Global Maize Market Integration: Exchange Rates, Macroeconomic Factors, and Threshold Effects Using Post-LASSO Inference

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Abstract

This paper investigates the degree of market integration, exchange rate pass-through, and the market factors that contribute to deviations from perfect integration. To analyze the price linkage dynamics, we apply the novel debiased LASSO for uniformly valid statistical inference, including linearity testing and Granger causality testing within the high-dimensional threshold regression models. Our findings reveal significant global maize market integration, particularly when incorporating threshold effects and key market factors. Notably, consumer prices and unemployment emerge as important determinants of price linkages, underscoring their relevance in the global commodity market. *Keywords*: Market Integration, Threshold Regression, Exchange Rate Pass-Through, Spatial trade

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1 Introduction

Efficient markets are expected to eliminate any opportunities for riskless profits through arbitrage, a principle known as the "Law of One Price" (LOP) (Samuelson (1964)). Economic arbitrage is based on the expectation that prices of homogeneous goods should converge over time, differing only by transportation and transaction costs in freely functioning markets. However, in reality, market frictions such as transaction costs, trade barriers, and external shocks disrupt this process. The presence of transaction costs can create threshold effects, where price deviations must exceed a certain threshold to trigger arbitrage and subsequent price movement. Recent research has increasingly focused on nonlinear models to better capture the influence of unobservable transaction costs on spatial price linkages. These models, often grounded in threshold modeling techniques, highlight the possibility of regime switching, where different price adjustment regimes represent trade and "no-trade" equilibria.

The global maize market is one of the most important agricultural commodity markets, playing a critical role in food security and international trade. Maize is not only a staple food in many parts of the world but also a key input in industries such as livestock feed and biofuel production. The United States, Argentina, and Ukraine are the top maize exporters, accounting for a significant portion of global maize exports. Given the economic and geopolitical importance of maize, understanding the dynamics of international maize markets is crucial for policymakers, traders, and investors. Trade policies, market shocks, and exchange rate fluctuations in these major exporting countries can have ripple effects across the global economy, influencing maize prices and availability in importing nations, particularly in developing economies that are dependent on imports for food security.

Several empirical studies have explored the integration of agricultural markets across different countries and regions. For example, Abdulai (2000) analyzed market integration in Ghanaian maize markets, identifying nonlinear price adjustments driven by transaction costs and market imperfections. Similarly, Baquedano and Liefert (2014) examined global grain markets, demonstrating how major exporters like the United States, Argentina, and Ukraine play pivotal roles in transmitting prices to other regions, particularly developing economies. Fackler and Goodwin (2001) provided an empirical framework for studying maize market integration, emphasizing the importance of price co-movements across geographically distinct markets, which can provide insight into the efficiency of the global maize trade.

Exchange-rate pass-through, or the degree to which exchange rate movements are reflected in prices, has been a topic of interest in international economics, though its application in global agricultural commodity markets is limited. For example, Chambers and Just (1981) used 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 found that exchange rate fluctuations had a significant impact on export volumes and the balance between exports and domestic use of these commodities. Similarly, Varangis and Duncan (1993) examined the impact of exchange rate changes on steel prices, demonstrating that exchange rate fluctuations are not fully passed through to final prices due to other influencing factors, such as production costs and industrial output. In international trade, many commodities are priced in U.S. dollars. While this may suggest that exchange rates are irrelevant to price linkages, local currency valuation after importation makes exchange rates relevant.

Barrett and Li (2002) emphasized that trade flows should be considered when assessing market integration, particularly when distinguishing between spatial market integration and competitive market equilibrium.

In addition to geographic and international factors, several macroeconomic variables also play critical roles in influencing commodity prices. For example, Frankel (2006) and Furlong et al. (1996) found that rising inflation often drives investors toward commodities as a hedge, leading to price increases. Moreover, Abbott et al. (2011) and Baffes and Haniotis (2010) demonstrated that agricultural commodity prices, such as those of maize and wheat, are significantly influenced by macroeconomic variables like inflation and interest rates, which affect both production costs and global demand. Additionally, Pindyck and Rotemberg (1990) and Sadorsky (1999) found that industrial output and unemployment rates also play crucial roles in determining commodity prices, as they influence both the supply and demand sides of the market. Higher production levels generally drive up demand for raw materials, while lower unemployment is indicative of stronger economic activity, boosting consumption. Finally, inventory levels are often viewed as a barometer for market tightness. Wright (2011) and Baumeister and Kilian (2016) demonstrated that fluctuations in grain and oilseed inventories can signal imbalances between supply and demand, thereby influencing price volatility and expectations in commodity markets.

