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

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). 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. 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.

Researchers aim to capture the nonlinear behavior of market integration and the effects of transaction costs, which are often unobserved but play a crucial role in determining spatial price linkages. A common approach to threshold modeling often involves a simple autoregressive model of the price differential. This model was applied by Goodwin and Piggott (2001) in an examination of corn prices at local markets. 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) study on 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 global 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 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

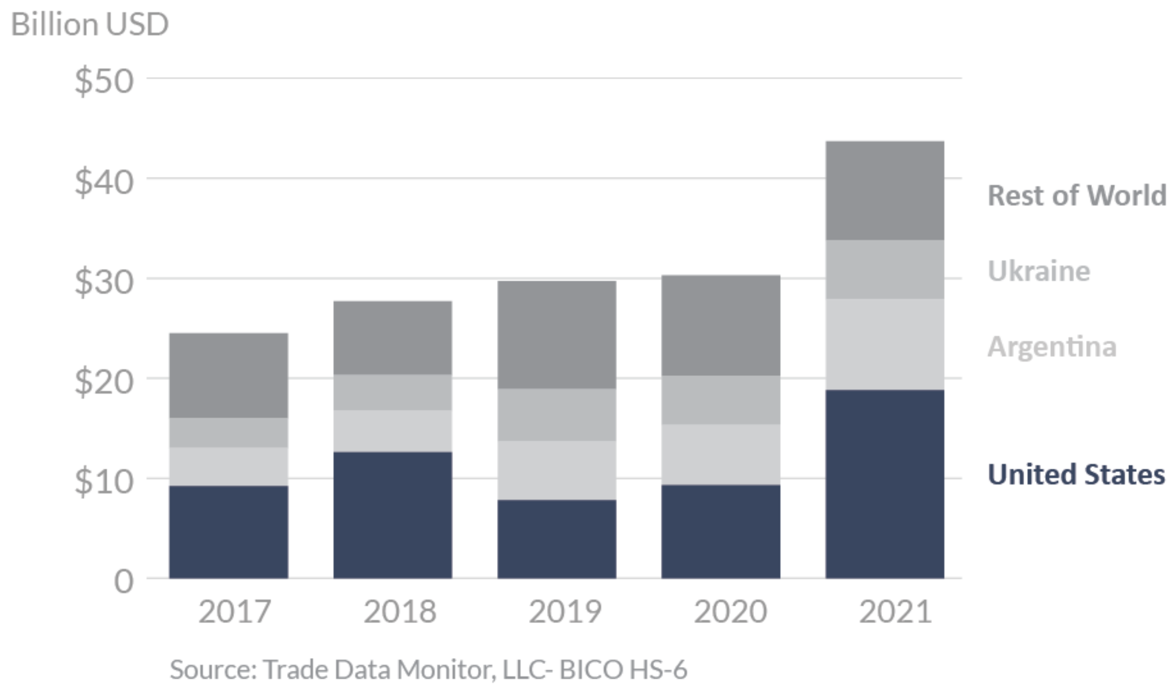

Figure 1: World Corn Exports by Country and Marketing Year

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 agricul- tural commodities. Likewise, a large related literature has examined how shocks to exchange rates affect domestic and export pricesa 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 $\beta_2 = 1$. If prices are invoiced in a common currency, as is often the case when trade is conducted in US dollar terms, the exchange rate is 1 and thus the logarithmic value of zero eliminates the exchange rate effect. 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 model that includes price differential, exchange rate, and exogenous shocks as well as their previous 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 lag length, 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.

To obtain an estimation that incorporates a broad range of variables, 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

$$(2.6) \quad \widehat{\alpha}(c) := \text{argmin}_{\alpha} \left\{ T^{-1} \sum_{t=1}^{T} \left(\Delta(p_t^1 - p_t^2) - [X_t', X_t' \mathbf{1}\{Q_t \geq c\}]' \alpha \right)^2 + \lambda \|\alpha\|_1 \right\},$$

Step 2.

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

$$(2.7) \quad \widehat{c} := \text{argmin}_{c \in \mathbb{C} \subset \mathbb{R}} \left\{ T^{-1} \sum_{t=1}^{T} \left(\Delta(p_t^1 - p_t^2) - [X_t', X_t' \mathbf{1}\{Q_t \geq c\}]' \widehat{\alpha}(c) \right)^2 + \lambda \|\widehat{\alpha}(c)\|_1 \right\}.$$

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. To obtain 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. The primary shipping route for most US corn exports is the Mississippi River. These markets include Gulf ports, LA, which is the main location for US Yellow Corn No. 2 exports, as well as St. Louis, MO; Omaha, NE; Central IL; Chicago, IL; Kansas City, MO; Toledo, OH; Memphis, TN; and Minneapolis, MN.

