Investigating Integration and Exchange Rate Pass-Through in World Maize Markets Using Inferential LASSO Methods

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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 on 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 Pass-Through

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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.

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 values. 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 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.

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. Although trade in agricultural commodities is typically invoiced in US dollars, exchange rate shocks may still exhibit imperfect pass-through, which will distort international price linkages. Furthermore, 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, exchange rates, 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 transaction 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.

2 Econometrics Models of Spatial Market Integration

Spatial market integration in agricultural product markets has been extensively studied in the literature. Consider a homogeneous commodity traded in a 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

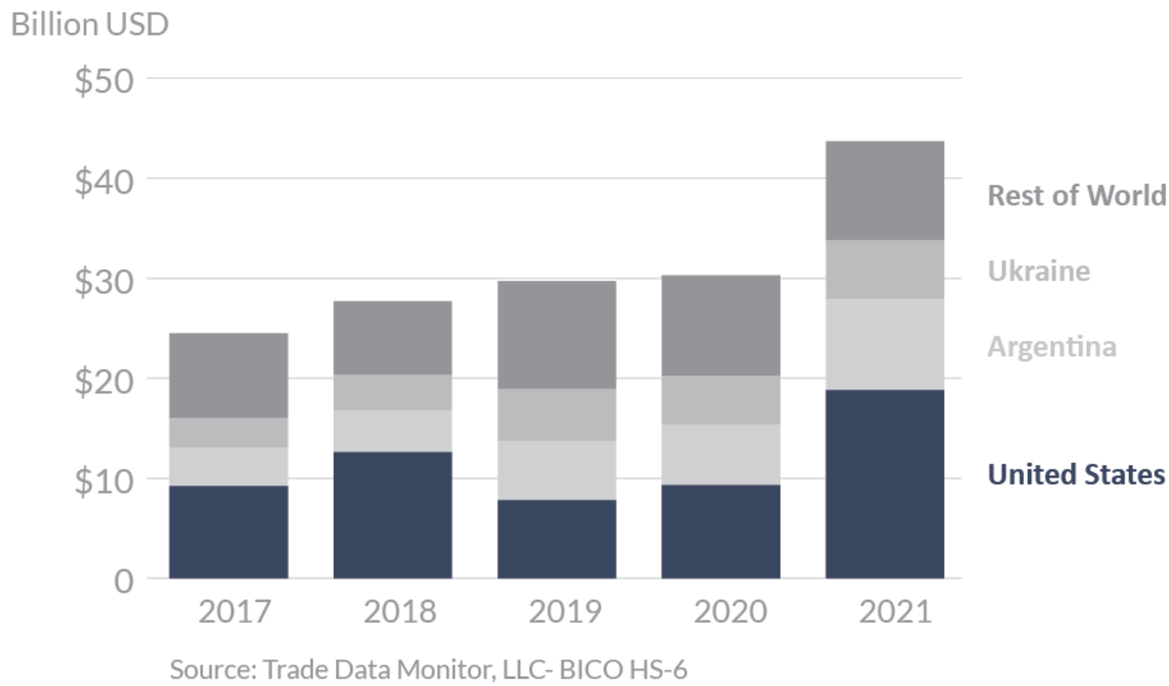

Figure 1: World Corn Exports by Country and Marketing Year

condition of perfect market integration reflects the equation $P_t^1/P_t^2 = \Pi_t^{12}$, 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.

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 reected 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 related 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:

$$\begin{aligned} \Delta(p_t^1 - p_t^2) =& \gamma_0 + \gamma_1 \Delta\pi_t^{12} + \gamma_2 \Delta Z_t^{12} \\ & + \mathbf{1}\{p_{t-1}^1 - p_{t-1}^2 \geq c\}(\delta_0 + \delta_1 \Delta\pi_t^{12} + \delta_2 \Delta Z_t^{12}) + \varepsilon_t, \\ t =& \{1, \ldots, T\} \end{aligned} \tag{2.4}$$

where γ_0 is a time trend coefficient if we add a linear time trend to equation (2.3).

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

$$\begin{aligned} \Delta(p_t^1 - p_t^2) =& \gamma_0 + \sum_{l=0}^{L} \gamma_{1l} \Delta\pi_{t-l}^{12} + \sum_{l=0}^{L} \gamma_{2l} \Delta z_{t-l}^{12} \\ & + \mathbf{1}\{Q_t \geq c\} \left[\delta_0 + \sum_{l=0}^{L} \delta_{1l} \Delta\pi_{t-l}^{12} + \sum_{l=0}^{L} \delta_{2l} \Delta z_{t-l}^{12} \right] + \varepsilon_t \\ t =& \{1, \ldots, T\}, \end{aligned} \tag{2.5}$$

where L is the maximal possible lag, which can 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. This framework may provide 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 exchange rate pass-through. Therefore, it is essential to investigate the impact of transaction costs on the market's response to an exchange rate shock. 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.

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

$$\alpha = (\gamma_0, \gamma_{10} \cdots, \gamma_{1L}, \gamma_{20} \cdots, \gamma_{2L}, \delta_0, \delta_{10} \cdots, \delta_{1L}, \delta_{20} \cdots, \delta_{2L})'$$

be slope parameter vector, The dimension of α is $2 + 2(1 + p)(L + 1)$, where p is number of other exogenous shocks. Let $\mathbf{X}$ be a $T \times [1+(1+p)(L+1)]$ 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)
$$\widehat{\alpha}(c) := \operatorname{argmin}_{\alpha} \left\{ T^{-1} \sum_{t=1}^{T} \left(\Delta(p_t^1 - p_t^2) - [X_t', X_t' \mathbf{1}\{Q_t \geq c\}]' \alpha \right)^2 + \lambda \left\| \mathbf{D}(c) \alpha \right\|_1 \right\},$$

where we can rewrite the ℓ_1 penalty as

$$\lambda \left\| \mathbf{D}(c)\alpha \right\|_1 = \lambda \sum_{j=1}^{1+(1+p)(L+1)} \left[\left\| X^{(j)} \right\|_n \left| \alpha^{(j)} \right| + \left\| X^{(j)}(\tau) \right\|_n \left| \alpha^{(1+(1+p)(L+1)+j)} \right| \right],$$

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

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 $(\delta_0, \delta_{10}, \cdots, \delta_{1L}, \delta_{20}, \cdots, \delta_{2L})$. 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 $(\delta_0, \delta_{11}, \cdots, \delta_{1L}, \delta_{20}, \cdots, \delta_{2L})$ 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:

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

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 the international corn markets, specifically on three major exporting markets: the US, Argentina, and Ukraine. Additionally, we investigate the farthest two regional markets in the US as a comparison. The corn market is a highly significant commodity traded across large distances, making it a subject of great interest for economic research. Despite its widespread consumption and spatial dispersion, 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 and are discussed below. As mentioned above, the main dependent variable of interest in this study is the maize price data for 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 tonne. 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, they account 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.

The basic unit of analysis used throughout the analysis 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 was collected and

[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.

covers the period from January 2000 to April 2022, comprising a total of 267 monthly observations.

The data for the logarithmic price in all nine US markets were available from January 2000 to January 2023, resulting in 277 monthly observations, as shown in Figure 6. Specifically, Figure 7 illustrates the logarithmic prices in Kansas City, MO, and Gulf ports, LA. The spatial linkages of the corn market within the United States are particularly noteworthy. Gulf ports in LA 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.

To analyze the properties of time series prices and determine the most suitable model for assessing spatial price linkages, we conducted augmented Dickey-Fuller tests for each pair of price differentials. 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 7 in the appendix, which indicates that the null hypothesis of nonstationarity of the price differentials is strongly rejected in every case. A finding of nonstationarity in the price differentials would suggest a lack

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/MN	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

of price parity in that individual market prices are allowed to wander arbitrarily far apart. Additionally, we performed ADF tests on the first difference of the logarithmic exchange rate and other exogenous shocks in Table 8 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.

