployment Rate		-			
lag_6_FD_US Unemployment Rate		-			
trade_lag_5_FD_US Unemployment Rate		-			
trade_lag_4_FD_Ukraine Unemployment Rate		+			
trade_lag_6_FD_Ukraine Unemployment Rate		-			
lag_6_Baltic_Freight Percent Change		-			
trade_lag_4_Baltic_Freight Percent Change		+			
lag_1_FD_US Monthly Inflation		+			
lag_3_FD_US Monthly Inflation		+			
lag_3_FD_LN_US Corn Stock		+			
lag_5_FD_LN_US Corn Stock		+			
lag_6_FD_LN_US Corn Stock		-			
FD_US Monthly Industrial Production Index		-			
trade_lag_1_FD_US Monthly Industrial Production Index		+			
lag_3_FD_Ukraine Monthly Industrial Production Index		+			
trade_lag_1_FD_Ukraine Monthly Industrial Production Index		+			
trade_lag_6_FD_US Interest Rate		+			
lag_6_FD_Ukraine Monthly Inflation			+		
trade_lag_6_US Monthly Gas Price Percent Change			+		
UAH_USDollar Percent Percent Change			+		
FD_US Interest Rate			+		
FD_US Monthly Inflation			+		
trade_lag_6_FD_US Monthly Inflation			+		
trade_lag_1_Baltic_Freight Percent Change			+		
FD_LN_US Corn Stock			+		
lag_3_FD_LN_US Corn Stock			+		
trade_lag_2_FD_LN_US Corn Stock			+		
trade_lag_5_FD_LN_US Corn Stock			-		
lag_4_US Monthly Gas Price Percent Change			-		
lag_5_FD_Ukraine Monthly Industrial Production Index			-		
lag_6_FD_Ukraine Monthly Industrial Production Index			-		
lag_6_FD_US Monthly Industrial Production Index			-		
trade_lag_3_FD_US Monthly Inflation				+	
trade_lag_6_FD_Ukraine Monthly Industrial Production Index				+	
trade_lag_4_US Monthly Gas Price Percent Change					+
lag_3_US Monthly Gas Price Percent Change					+
trade_lag_5_FD_US Interest Rate					+
lag_1_FD_US Interest Rate					-
lag_6_FD_US Interest Rate					-
lag_5_FD_Ukraine Monthly Inflation					-
lag_6_FD_Ukraine Monthly Inflation					-
FD_US Unemployment Rate					-
lag_5_Baltic_Freight Percent Change					-
lag_3_FD_Ukraine Unemployment Rate					-
trade_lag_3_UAH_USDollar Percent Change					-

Table 18: US Ukraine Signs of Significant Estimates

Model	US/Argentina	pre break 2008	post break 2008
lag_2_Baltic_Freight % Change		+	
lag_4_FD_Argentina Monthly I.P.I % Change		+	
lag_5_FD_US Interest Rate		+	
trade_lag_2_FD_US Monthly Inflation		+	
lag_2_FD_Argentina Monthly Inflation		-	
lag_2_Peso_USDollar % Change		-	
lag_4_Baltic_Freight % Change		-	
lag_5_FD_LN_US Corn Stock		-	+
lag_6_FD_LN_US Corn Stock		-	
lag_3_FD_LN_US Corn Stock			+
lag_3_FD_US Unemployment Rate			+
lag_6_FD_US Unemployment Rate			+
lag_6_Peso_USDollar % Change			+
trade_lag_2_Peso_USDollar % Change			+
trade_lag_6_FD_Argentina Monthly Inflation			+
lag_1_Baltic_Freight % Change			-
lag_5_Baltic_Freight % Change			-
lag_6_Baltic_Freight % Change			-
lag_3_FD_Argentina Monthly I.P.I % Change			-
trade_cos			-
trade_lag_1_FD_Argentina Monthly Inflation			-
trade_lag_5_FD_Argentina Unemployment Rate			-

Table 19: US/Argentina Signs of Significant Estimates

Model	Gulfs/KCMO	pre break 2008	post break 2008
lag_5_FD_US Unemployment Rate		-	
FD_LN_US Corn Stock		-	
Baltic_Freight % Change		+	
lag_6_Baltic_Freight % Change		-	
FD_US Monthly I.P.I % Change		+	
lag_6_FD_US Monthly I.P.I % Change		+	
lag_2_FD_US Monthly I.P.I % Change		-	
lag_1_FD_US Monthly Inflation		-	
lag_3_FD_US Monthly Inflation		-	
lag_3_US Monthly Gas Price % Change		+	
lag_4_US Monthly Gas Price % Change		-	
lag_5_US Monthly Gas Price % Change		-	

Table 20: GulfsLA/KCMO Signs of Significant Estimates