Our dataset spans from January 2000 to January 2023, comprising 277 monthly observations for each series. However, some missing values were present in the series, which we replaced using a weighted moving average during our selected period. Specifically, data for Ukraine's export price was available from January 2000 to April 2022. Therefore, the analysis of Ukraine's export price only used data from this sub-period. Additionally, we obtained the Ukraine UAH to USD exchange rate and Argentina Peso to USD exchange rate. Exogenous shocks such as interest rates, nominal inflation rates, unemployment rates in US markets, and US gas prices were obtained from the Federal Reserve Economic Data (FRED). 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. The price data were available from January 2000 to April 2022, yielding 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. Especially, we show the logarithmic prices in Minneapolis MN, and Gulf ports, LA as shown in Figure 7. The spatial linkage of the corn market are of particular interest due to its widespread trade across long distances, even within the US continent. For instance, Gulf ports, LA, serves as the primary location for US Yellow Corn exports, while Minneapolis, MN is the farthest market from the Gulf. Therefore, we aim to compare spatial linkages in the corn market across different regions in the US, as well as between the US and Ukraine, and Argentina.

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, except for the fourth panel, show a relatively symmetrical distribution of

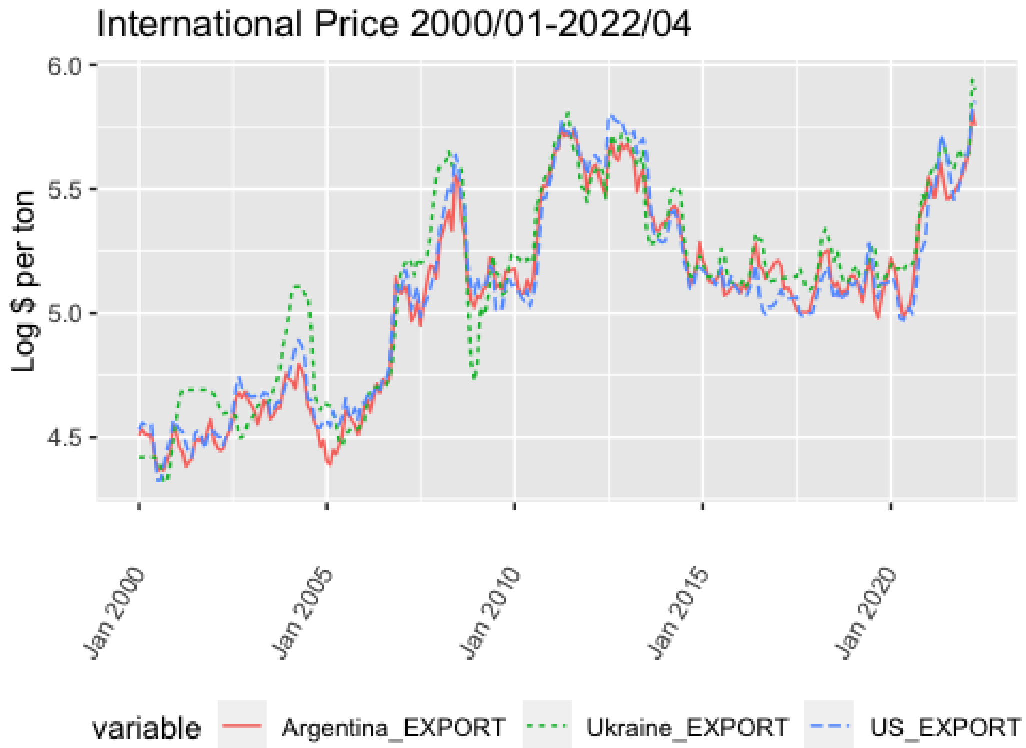

Figure 2: World Corn Export price by Country

points around the 45-degree line. The panel for Minneapolis, MN, and Gulf ports, LA, highlights that the market price in Minneapolis, MN, is consistently lower than that in Gulf ports, LA, which is expected given that the primary shipping route for most US corn exports is the Mississippi River, and trade occurs in one direction from Minneapolis, MN, to Gulf ports, LA. All the points in this panel are below the 45-degree line.

The plots also exhibit distinct basis patterns, where one price tends to be higher or lower than the other, likely reflecting the transaction costs associated with regionally distinct market trade. It is reasonable to expect that significant price disparities arise when one of the pair of prices is either unusually high or low, resulting in a higher absolute value of the price differential. 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