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.

The standard threshold model assumes a fixed threshold, which may be a strong assumption. However, it is plausible that these relationships can vary over time, indicating structural changes in the underlying economic dynamics. To explore this possibility, it is natural to take into account partitions that reflect macroeconomic variables changes. We partition the data into two periods based on two significant economic shocks: the 2014 Crimean crisis and the global financial/economic crisis of 2008-09. Specifically, the breakpoints for these events are identified as February 2014 and October 2008, respectively. Table 10, 11, 12, and 13 in the appendix present the AIC values for the threshold Lasso estimation, considering various forcing variables. These tables provide a comprehensive overview of the AIC values, allowing for comparisons of different estimation scenarios and their respective goodness-of-fit. Table 9 presents the AIC values for the threshold Lasso estimation, which is used to select the lag structure for the forcing variable Q_t. The lagged price differential $|p^1_{t-d} - p^2_{t-d}|$ is transformed into $Q_t = \widehat{F}(p^1_{t-d} - p^2_{t-d})$, where $\widehat{F}$ is the empirical distribution function of the data $p^1_1 - p^2_1, \cdots p^1_{T-d} - p^2_{T-d}$. It is assumed that all Q_t are distinct, and $\widehat{F}$ is a one-to-one function, making it possible to get the estimate of threshold parameter by the inverse function of $\widehat{F}$.

To determine the optimal lag structure for the forcing variable, we select the lag order with the lowest AIC value for each model and present the corresponding parameter estimates in Table 2[3]. In this table, the quantile estimates provide insights into the likelihood of each month in the selected period falling into the trade regime or the no-trade regime, depending on whether the quantile is above 0.5 or below 0.5. Furthermore, we expect that unobservable transaction costs will be higher when the threshold estimates are larger. Thus, the threshold estimates in Table 2 can provide an indication of the magnitude of the unobservable transaction costs.

When considering the magnitude of the estimates, we observe that for the Argentina/Ukraine markets, the estimates for the entire period and the period before the 2014 Crimean crisis are very similar. However, if we run the model using only the data starting from the breakpoint (2014), both the quantile estimates and the parameter estimates become lower compared to the pre-break period. This suggests that there may be a significant change or shift in the market following the breakpoint, resulting in lower estimates for the post-break period.

Regarding the US and Argentina markets, we find that the estimates for the entire

[3]The term " 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.

period and the period after the 2008-09 world financial/economic crisis are quite similar. However, the quantile estimate for the pre-break period is lower compared to the other two quantiles. This suggests that trade happens more frequently after the breakpoint, indicating there is a higher probability of observing trade activity in the post-break period compared to the pre-break period.

For the US/Ukraine market, when we divide the data into two parts, namely before and after the 2014 Crimean crisis, we observe a decrease in the quantile of the threshold after the break. Additionally, the estimates suggest that the unobservable transaction costs are lower in the post-break period compared to the pre-break period. Similarly, when we divide the data into two parts, before and after the 2008-09 world financial/economic crisis, we again observe the same pattern. There is a decrease in the quantile of the threshold after the break, and the estimates indicate lower unobservable transaction costs in the post-break period compared to the pre-break period. However, Table 2 provides evidence suggesting that unobservable transaction costs are higher for US domestic markets compared to the US and international markets. This result can be attributed to the fact that all three export prices are free-on-board prices, whereas the domestic prices are not. As a result, the price differentials between gulfs and Kansas City tend to be larger compared to the price differentials among any two export markets.

The estimated coefficients obtained through desparsified LASSO corresponding to models in Table 2 are reported in Table 3, Table 5, Table 4 and Table 6. Notably, the desparsified LASSO estimates are statistically insignificant when the LASSO estimates based on equations (2.6) and (2.7) are zero. As a result, we only present the estimates that are determined to be non-zero by the LASSO method. The details of the desparsified LASSO estimates in all models can be found in the Appendix.

The basic framework illustrates that if the exchange rate pass-through effect or any exogenous shock effect is regime-specific, it means that the impact of exchange rates or exogenous shock on price differentials among two distinct markets differs depending on the magnitude of a certain forcing variable. A straightforward way to illustrate the relationship between the exchange rate, market factors, or exogenous shocks and potential deviations from perfect market integration is by examining the coefficient estimates obtained from our analysis. These estimates represent the derivative of the price differential in time t and with respect to the lagged value of the exchange rate, market factors, or exogenous shocks.

In general, when considering the entire period, the four estimation tables show that fewer variables are selected by the Lasso estimation procedure, except for the US/Ukraine market. However, even among the selected variables, only a few estimates are found to be statistically significant. Interestingly, we do not observe a significantly imperfect exchange rate pass-through effect in the US/Argentina, US/Ukraine, and Argentina/Ukraine markets.

However, when incorporating the structural break into the model, the number of nonzero estimates increases. This indicates that the sub-periods exhibit more dynamic magnitudes compared to the long-run entire period. In many cases, shocks in the trade regime lead to greater adjustments compared to the no-trade regime. Specifically, for the exchange rate pass-through effect, significantly imperfect exchange rate pass-through is observed in every case.

4 Summary and Concluding Remarks

We develop a model of price linkages in spatially distinct regional markets for maize under perfect integration to investigate exchange rate pass-through and other market factor effects. The models are developed within the framework of high-dimensional threshold models. We view such nonlinear models as natural extensions to an extensive literature that has developed an increasingly rich set of factors in models of market integration. 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. However, in one case—US/Argentina export market—responses to shocks of exchange rate or market factors are estimated as zero, suggesting that the two markets may be fully integrated.

	forcing variable	threshold estimate squantile	threshold estimates price differentials
Argentina/Ukraine	$\lvert p^1_{t-5} - p^2_{t-5}\rvert$	0.64	0.09584621
Argentina/Ukraine_pre_break_2014	$\lvert p^1_{t-4} - p^2_{t-4}\rvert$	0.70	0.09097013
Argentina/Ukraine_post_break_2014	$\lvert p^1_{t-1} - p^2_{t-1}\rvert$	0.52	0.04730247
US/Ukraine	$\lvert p^1_{t-3} - p^2_{t-3}\rvert$	0.55	0.08861166
US/Ukraine_pre_break_2014	$\lvert p^1_{t-4} - p^2_{t-4}\rvert$	0.67	0.1219093
US/Ukraine_post_break_2014	$\lvert p^1_{t-1} - p^2_{t-1}\rvert$	0.38	0.05842136
US/Ukraine_pre_break_2008	$\lvert p^1_{t-1} - p^2_{t-1}\rvert$	0.58	0.1112816
US/Ukraine_post_break_2008	$\lvert p^1_{t-6} - p^2_{t-6}\rvert$	0.28	0.0461198
US_Argentina	$\lvert p^1_{t-5} - p^2_{t-5}\rvert$	0.71	0.07225907
US/Argentina_pre_break_2008	$\lvert p^1_{t-1} - p^2_{t-1}\rvert$	0.36	0.04512331
US/Argentina_post_break_2008	$\lvert p^1_{t-1} - p^2_{t-1}\rvert$	0.62	0.06196773
Gulfs/KCMO	$\lvert p^1_{t-3} - p^2_{t-3}\rvert$	0.77	0.1711215
Gulfs/KCMO_pre_break_2008	$\lvert p^1_{t-4} - p^2_{t-4}\rvert$	0.61	0.1656999
Gulfs/KCMO_post_break_2008	$\lvert p^1_{t-3} - p^2_{t-3}\rvert$	0.54	0.1286671