While previous studies have offered valuable insights into market integration and price transmission, they often rely on traditional econometric models that face limitations when dealing with the complexities of large datasets and numerous interacting variables. More modern approaches have emerged to address these limitations, particularly those involving nonlinear dynamics, such as regime switching and price asymmetries. The existence of distinct regimes—one representing profitable trade and the other indicating a lack of arbitrage opportunities—has led to the application of nonlinear time-series models, such as threshold autoregression (TAR) models. These models allow for more flexible representations of market integration by capturing unobservable transaction costs and other frictions that influence price transmission (Goodwin et al. (1990), Goodwin and Piggott (2001), Lence et al. (2018)). TAR models are particularly useful in identifying regime-switching behavior in commodity markets, where price responses may vary based on the level of transaction costs.

Recent advances in econometrics have shifted toward methods capable of accounting for complex interactions among multiple variables. For example, Goodwin et al. (2021) and Goodwin (2024) utilized generalized additive models to study price transmission in plywood/lumber, and cannabis markets. These semiparametric models have demonstrated their ability to capture nonlinearities in price transmission, further expanding the toolkit available for studying market integration.

Building on the limitations of traditional econometric approaches, recent advances have introduced methods capable of addressing the complexities of high-dimensional datasets. One such method is LASSO (Least Absolute Shrinkage and Selection Operator), which excels at variable selection and regularization in large datasets. LASSO simplifies models by shrinking the coefficients of less relevant variables to zero, improving interpretability without sacrificing performance. However, LASSO introduces shrinkage bias due to penalization, resulting in biased and inconsistent estimates. To overcome this issue, this study applies the debiased LASSO method, originally proposed by van de Geer et al. (2014) and extended to high-dimensional threshold models by Li and Yan (2024). This method corrects for the bias while preserving the benefits of variable selection. Additionally, it highlights the advantage of LASSO in threshold models, as it allows for the detection of regime switching in a data-driven manner, even if the regime switch is not explicitly present.

This approach, combined with high-dimensional threshold models, enables the capture of complex, dynamic interactions in the international maize market, offering a deeper understanding of price linkages across countries and time.

This study contributes to the literature by employing advanced econometric techniques, including debiased LASSO for high-dimensional threshold models, to better understand price linkages in the international maize market. These methods provide greater flexibility and robustness in capturing the dynamic interactions among exchange rates, macroeconomic variables, and commodity prices, offering a natural extension to existing research on spatial market integration.

Organization: The rest of the paper is organized as follows. Section 2 discusses the conceptual issues of spatial market integration and introduces the method proposed by Li and Yan (2024), including its extension to high-dimensional models. Section 3 applies this method to the case of international maize markets. Finally, Section 4 concludes the paper.

2 Econometrics Models of Spatial Market Integration

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

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

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

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

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

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

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

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

Perfect integration is implied when $\alpha = 0$ and $\beta = 1$. In cases where prices are invoiced in different currencies, perfect integration also requires perfect exchange rate pass-through, which occurs when $\gamma_2 = 1$. If prices are invoiced in a common currency, as is often the case when trade is conducted in US dollars, the exchange rate is effectively 1, and thus the logarithmic value of zero eliminates the exchange rate effect. However, exchange rate distortions may still influence price linkages, indicated by $\gamma_2 \neq 0$, even if prices are quoted in a common currency. If $\gamma_2 > 0$, it suggests that the price of a good in market j has increased excessively in response to the exchange rate change, overshooting the equilibrium level. Conversely, if $\gamma_2 < 0$, it indicates that after an exchange rate change, market j underreacts, which is referred to as undershooting the equilibrium.

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

$$p_t^j - p_t^k = \gamma_2 \pi_t^{jk} + \sum_{l=1}^{L} \boldsymbol{\gamma}_{3l}' \boldsymbol{z_{t-l}^{jk}} + \varepsilon_t, \tag{2.3}$$