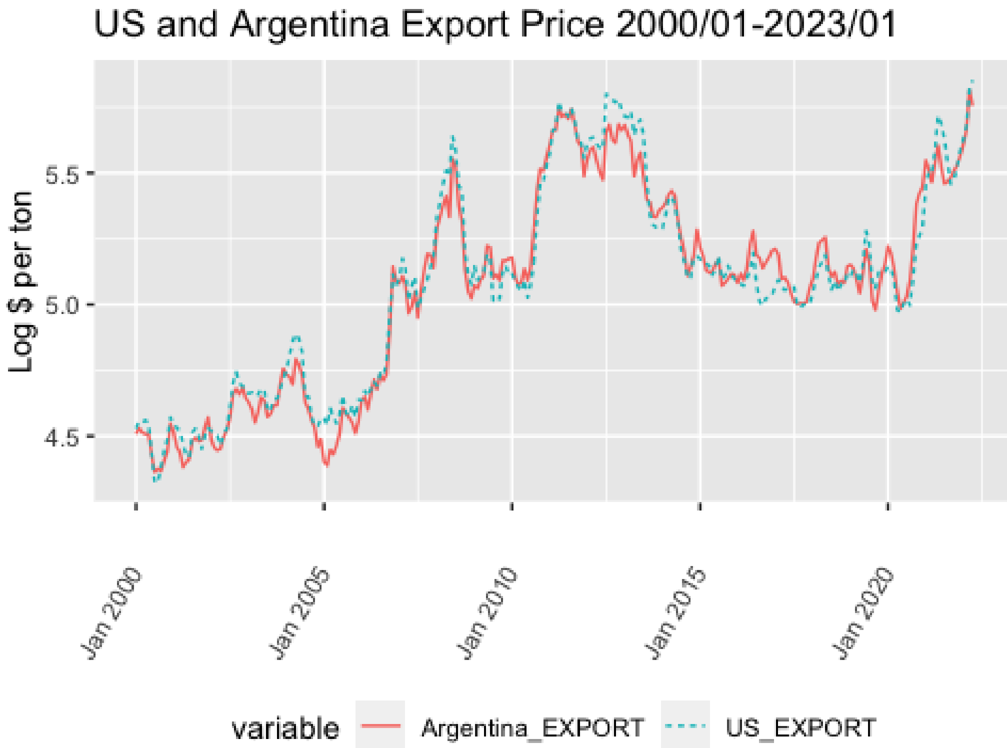

Figure 3: the U.S. and Argentina Corn Market Price

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 1, which indicate 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 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 and found that they were all significant in rejecting nonstationary series. Furthermore, we enhance the model by including the Baltic Exchange Dry Index, which captures the shipping cost of goods worldwide. Our augmented Dickey-Fuller test on the first difference of the logarithm of the index strongly rejects the null hypothesis of nonstationarity. Thus, we can implement equation (2.5) for estimating the model with the available data.

As previously noted, LASSO for threshold regression can handle variable selection

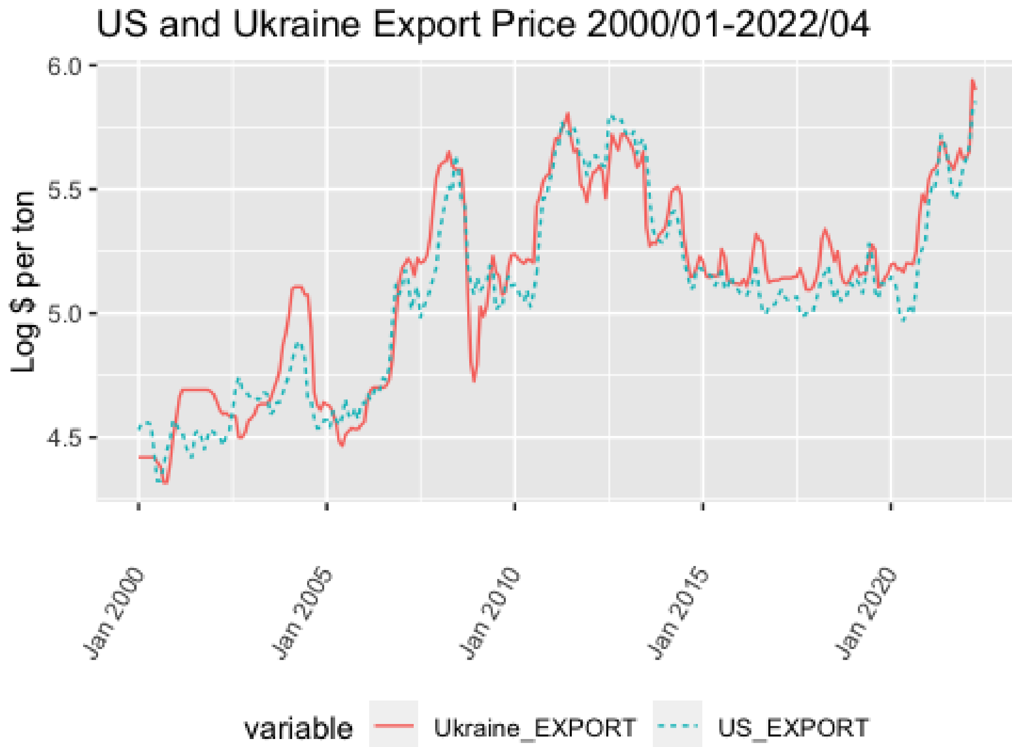

Figure 4: the U.S. and Ukraine Corn Market Price

and attain selection consistency under certain conditions. This feature eliminates the need for nonlinear tests, which are conventionally conducted in threshold models. The covariates in this study include the exchange rate, Baltic Exchange Dry Index, US CPI, US interest rate, and US unemployment rate. For the model of Minneapolis, MN to Gulf ports, LA, the exchange rate is replaced by the US gas price. Table 2 provides a list of all covariates used in the LASSO estimation for the four paired markets.