Table 2: Lasso Estimation of threshold parameter

Model	US/Ukraine	pre break 2014	post break 2014	pre break 2008	post break 2008
Baltic_Freight % Change	-		+		
FD_LN_US Corn Stock			+		
FD_US Interest Rate			+		
FD_US Monthly I.P.I % Change	-	-			-
FD_US Monthly Inflation			+		
FD_US Unemployment Rate	-				-
UAH_USDollar % Change			+		
lag_1_Baltic_Freight % Change	-				-
lag_1_FD_Ukraine Monthly Inflation		-			
lag_1_FD_US Interest Rate					-
lag_1_FD_US Monthly I.P.I % Change					+
lag_1_FD_US Monthly Inflation		+			
lag_1_US Monthly Gas Price % Change	-				
lag_2_FD_US Unemployment Rate		-			
lag_3_FD_LN_US Corn Stock			+		
lag_3_FD_LN_US Corn Stock		+			
lag_3_FD_Ukraine Monthly I.P.I % Change		+			
lag_3_FD_Ukraine Unemployment Rate					-
lag_3_FD_US Monthly Inflation	+	+			
lag_3_US Monthly Gas Price % Change					+
lag_4_FD_LN_US Corn Stock	+				
lag_4_FD_Ukraine Monthly I.P.I % Change		+			
lag_4_FD_US Monthly I.P.I % Change					-
lag_4_FD_US Monthly Inflation		+			
lag_4_US Monthly Gas Price % Change			-		
lag_5_Baltic_Freight % Change	-				-
lag_5_FD_LN_US Corn Stock		+			
lag_5_FD_Ukraine Monthly I.P.I % Change			-		
lag_5_FD_Ukraine Monthly Inflation					-
lag_6_Baltic_Freight % Change		-			
lag_6_FD_LN_US Corn Stock		-			
lag_6_FD_Ukraine Monthly I.P.I % Change			-		
lag_6_FD_Ukraine Monthly Inflation			+		-
lag_6_FD_US Interest Rate					-
lag_6_FD_US Monthly I.P.I % Change			-		
lag_6_FD_US Unemployment Rate		-			
trade_FD_Ukraine Monthly Inflation					-
trade_FD_US Monthly Inflation				+	
trade_lag_1_Baltic_Freight % Change			+		
trade_lag_1_FD_Ukraine Monthly I.P.I % Change		+			
trade_lag_1_FD_US Monthly I.P.I % Change		+			
trade_lag_1_FD_US Unemployment Rate					-
trade_lag_2_FD_LN_US Corn Stock			+		
trade_lag_3_FD_US Monthly Inflation				+	
trade_lag_3_UAH_USDollar Percent % Change					-
trade_lag_4_Baltic_Freight % Change		+			
trade_lag_4_FD_Ukraine Unemployment Rate		+			
trade_lag_4_US Monthly Gas Price % Change					+
trade_lag_5_FD_LN_US Corn Stock			-		
trade_lag_5_FD_US Interest Rate					+
trade_lag_5_FD_US Unemployment Rate		-			
trade_lag_6_FD_Ukraine Monthly I.P.I % Change				+	
trade_lag_6_FD_Ukraine Unemployment Rate		-			
trade_lag_6_FD_US Interest Rate		+			
trade_lag_6_FD_US Monthly Inflation			+		
trade_lag_6_US Monthly Gas Price % Change			+		

Table 3: US Ukraine Estimates

Model	US/Argentina	pre break 2008	post break 2008
Baltic_Freight % Change			-
lag_1_Baltic_Freight % Change			-
lag_2_Baltic_Freight % Change		+	
lag_2_FD_Argentina Monthly Inflation		-	
lag_2_Peso_USDollar % Change		-	
lag_3_FD_Argentina Monthly I.P.I % Change			-
lag_3_FD_LN_US Corn Stock			+
lag_3_FD_US Unemployment Rate			+
lag_4_Baltic_Freight % Change		-	
lag_4_FD_Argentina Monthly I.P.I % Change		+	
lag_4_FD_US Interest Rate			+
lag_5_Baltic_Freight % Change			-
lag_5_FD_LN_US Corn Stock		-	+
lag_5_FD_US Interest Rate		+	
lag_6_Baltic_Freight % Change			-
lag_6_FD_LN_US Corn Stock		-	
lag_6_FD_US Monthly I.P.I % Change			+
lag_6_FD_US Unemployment Rate			+
lag_6_Peso_USDollar % Change			+
trade_cos			-
trade_lag_1_FD_Argentina Monthly Inflation			-
trade_lag_1_FD_US Interest Rate			+
trade_lag_2_FD_US Monthly Inflation		+	
trade_lag_2_FD_US Unemployment Rate			+
trade_lag_2_Peso_USDollar % Change			+
trade_lag_3_FD_Argentina Monthly Inflation		-	
trade_lag_4_FD_LN_US Corn Stock			+
trade_lag_5_FD_Argentina Unemployment Rate			-
trade_lag_6_FD_Argentina Monthly Inflation			+
trade_lag_6_FD_US Interest Rate			+

Table 4: US/Argentina Estimates

Model	Argentina/Ukraine	pre break 2014	post break 2014
cos			+
FD_Ukraine Unemployment Rate			-
lag_1_FD_Ukraine Monthly I.P.I % Change			-
lag_3_Baltic_Freight % Change			-
lag_4_FD_Argentina Monthly I.P.I % Change			-
lag_4_FD_Ukraine Monthly Inflation			-
lag_4_Peso_UAH % Change			-
lag_5_FD_Argentina Monthly Inflation		-	
lag_5_FD_Ukraine Monthly Inflation			-
lag_6_FD_Argentina Monthly I.P.I % Change			-
lag_6_FD_Argentina Unemployment Rate			+
trade_FD_Argentina Unemployment Rate			-
trade_lag_1_FD_Argentina Monthly Inflation			+
trade_lag_2_Baltic_Freight % Change		+	-
trade_lag_2_FD_Argentina Unemployment Rate			+
trade_lag_2_FD_Ukraine Monthly Inflation			-
trade_lag_3_FD_Argentina Unemployment Rate		-	
trade_lag_4_FD_Ukraine Unemployment Rate		+	

Table 5: Argentina Ukraine Estimates

Model	Gulfs/KCMO	pre break 2008	post break 2008
Baltic_Freight % Change		+	
FD_LN_US Corn Stock		-	
FD_US Monthly I.P.I % Change		+	
lag_1_FD_LN_US Corn Stock	-		-
lag_1_FD_US Monthly Inflation		-	
lag_2_FD_LN_US Corn Stock		+	
lag_2_FD_US Monthly I.P.I % Change		-	
lag_3_FD_US Monthly Inflation		-	
lag_3_US Monthly Gas Price % Change		+	
lag_4_US Monthly Gas Price % Change		-	
lag_5_FD_LN_US Corn Stock			-
lag_5_FD_US Monthly Inflation		+	
lag_5_FD_US Unemployment Rate		-	
lag_5_US Monthly Gas Price % Change		-	
lag_6_Baltic_Freight % Change		-	
lag_6_FD_US Monthly I.P.I % Change		+	