Here, L represents the maximum lag, and $\boldsymbol{z_{t-l}^{jk}}$ is a set of factors that may be conceptually relevant to price linkages. The vector of parameters $\boldsymbol{\gamma}_3 = [\boldsymbol{\gamma}_{31}', \cdots, \boldsymbol{\gamma}_{3L}']'$ is a vector of parameters corresponding to $[(\boldsymbol{z}_{t-1}^{jk})', \cdots, (\boldsymbol{z}_{t-L}^{jk})']'$. We assume that the maximal lag order L is known. We consider that the exogenous shocks $\boldsymbol{z_{t-l}^{jk}}$ can react contemporaneously to the exchange rates π_t^{jk} and therefore only enter the equation with lag structures. The lag coefficients vector $\boldsymbol{\gamma_{3l}}$ for $l = \{1, \cdots L\}$ represent the lag distribution and define the pattern of how $\boldsymbol{z_{t-l}^{jk}}$affects $\Delta(p_t^1 - p_t^2)$over time. The dynamic marginal effect of $\boldsymbol{z_{t-l}^{jk}}$ at the l-th lag is $\frac{\partial \Delta(p_t^j - p_t^k)}{\partial \boldsymbol{z_{t-l}^{jk}}} = \boldsymbol{\gamma_{3l}}$. The dynamic marginal effect is essentially an effect of a temporary change in $\boldsymbol{z_{t-l}^{jk}}$ on $\Delta(p_t^j - p_t^k)$, whereas the long-run cumulative effect $\sum_{l=1}^{L} \boldsymbol{\gamma_{3l}}$ measures how much $\Delta(p_t^j - p_t^k)$ will be changed in response to a permanent change in $\boldsymbol{z^{jk}}$. These factors include exogenous shocks such as exchange rates, interest rates, unemployment rates, and nominal inflation rates, which are relevant to price linkages and largely serve as proxies for unobservable market factors.

A distributed lag model (Almon (1965)) is utilized to reveal both short- and long-run dynamic effects between explanatory variables and response variables. In the model above, while the 'error correction' process captures long-run relationships, exchange rate pass-through reflects the market's reaction to international market. All exogenous shocks are measured as percentage changes from the previous time period, which allows a focus on immediate changes in the variables.

To further analyze spatial price linkages, we propose an extension to the conventional framework of spatial market integration that includes two regimes. We use 'error correction' models to account for the regime switching implied by thresholds. This approach evaluates deviations from a price parity condition, considering threshold effects of price differentials, exchange rate pass-through, and isolated shocks in spatially distinct markets. One regime represents a case of 'no-trade', while the other represents conditions of profitable trade and arbitrage. The regime switch depends on a forcing variable, usually a lagged price differential. Besides, to assess the potential presence of transaction costs and other factors affecting price relationships, we consider a threshold model with a multivariate distributed lag structure and 'error correction' as follows:

$$\begin{aligned}\Delta(p_t^j - p_t^k) =& \gamma_1(p_{t-1}^j - p_{t-1}^k) + \gamma_2\pi_t^{jk} + \sum_{l=1}^{L} \boldsymbol{\gamma}_{3l}' \boldsymbol{z_{t-l}^{jk}} \\ &+ \mathbf{1}\{Q_{t-1} > c\}\left[\delta_1(p_{t-1}^j - p_{t-1}^k) + \delta_2\pi_{t-l}^{jk} + \sum_{l=1}^{L} \boldsymbol{\delta}_{3l}' \boldsymbol{z_{t-l}^{jk}}\right] + \varepsilon_t\end{aligned} \tag{2.4}$$

In the model, L represents the maximum possible lag, which may increase with the sample size and potentially grow slowly to infinity. The forcing variable $Q_{t-1} = |p_{t-1}^j - p_{t-1}^k|$ triggers the regime switch. The parameters γ_1 and δ_1 reflect the degree of market integration. In particular, γ_1 and δ_1 represent the degree of 'error correction' characterizing departures from price parity, which are reflected in large values of p_{t-1}^j-

p^k_{t-1}. The threshold parameter c represents the amount of proportional transaction costs that a price differential must exceed to cross the threshold and trigger the 'trade' regime adjustments. We allow δ_1,δ_2 and $\boldsymbol{\delta_3}$ to nonzero according to whether $|p^j_{t-1} - p^k_{t-1}|$ is within (i.e., $|p^j_{t-1} - p^k_{t-1}| \leq c$) or outside (i.e., $|p^j_{t-1} - p^k_{t-1}| > c$) of a symmetric band. In the context of the threshold regression model considered here, γ_1 ,γ_2 and $\boldsymbol{\gamma_3}$ represent the effect regardless of the status of the forcing variable $|p^j_{t-1} - p^k_{t-1}|$, termed the structural effect. On the other hand, δ_1 ,δ_2 and $\boldsymbol{\delta_3}$ represent the effect when $|p^j_{t-1} - p^k_{t-1}| > c$, referred to as the threshold effect.