Table 3 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 $\widehat{F}$. Based on the least AIC value for each model, we select $p^1_{t-8} - p^2_{t-8}$ for the US/Argentina pair, $p^1_{t-11} - p^2_{t-11}$ for the

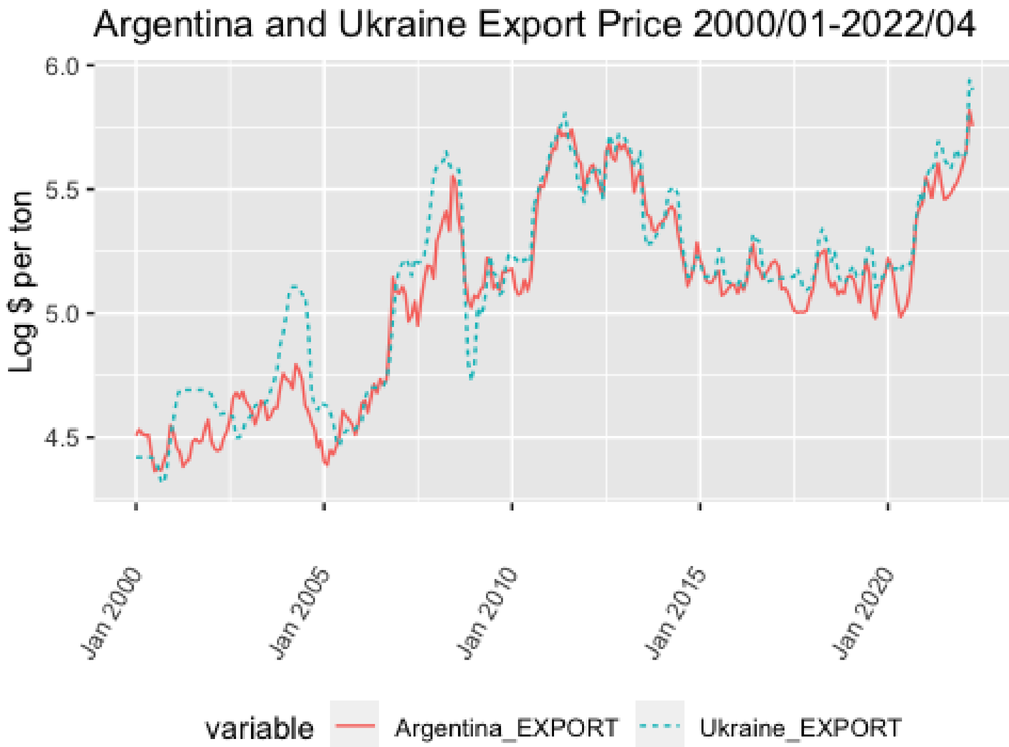

Figure 5: Argentina and Ukraine Corn Market Price

US/Ukraine pair, $p^1_{t-7} - p^2_{t-7}$ for the Argentina/Ukraine pair, and $p^1_{t-9} - p^2_{t-9}$ for the Gulfs/MN pair. We check the LASSO estimates for the 4 selected models, and we reject that each model is linear for US/Ukraine, Argentina/Ukraine, and Gulfs/MN pair. Therefore, we implement the desparsified LASSO estimator through (2.8) for them. However, for US/Argentina, the LASSO estimate only selects one intercept γ_0 to be nonzero, which implies there is not enough evidence to reject that the model is linear. Due to the consistency of LASSO estimator, all coefficients of shocks and exchange rate are zero except γ_0. For this reason, we will focus on the following analysis of the US/Ukraine, Argentina/Ukraine, and Gulfs/MN.

The results of the desparsified LASSO estimated coefficients are presented in Tables 5, 6, and 7. It is worth noting that the desparsified LASSO estimates are always insignificant if the LASSO estimates using equations (2.6) and (2.7) are zero. Therefore, we only report estimates that are significantly non-zero in Tables 5, 6, and 7.