Table 6: GulfsLA/KCMO Regression Results

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5 Appendix

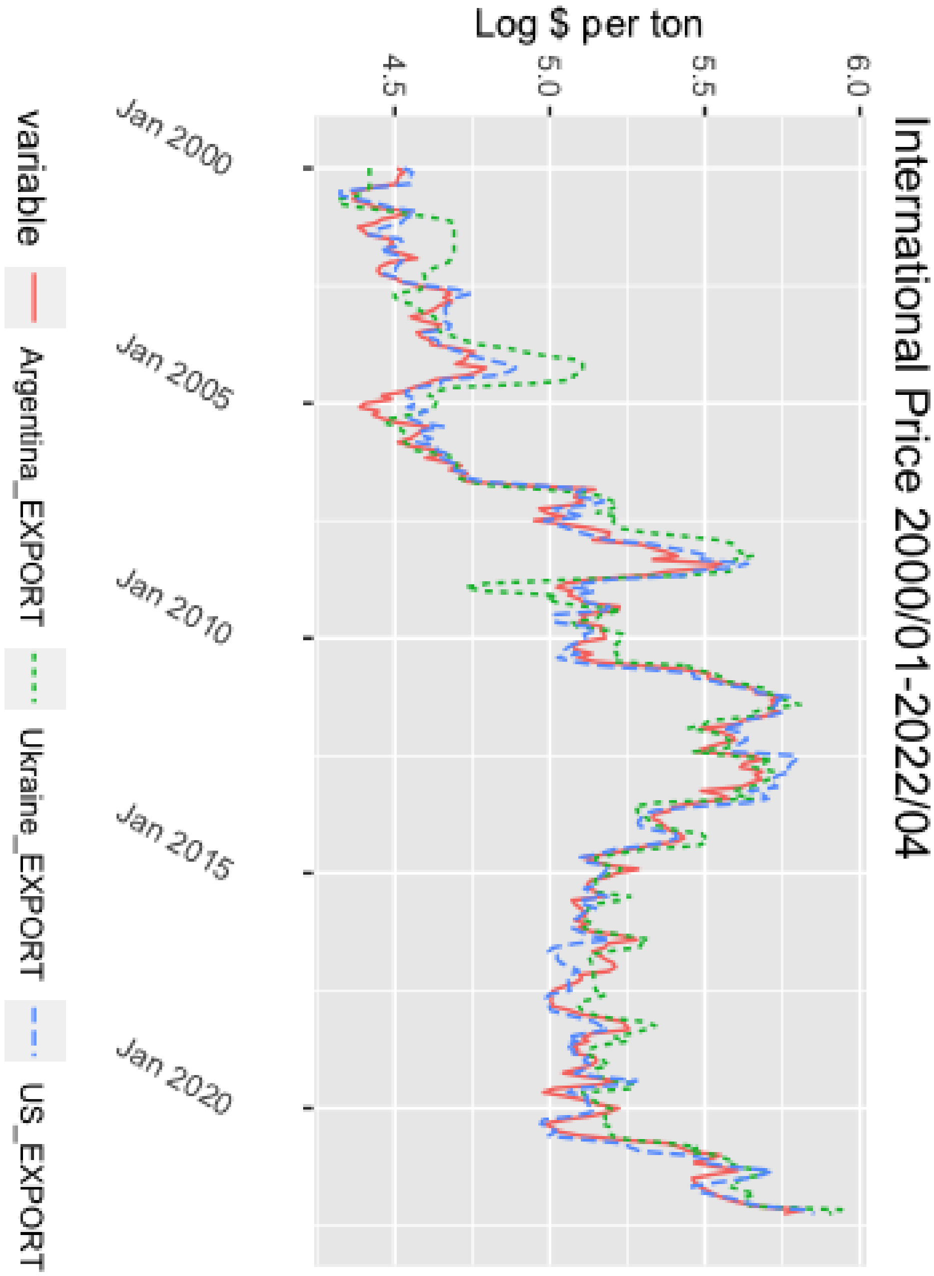

Figure 2: World Corn Export price by Country

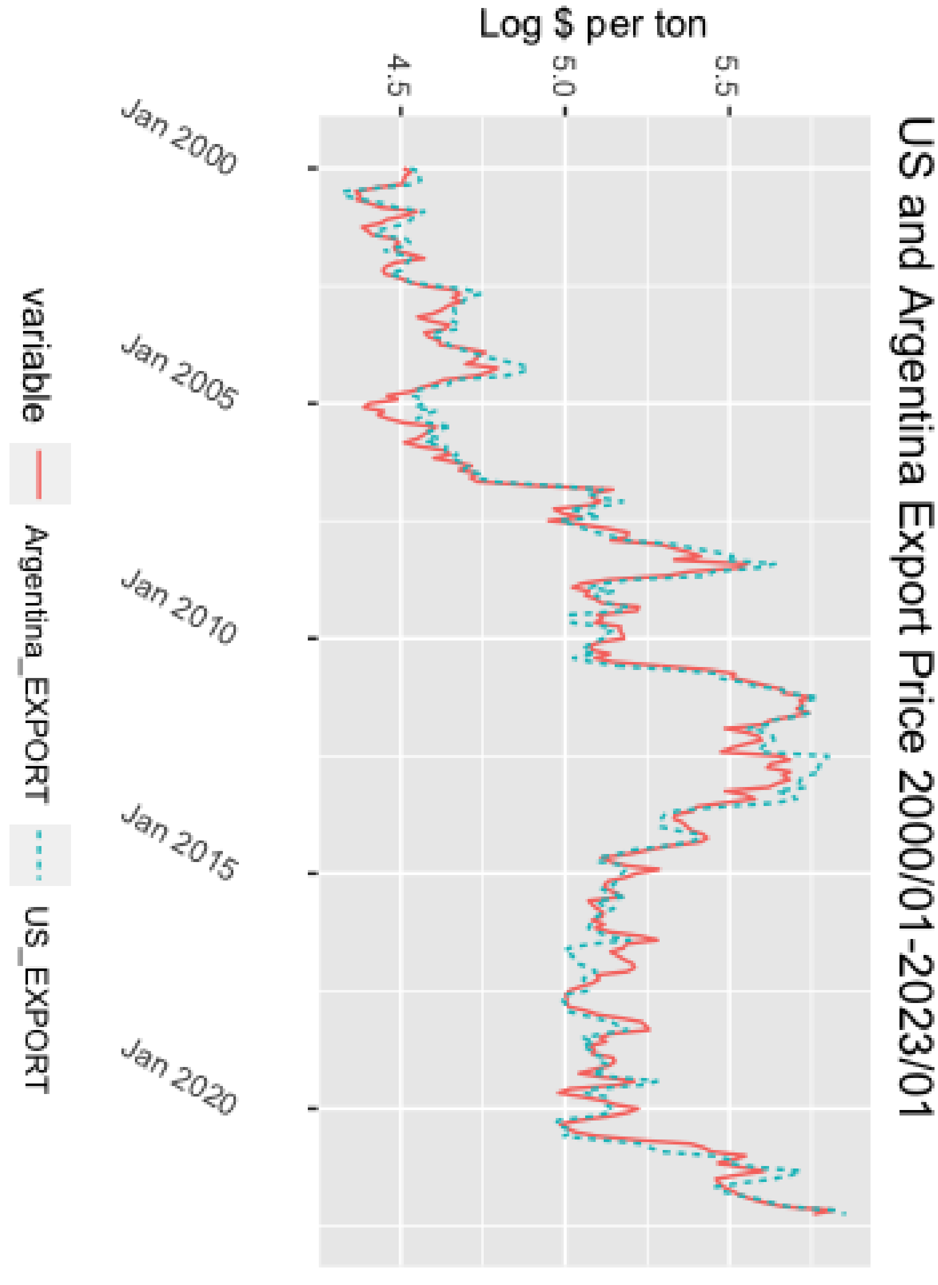

Figure 3: the U.S. and Argentina Corn Market Price

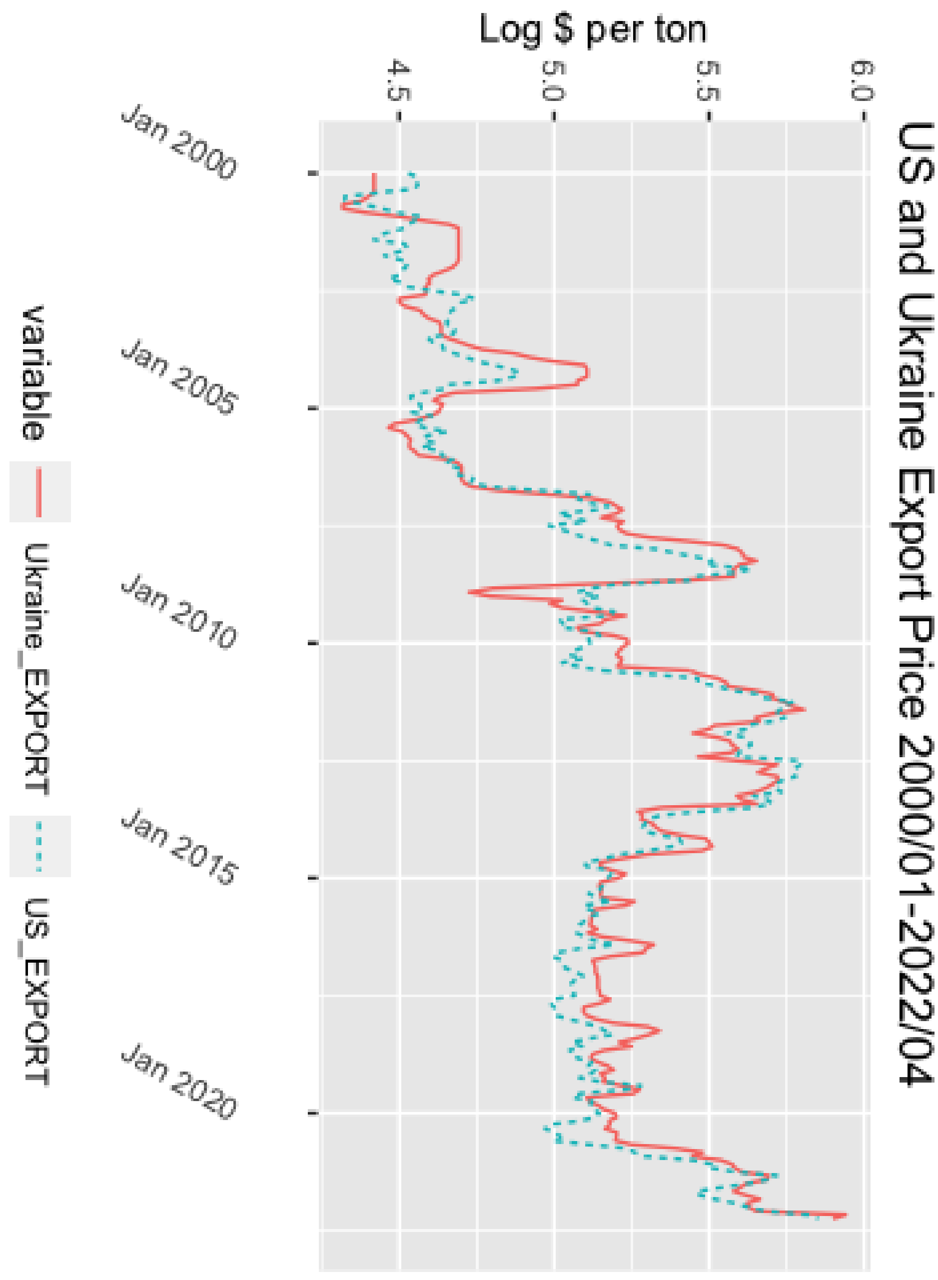

Figure 4: the U.S. and Ukraine Corn Market Price

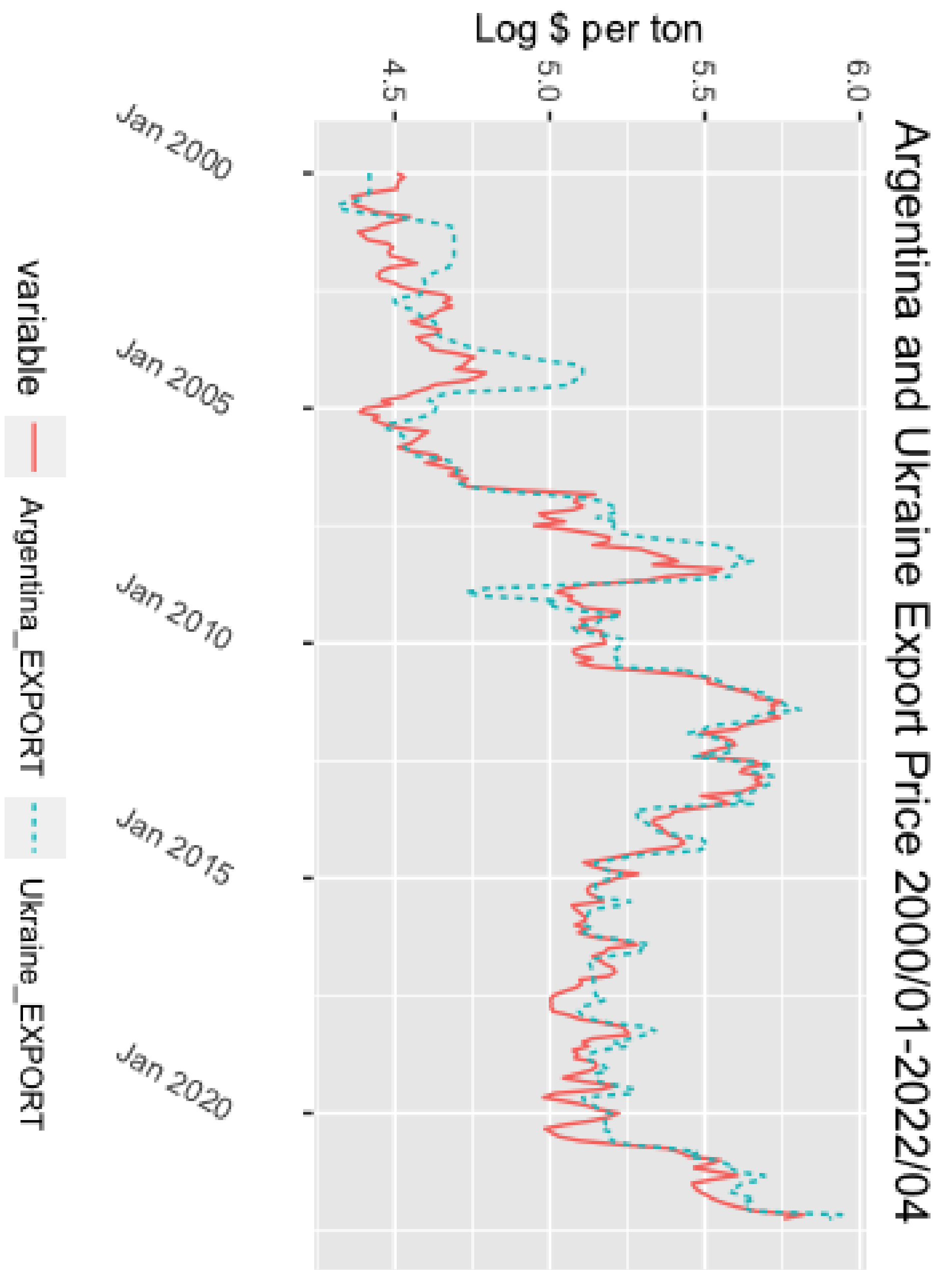

Figure 5: Argentina and Ukraine Corn Market Price

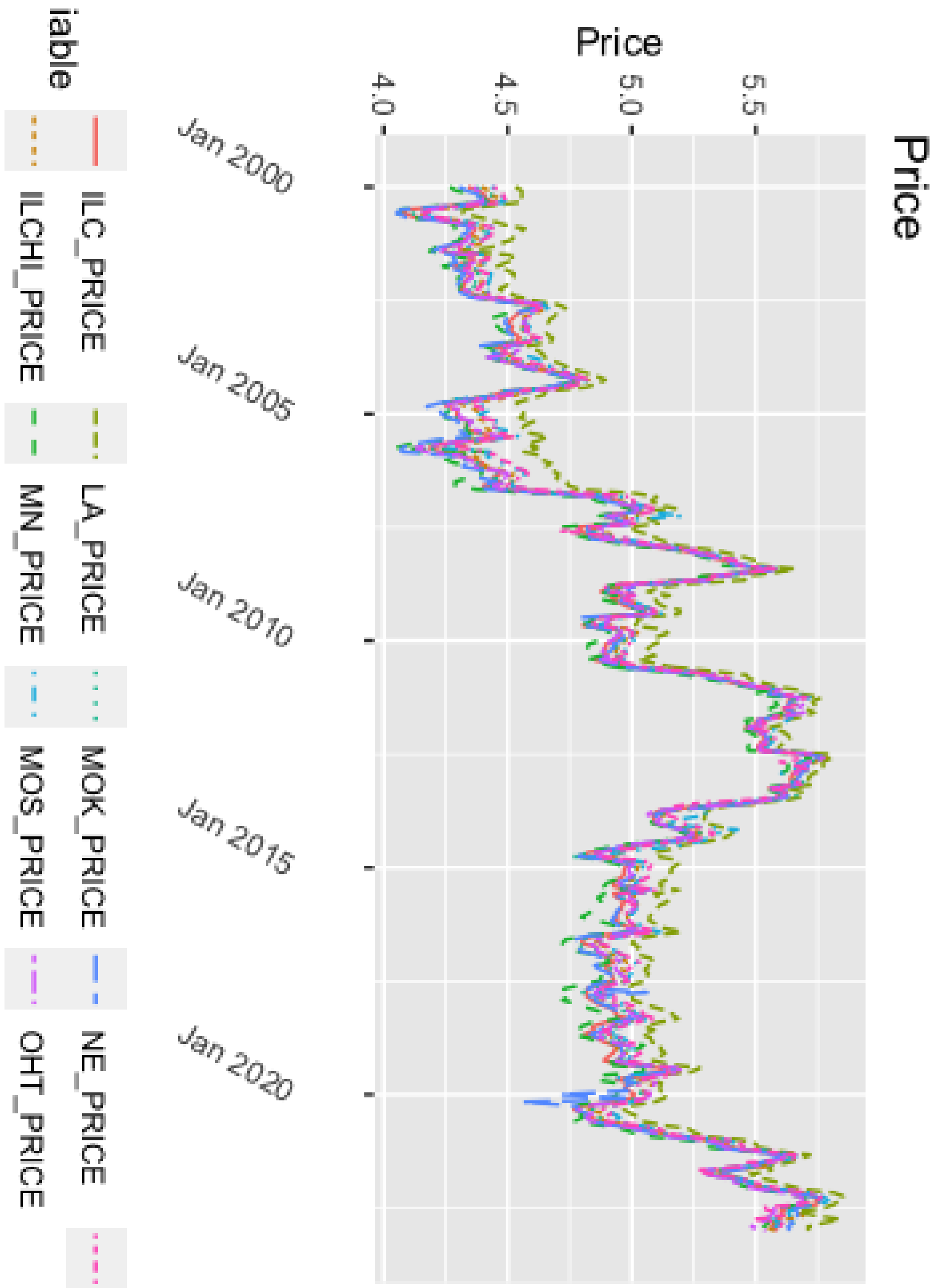

Figure 6: the U.S. Corn Market Price by Location

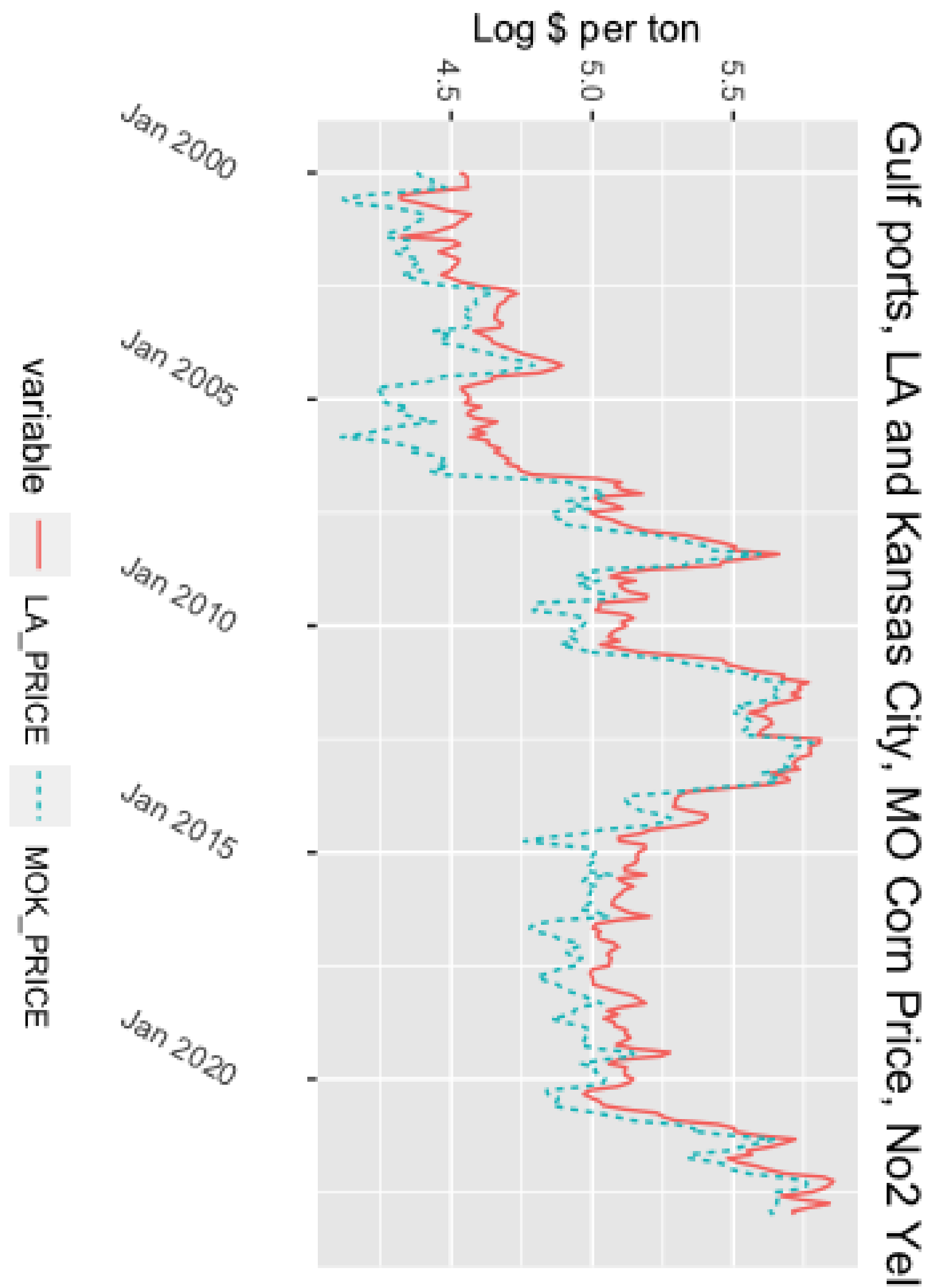

Figure 7: the U.S. Corn Market Price-Kansas City, MO&Gulf ports, LA

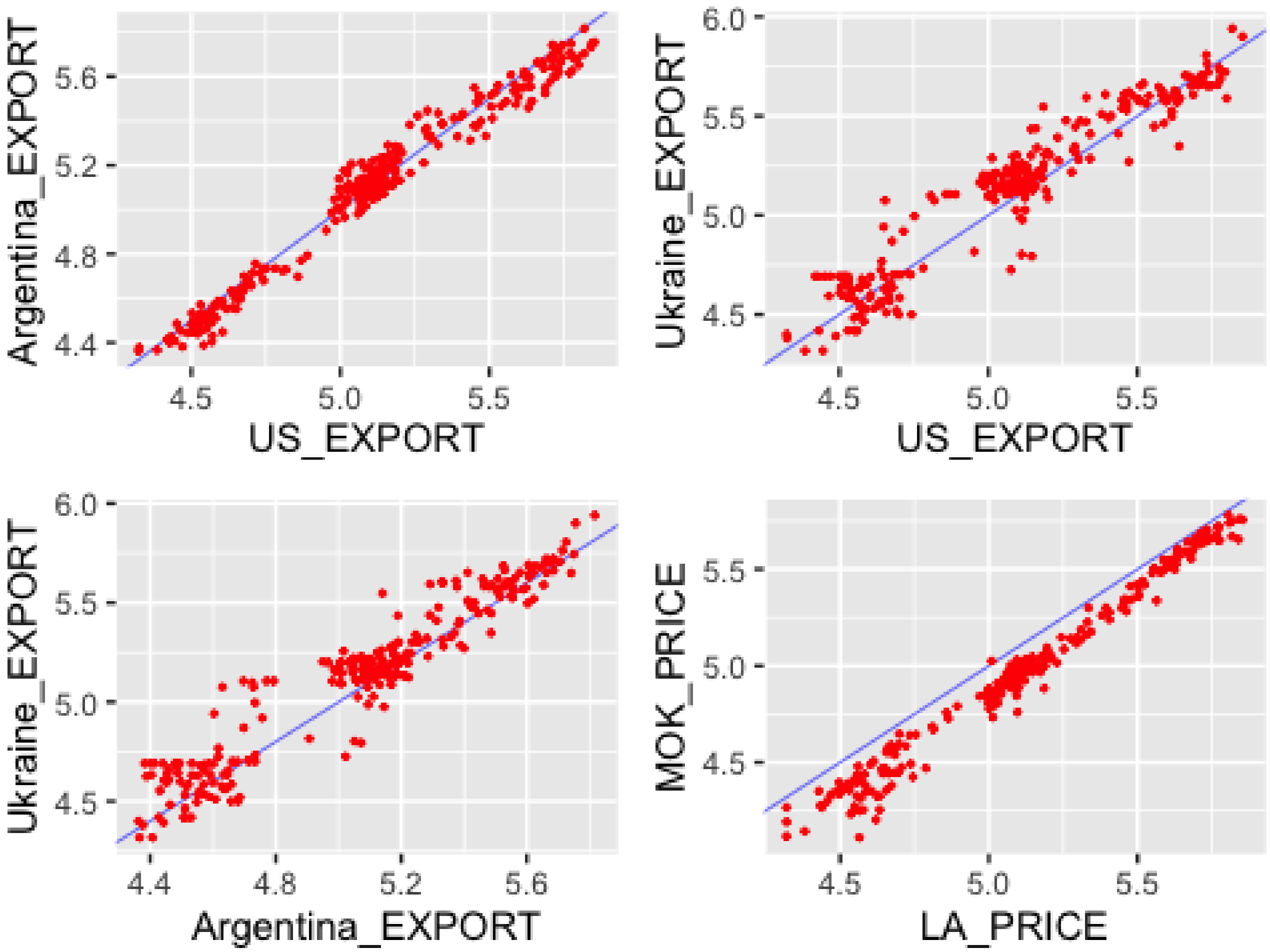

Figure 8: Corn Market Logarithmic Prices pairs