The basic framework illustrates that if exchange rate pass-through effect or any

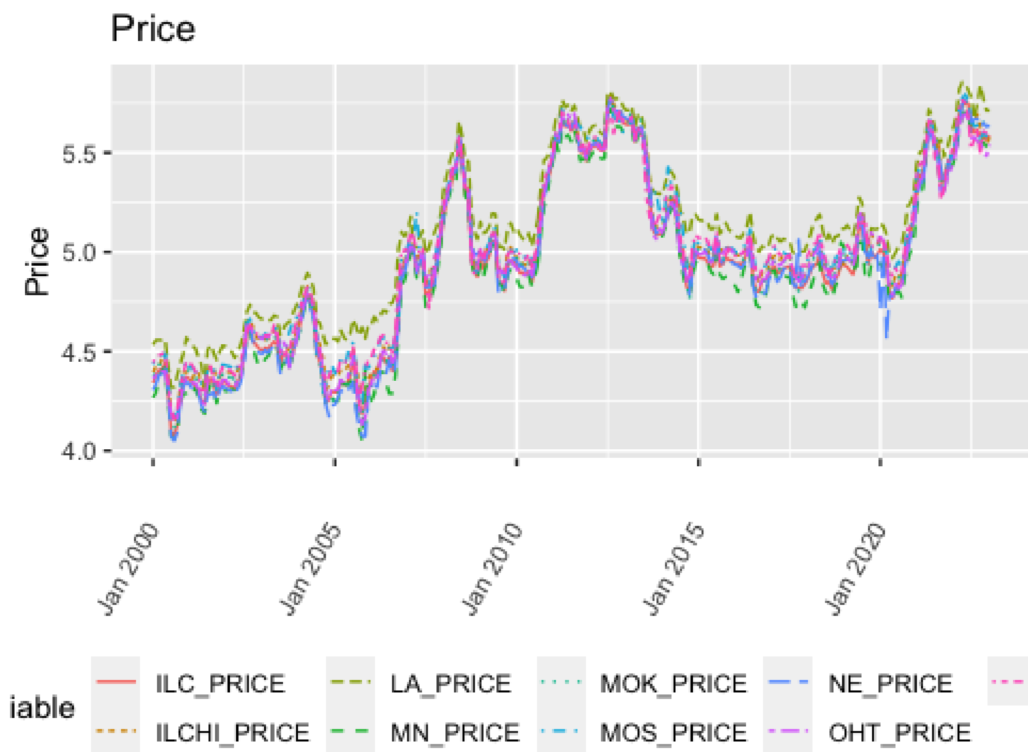

Figure 6: the U.S. Corn Market Price by Location

exogenous shock effect is regime-specific, it means that the impact of exchange rates on price differentials among two international markets differs depending on the magnitude or direction of a certain forcing variable. A straightforward way to illustrate the relationship between 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 first-differenced price differential in time t and with respect to the lagged value of the exchange rate, market factors, or exogenous shocks.

In summary, our findings provide strong evidence of efficient linkages among spatially distinct markets. We observe significant differences in market integration when the price differential deviates from its expected value, resulting in a higher absolute value of price differences. As mentioned earlier, the integration between the corn markets of Minneapolis, MN, and Gulf ports, LA in the U.S. is consistent with the fact that commodity trade tends to flow downstream along the Mississippi River. Do-

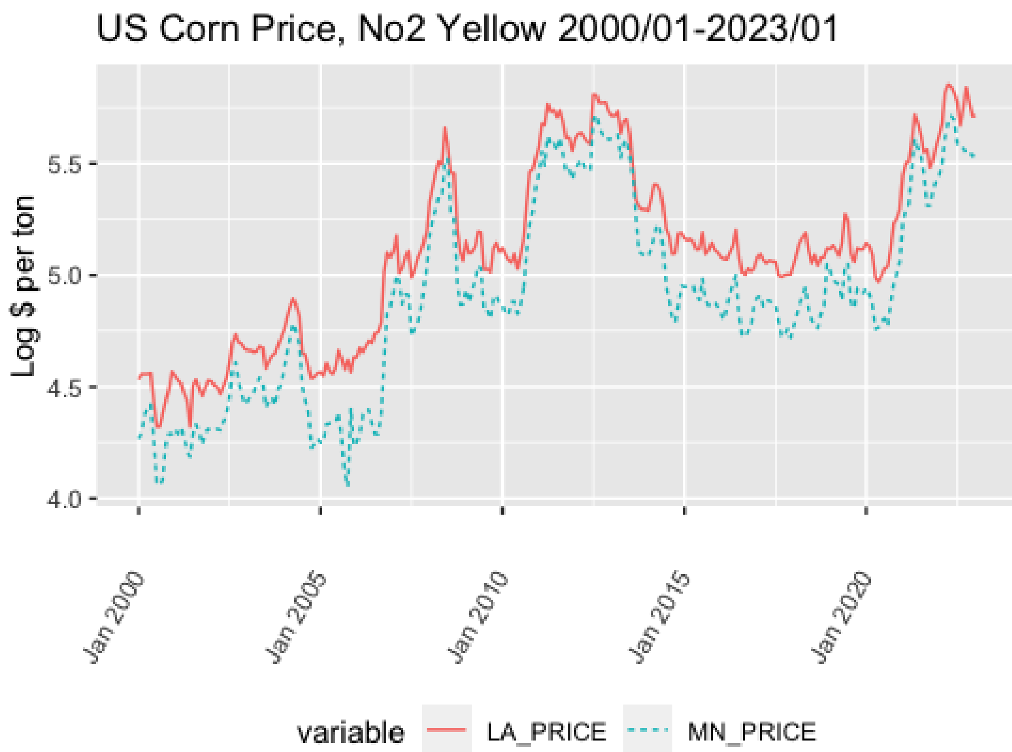

Figure 7: the U.S. Corn Market Price-Minneapolis, MN&Gulf ports, LA

mestic market regions typically ship to export market regions, but not the other way around. We also have an intuitive expectation that unobservable transaction costs are greater when the estimates of the threshold are higher. However, Table 4 indicates that unobservable transaction costs are higher between US domestic markets than between the US and international markets. This may be explained by the fact that the model we considered includes different covariates and the lagged logarithmic price differentials may be discounted to different current period values, which are relevant to the transit time or transaction procedures between the markets.

Recall that our threshold effect coefficients represent the difference between coefficients in the trade regime and those in the no-trade regime. A structural effect refers to the presence of an effect, such as exchange rate pass-through effects or exogenous shocks, that causes a distortion of the expected value of the first-differenced price differential in either the trade or no-trade regime. Our results show that when a structural effect is present, it appears in both the trade and no-trade regimes, and

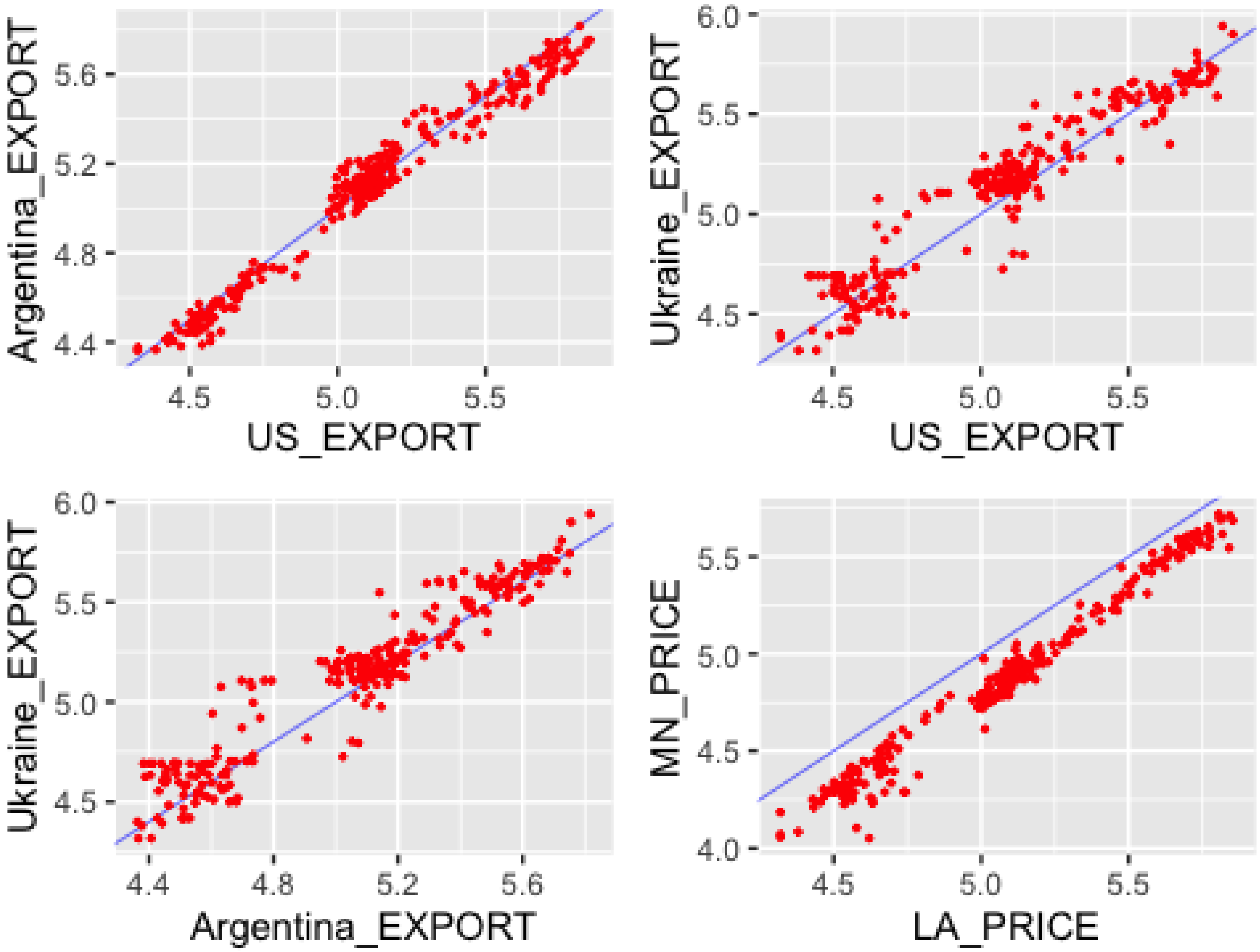

Figure 8: Corn Market Logarithmic Prices pairs

the overall effect (sum of structure effect and threshold effect) is typically larger in magnitude in the trade regime than in the no-trade regime. On the other hand, if there is no structural effect but only a threshold effect in the trade regime, it is consistent with the nonlinear adjustments that occur faster when prices are far apart, as observed in the trade regime.