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 7: 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 8: Augmented Dickey-Fuller Test Results of First Difference of Time Series

		$p^1_{t-1} - p^2_{t-1}$	$p^1_{t-2} - p^2_{t-2}$	$p^1_{t-3} - p^2_{t-3}$	$p^1_{t-4} - p^2_{t-4}$	$p^1_{t-5} - p^2_{t-5}$	$p^1_{t-6} - p^2_{t-6}$
	AIC	-1.553418	-1.737098	-1.569497	-2.900425	-2.956548	-1.653093
US/Argentina	λ_T	5.111050e-07	2.210048e-06	1.152693e-06	2.536086e-04	3.149909e-04	2.442470e-06
	$\widehat{c}$	0.49	0.56	0.57	0.42	0.71	0.59
	AIC	-0.5051949	-1.1103581	-1.1205013	-0.7260766	-0.4189850	-0.9699245
US/Ukraine	λ_T	1.133271e-06	1.019725e-04	6.635313e-05	1.449089e-05	1.542151e-06	4.878110e-05
	$\widehat{c}$	0.61	0.75	0.55	0.60	0.39	0.50
	AIC	-1.3375471	-1.3777247	-1.2114806	-1.2856019	-1.4808931	-0.8535025
Argentina/Ukraine	λ_T	2.153163e-04	2.795255e-04	1.250354e-04	2.249827e-04	4.341559e-04	4.663529e-05
	$\widehat{c}$	0.70	0.72	0.67	0.61	0.64	0.68
	AIC	-2.515462	-2.824062	-2.859255	-2.812807	-2.762981	-2.776374
Gulfs/KCMO	λ_T	2.960595e-05	1.780808e-04	2.515030e-04	2.099041e-04	1.972637e-04	1.900545e-04
	$\widehat{c}$	0.76	0.84	0.77	0.76	0.69	0.73

Table 9: Lasso Estimation

		$p^1_{t-1} - p^2_{t-1}$	$p^1_{t-2} - p^2_{t-2}$	$p^1_{t-3} - p^2_{t-3}$	$p^1_{t-4} - p^2_{t-4}$	$p^1_{t-5} - p^2_{t-5}$	$p^1_{t-6} - p^2_{t-6}$
	AIC	-0.5051949	-1.1103581	-1.1205013	-0.7260766	-0.4189850	-0.9699245
US/Ukraine	λ_T	1.133271e-06	1.019725e-04	6.635313e-05	1.449089e-05	1.542151e-06	4.878110e-05
	$\widehat{c}$	0.61	0.75	0.55	0.60	0.39	0.50
	AIC	0.2719879	0.2384729	0.2584657	0.1553439	0.3059618	0.1965868