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

Unit Root Test Result		
Variable (1st diff)		ADF
Unit Root		
price_diff _US_Argentina		-5.33
price_diff _US_Ukraine		-4.71
price_diff _Argentina_Ukraine		-4.81
Apeso		-13.44
UAH		-13.05
Baltic Index		-15.34
CPI		-17.6
Unrate		-16.11
Interest rate		-6.93
US GAS PRICE		-11.57
price_diff _Gulf_MN(with drift)		-6.21
critical value no trend no drift	T=250	
1%	-2.58	
5%	-2.23	
critical value no trend with drift	T=250	
1%	-3.46	
5%	-2.88	

Table 1: Unit Root Test Result of first difference of series

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 largely 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	Variable
US/Argentina	Exchange rate(USD to Argentina Peso),Baltic Exchange Dry Index, US CPI, US Interest Rate, US Unemployment Rate
US/Ukraine	Exchange rate(USD to Ukrainian hryvnia),Baltic Exchange Dry Index, US CPI, US Interest Rate, US Unemployment Rate
Argentina/Ukraine	Exchange rate(USD to Argentina Peso),Baltic Exchange Dry Index, US CPI, US Interest Rate, US Unemployment Rate
Gulfs/MN	US Gas Price ,Baltic Exchange Dry Index, US CPI, US Interest Rate, US Unemployment Rate

Table 2: Dependent Variables in Each pair of markets

market—responses to shocks of exchange rate or market factors are estimated as zero, suggesting that the two markets may be fully integrated.

		$p^1_{t-1}-p^2_{t-1}$	$p^1_{t-2}-p^2_{t-2}$	$p^1_{t-3}-p^2_{t-3}$	$p^1_{t-4}-p^2_{t-4}$	$p^1_{t-5}-p^2_{t-5}$	$p^1_{t-6}-p^2_{t-6}$
	AIC	-2.824995	-2.573053	-2.804386	-2.780723	-2.671034	-2.642986
US/Argentina	λ_T	0.001187017	0.000376935	0.000902666	0.001106442	0.000575098	0.000716167
	$\widehat{c}$	0.685	0.705	0.755	0.74	0.725	0.76
	AIC	-1.423406	-1.287392	-1.553422	-0.9969952	-1.532915	-1.43402
US/Ukraine	λ_T	0.000642867	0.000540667	0.001553862	1.28E-04	0.001192144	0.000753472
	$\widehat{c}$	0.73	0.675	0.405	0.645	0.595	0.75
	AIC	-1.476612	-1.232262	-1.073961	-1.130409	-1.311761	-0.974294
Argentina/Ukraine	λ_T	0.000508462	0.000300266	0.00011797	0.000190229	0.000409909	5.90E-05
	$\widehat{c}$	0.755	0.735	0.55	0.725	0.67	0.715
	AIC	-1.497261	-1.540343	-1.624436	-1.851104	-1.464369	-1.586263
Gulfs/MN	λ_T	4.82E-05	1.88E-05	3.97E-05	0.000198736	2.50E-05	9.98E-05
	$\widehat{c}$	0.745	0.76	0.785	0.85	0.745	0.635
		$p^1_{t-7}-p^2_{t-7}$	$p^1_{t-8}-p^2_{t-8}$	$p^1_{t-9}-p^2_{t-9}$	$p^1_{t-10}-p^2_{t-10}$	$p^1_{t-11}-p^2_{t-11}$	$p^1_{t-12}-p^2_{t-12}$
	AIC	-2.627469	-2.849149	-2.291511	-2.24121	-2.635103	-2.306418
US/Argentina	λ_T	0.000567915	0.001597818	0.000121544	0.000105162	0.000350855	0.000143222
	$\widehat{c}$	0.67	0.625	0.705	0.63	0.7	0.67
	AIC	-1.439564	-1.61988	-1.557229	-1.340752	-1.641491	-1.374107
US/Ukraine	λ_T	0.000718912	0.001815354	0.00210552	0.000588635	0.003277996	0.000657973
	$\widehat{c}$	0.625	0.36	0.595	0.555	0.5	0.76
	AIC	-1.55518	-1.113698	-1.208401	-1.394443	-1.439553	-1.343807
Argentina/Ukraine	λ_T	0.000675299	0.000183883	0.000353875	0.000592037	0.000711895	0.000360019
	$\widehat{c}$	0.815	0.72	0.735	0.755	0.62	0.67
	AIC	-1.487527	-1.612286	-1.963068	-1.669308	-1.670481	-1.607491
Gulfs/MN	λ_T	6.64E-05	7.02E-05	0.000110334	1.07E-05	8.18E-06	3.24E-05
	$\widehat{c}$	0.695	0.745	0.845	0.755	0.745	0.805