US/Ukraine_pre_break_2014	λ_T	2.404328e-05	2.328192e-05	1.912262e-05	1.892201e-05	2.046114e-05	2.671763e-05
	$\widehat{c}$	0.58	0.45	0.56	0.67	0.36	0.58
	AIC	-0.7497784	-0.5824867	-0.5695269	-0.7033671	-0.5125117	-0.6625862
US/Ukraine_post_break_2014	λ_T	1.133271e-06	1.019725e-04	6.635313e-05	1.449089e-05	1.542151e-06	4.878110e-05
	$\widehat{c}$	0.38	0.42	0.35	0.43	0.46	0.35
	AIC	-0.03886665	0.26819724	0.12303875	0.02702780	0.21128141	0.34608808
US_Ukraine_pre_break_2008	λ_T	2.044458e-05	1.996483e-05	1.859907e-05	2.376336e-05	1.966192e-05	1.978563e-05
	$\widehat{c}$	0.58	0.46	0.64	0.47	0.53	0.50
	AIC	-0.4001896	-0.2095196	-0.3998089	-0.3242917	-0.5911825	-0.8037958
US_Ukraine_post_break_2008	λ_T	1.720884e-06	5.482831e-07	1.416099e-06	1.641082e-06	1.769928e-06	1.058156e-05
	$\widehat{c}$	0.48	0.52	0.52	0.46	0.39	0.28