Table 3: Lasso Estimation

	forcing variable	threshold estimates quantile	threshold estimates price differentials
US/Ukraine	$p^1_{t-11}-p^2_{t-11}$	0.5	0.08680252
Argentina/Ukraine	$p^1_{t-7}-p^2_{t-7}$	0.815	0.159708
Gulfs/MN	$p^1_{t-9}-p^2_{t-9}$	0.845	0.269785

Table 4: Lasso Estimation of threshold parameter

US/Ukraine			
Variable	debiased_lasso_estimator	stderror	t_stat
lag_10_USDUAH	0.122619***		2.241733
	0.054698		
Baltic_Freight	-0.02015 ***		-5.17493
	0.003895		
lag_12_Baltic_Freight	-0.0061 ***		-1.73215
	0.003524		
UNRATE	-0.01196 ***		-2.45899
	0.004862		
lag_10_FEDFUNDS	-0.03144 ***		-7.10013
	0.004428		
trade_USDUAH	0.10039 ***		2.966467
	0.033842		
trade_USDUAH	0.10039 ***		2.966467
	0.033842		
trade_lag_2_USDUAH	-0.16222 ***		-2.08835
	0.077677		
trade_lag_5_USDUAH	0.309446 ***		2.051505
	0.150838		
trade_lag_12_USDUAH	-0.13477 ***		-2.33405
	0.057742		
trade_Baltic_Freight	-0.07788 ***		-5.03834
	0.015458		
trade_lag_8_Baltic_Freight	0.038886 ***		11.0055
	0.003533		
trade_UNRATE	-0.02552 ***		-2.18144
	0.011699		
trade_lag_8_UNRATE	-0.06418 ***		-1.95875
	0.032764		
trade_lag_6_CPI	0.020325 ***		15.85915
	0.001282		
trade_lag_3_FEDFUNDS	0.032324 ***		1.964646
	0.016453		
trade_lag_11_FEDFUNDS	-0.02462 ***		-19.7296
	0.001248		

Table 5: Regression Results (only significant estimates)

Argentina/Ukraine		
Variable	debiased_lasso_estimator	t_stat
Baltic_Freight	-0.031270225 *** 0.003343817	-9.351655816
lag_11_Baltic_Freight	0.010977801*** 0.0009662	11.36182676
lag_12_Baltic_Freight	-0.057000444*** 0.023373174	-2.438712124
lag_1_UNRATE	-0.004115274*** 0.000561215	-7.332799123
lag_8_UNRATE	0.002237776*** 0.000627863	3.564117153
lag_12_UNRATE	0.028318671*** 0.016899185	1.67574179
lag_1_CPI	-0.038395416 *** 0.013202634	-2.908163237
lag_2_CPI	-0.016866705*** 0.005743973	-2.936418139
lag_5_CPI	-0.012524509 *** 0.001545434	-8.10420123
lag_8_CPI	0.01303886 *** 0.001743185	7.479908061
lag_12_CPI	-0.040195116 *** 0.01193159	-3.36879805
lag_2_Peso_Dollar	0.16296333 *** 0.076704649	2.124556109
trade_lag_5_Baltic_Freight	-0.075094871 *** 0.023068501	-3.255299173
trade_lag_10_Baltic_Freight	0.049552887 *** 0.026467494	1.872216834
trade_lag_6_UNRATE	0.163325712 *** 0.083289591	1.960937846
trade_lag_8_UNRATE	-0.103046791 *** 0.060864578	-1.69305029
trade_lag_2_CPI	-0.053005189 *** 0.015621566	-3.393077823
trade_lag_9_CPI	-0.041587394 *** 0.024350564	-1.707861624
trade_lag_11_CPI	-0.153115668 *** 0.050901538	-3.008075469
trade_lag_12_CPI	0.045855735 *** 0.021032761	2.180205174
trade_lag_7_FEDFUNDS	-0.177384182 *** 0.104621345	-1.69548749
trade_lag_7_Peso_Dollar	0.203389067 *** 0.10544381	1.928885783

Table 6: Regression Results (only significant estimates)

GulfsLA/MN		
Variable	debiased_lasso_estimator	t_stat
trade_Gas_Price	0.186175***	1.993532
	(0.09339)	
trade_lag_3_Baltic_Freight	-0.066 ***	-12.675
	(0.005207)	
trade_lag_6_CPI	0.045272 ***	2.512284
	(0.01802)	

Table 7: Regression Results (only significant estimates)

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