Table 10: Lasso Estimation

		$p^1_{t-1} - p^2_{t-1}$	$p^1_{t-2} - p^2_{t-2}$	$p^1_{t-3} - p^2_{t-3}$	$p^1_{t-4} - p^2_{t-4}$	$p^1_{t-5} - p^2_{t-5}$	$p^1_{t-6} - p^2_{t-6}$
	AIC	-1.3375471	-1.3777247	-1.2114806	-1.2856019	-1.4808931	-0.8535025
Argentina/Ukraine	λ_T	2.153163e-04	2.795255e-04	1.250354e-04	2.249827e-04	4.341559e-04	4.663529e-05
	$\widehat{c}$	0.70	0.72	0.67	0.61	0.64	0.68
	AIC	-0.122555394	-0.007617291	-0.219495484	-0.793025568	0.061087460	-0.359462421
Argentina/Ukraine_pre_break_2014	λ_T	6.612904e-07	1.282999e-06	1.541017e-06	5.816458e-05	4.822867e-07	1.483879e-05
	$\widehat{c}$	0.69	0.56	0.65	0.70	0.54	0.67
	AIC	-0.8867073	-0.7710295	-0.7334242	-0.7761687	-0.6126150	-0.7970872
Argentina/Ukraine_post_break_2014	λ_T	1.477595e-05	1.592034e-05	1.441506e-05	1.381054e-05	1.552746e-05	1.409800e-05
	$\widehat{c}$	0.52	0.52	0.54	0.69	0.34	0.59

Table 11: Lasso Estimation

		$p^1_{t-1} - p^2_{t-1}$	$p^1_{t-2} - p^2_{t-2}$	$p^1_{t-3} - p^2_{t-3}$	$p^1_{t-4} - p^2_{t-4}$	$p^1_{t-5} - p^2_{t-5}$	$p^1_{t-6} - p^2_{t-6}$
	AIC	-1.553418	-1.737098	-1.569497	-2.900425	-2.956548	-1.653093
US/Argentina	λ_T	5.111050e-07	2.210048e-06	1.152693e-06	2.536086e-04	3.149909e-04	2.442470e-06
	$\widehat{c}$	0.49	0.56	0.57	0.42	0.71	0.59
	AIC	-1.2518930	-1.0846773	-0.9888356	-1.0262127	-0.8711668	-0.8109077
US_Argentina_pre_break_2008	λ_T	1.612861e-05	1.382888e-05	1.355596e-05	1.443525e-05	1.347417e-05	1.424458e-05
	$\widehat{c}$	0.36	0.52	0.56	0.38	0.56	0.45
	AIC	-1.498117	-1.320319	-1.311259	-1.458662	-1.345537	-1.381769
US_Argentina_post_break_2008	λ_T	8.515443e-06	8.506276e-06	8.842351e-06	9.359523e-06	8.284913e-06	8.514304e-06
	$\widehat{c}$	0.62	0.62	0.46 0	.33	0.62	0.57

Table 12: Lasso Estimation

		$p^1_{t-1} - p^2_{t-1}$	$p^1_{t-2} - p^2_{t-2}$	$p^1_{t-3} - p^2_{t-3}$	$p^1_{t-4} - p^2_{t-4}$	$p^1_{t-5} - p^2_{t-5}$	$p^1_{t-6} - p^2_{t-6}$
	AIC	-2.515462	-2.824062	-2.859255	-2.812807	-2.762981	-2.776374
Gulfs/KCMO	λ_T	2.960595e-05	1.780808e-04	2.515030e-04	2.099041e-04	1.972637e-04	1.900545e-04
	$\widehat{c}$	0.76	0.84	0.77	0.76	0.69	0.73
	AIC	-1.441488	-1.490309	-1.481012 -	1.747033	-1.496295	-1.437110
Gulfs/KCMO_pre_break_2008	λ_T	1.776039e-05	1.461754e-05	1.813944e-05	2.550446e-05	1.562376e-05	1.357873e-05
	$\widehat{c}$	0.55	0.72	0.64	0.61	0.61	0.57
	AIC	-2.253965	-2.535333	-3.114062	-2.411973	-3.023359	-3.052794
Gulfs/KCMO_post_break_2008	λ_T	9.445343e-06	2.851834e-05	4.483806e-04	2.117865e-05	3.439096e-04	3.438341e-04
	$\widehat{c}$	0.66	0.47	0.54	0.45	0.43	0.39

Table 13: Lasso Estimation

Var Name	Scaled Lasso	Debiased Lasso	t-statistic
Peso_UAH Percent Change	-0.064	-0.033 (0.030)	-1.102
Baltic_Freight Percent Change	-0.020	-0.073 (0.053)	-1.375
lag_2_Peso_UAH Percent Change	0.032	0.255 (0.223)	1.144
lag_1_Baltic_Freight Percent Change	-0.018	-0.059 (0.040)	-1.460
lag_1_FD_Argentina Unemployment Rate	-2.876	20.124 (23.000)	0.875
lag_2_FD_Argentina Monthly Industrial Production Index Percent Change	0.015	-0.281 (0.296)	-0.949
lag_5_FD_Ukraine Monthly Industrial Production Index Percent Change	-0.006	-0.197 (0.191)	-1.030
trade_Baltic_Freight Percent Change	-0.032	0.036 (0.068)	0.529
trade_lag_1_FD_Argentina Unemployment Rate	-0.680	-13.140 (12.460)	-1.055
trade_lag_5_FD_Argentina Unemployment Rate	0.932	-32.657 (33.588)	-0.972
trade_lag_6_FD_Argentina Monthly Inflation	0.102	-1.609 (1.711)	-0.940
trade_lag_1_FD_Ukraine Monthly Inflation	0.122	-0.813 (0.935)	-0.870
trade_lag_3_FD_Ukraine Monthly Industrial Production Index Percent Change	0.080	0.961 (0.880)	1.091
trade_lag_5_FD_Ukraine Monthly Industrial Production Index Percent Change	-0.024	0.112 (0.136)	0.824

Table 14: Argentina Ukraine Regression Results

Var Name	Scaled Lasso	Debiased Lasso	t-statistic
lag_3_FD_LN_US Corn Stock	0.006	0.056 (0.051)	1.111
lag_6_FD_LN_US Corn Stock	-0.001	-0.111 (0.110)	-1.009
lag_4_FD_US Unemployment Rate	-0.384	-3.905 (3.521)	-1.109
lag_2_FD_US Monthly Inflation	0.540	3.490 (2.950)	1.183
lag_4_FD_US Monthly Inflation	-0.193	-9.803 (9.610)	-1.020
lag_6_FD_US Monthly Industrial Production Index Percent Change	0.109	2.928 (2.818)	1.039
trade_FD_Argentina Unemployment Rate	0.392	-18.560 (18.952)	-0.979
trade_lag_4_Baltic_Freight Percent Change	0.023	-0.086 (0.109)	-0.792
trade_lag_4_FD_LN_US Corn Stock	0.007	-0.124 (0.130)	-0.947
trade_lag_2_FD_Argentina Monthly Inflation	-0.158	-0.720 (0.562)	-1.281

Table 15: US/Argentina Regression Results

Var Name	Scaled Lasso	Debiased Lasso	t-statistic
FD_LN_US Corn Stock	-0.004	-0.011 (0.007)	-1.587
lag_2_Baltic_Freight Percent Change	-0.002	0.004 (0.005)	0.664
lag_1_FD_LN_US Corn Stock	-0.019	-0.040*** (0.021)	-1.904
lag_5_FD_LN_US Corn Stock	-0.008	0.031 (0.039)	0.793
lag_6_FD_US Unemployment Rate	0.019	-0.042 (0.061)	-0.682
trade_FD_US Monthly Industrial Production Index Percent Change	0.257	0.150 (0.107)	1.407
trade_lag_4_Baltic_Freight Percent Change	-0.033	0.042 (0.075)	0.563
trade_lag_2_US Monthly Gas Price Percent Change	0.109	-0.617 (0.727)	-0.850
trade_lag_2_FD_US Monthly Industrial Production Index Percent Change	-0.236	2.922 (3.159)	0.925

Table 16: GulfsLA/KCMO Regression Results