Economic agents adjust their expectations of price differentials based on the level of transaction costs that pertain to previous periods. If the price differential exceeds certain thresholds, agents anticipate profitable gains from arbitrage and trade. The specified model offers the advantage of capturing simultaneous relationships between exchange rates and other relevant variables. Linear modeling techniques may not accurately capture the nonlinearities present in the model. Therefore, it is essential to investigate the impact of transaction costs on the market's response to an exchange rate shock or other market shocks nonlinearly. The existence of different levels of transaction costs can influence how price differentials respond to exchange rates or other shocks, as it determines the presence or absence of arbitrage opportunities. Indeed, a limitation of most existing threshold models of spatial price linkages lies in the typical assumption that transactions costs are constant (in levels or proportional terms). We allow transactions costs, which are inherently unobservable, to vary according to many conceptually relevant economic variables. The proposed model recognizes that the movements in the exchange rate can adjust how markets respond to changes, leading to different regimes based on transaction costs. By considering the effects of transaction costs, we can gain a more comprehensive understanding of the dynamics of the exchange rate pass-through mechanism and the effect of market factors.

For this model, there are several reasons for model selection. Firstly, although theory suggests nonlinear relationships among prices, conventional threshold models often require specific nonlinear tests with estimation. This is a key consideration in the model selection issue for our model (2.4).

Secondly, while a range of economic variables may be conceptually relevant to price linkages, there is uncertainty about which factors are directly related to price relationships, such as local policies, product heterogeneity, and unobservable transaction costs. The exact choice of variables and the resulting model specification are not clear. Transaction costs, local policies, and other economic phenomena can influence price linkages between international markets as well as between import and domestic markets.

Thirdly, when dealing with time-lagged relationships, selecting the appropriate lag length is crucial in time series modeling. Typically, a well-defined lag length is chosen, and all lags up to that period are included in the model. However, in our context, where we examine the dynamic relationship between price linkages, exchange rates, and market factors in agricultural commodities, the delivery time between markets spans several weeks to months. Consequently, not all lags are equally important for capturing price linkages in response to market shocks.

In such scenarios, the presence of two regimes, a comprehensive set of control variables, and the maximum possible lag, which may potentially grow to infinity, causes the model high-dimensional. Therefore, threshold detection, along with variable selection and lag selection in a distributed lag model, facilitated by LASSO—a shrinkage method—is particularly effective. Shrinkage methods assume a certain structure on the parameter vector. Typically, sparsity is assumed, where only a small, unknown subset of the variables is thought to have 'significantly non-zero' coefficients, and all the other variables have negligible – or even exactly zero – coefficients. LASSO estimation allows for a more precise representation of dynamic relationships in agricultural commodity markets, offering a richer evaluation of price dynamics and patterns of adjustment.

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 limiting distribution of the LASSO estimator. Therefore, to conduct valid statistical inference, we need to remove this bias. To obtain valid statistical inferences for model (2.4), we employ the debiased LASSO method for high-dimensional threshold regression, recently developed by Li and Yan (2024), building upon the foundational work of Lee et al. (2016) and van de Geer et al. (2014). This method allows for asymptotically valid confidence bands for a low-dimensional subset of the high-dimensional parameter vector, providing insights into the changes in transaction costs and threshold effects over time.

Unlike conventional nonlinear regression models, the shrinkage methods for threshold models proposed by Lee et al. (2016) and Callot et al. (2017) do not require a preliminary nonlinear test before estimation. 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 (Hansen, 1999), Tsay's linearity test (Tsay, 1989), and neural network tests of linearity, are utilized to detect nonlinearity. This allows for estimation without the need to pre-specify the existence of a threshold effect. Although lasso-type methods, such as those discussed in these papers, are appealing for their ability to perform variable selection, they present significant challenges for inference on the estimated parameters. Specifically, performing inference on a model selected in a data-driven manner without accounting for the selection process can lead to invalid results. The post-selection inference procedures developed by Li and Yan (2024) via the debiased lasso method effectively address these issues, enabling valid inference even without specifying the existence of a threshold effect.

High-dimensional inference is a critical topic in statistics and econometrics; for instance, estimating impulse response functions is an essential aspect of econometric inference in time series models. Li and Yan (2024) also demonstrate that the debiased LASSO estimator for threshold models can be effectively used to estimate impulse responses through local projections in high-dimensional settings, following the approach of Adamek et al. (2024).

To simplify, let

$$\boldsymbol{\alpha} = [\gamma_1, \gamma_2, \cdots, \boldsymbol{\gamma}'_{\mathbf{31}} \cdots, \boldsymbol{\gamma}'_{\mathbf{3L}}, \delta_1, \delta_2, \boldsymbol{\delta}'_{\mathbf{31}} \cdots, \boldsymbol{\delta}'_{\mathbf{3L}}]'$$

be the slope parameter vector with a dimension of $4 + 2pL$, where p is the number of other exogenous shocks. Let X_t be a $2 + pL$ vector representing all regressors at time t, $X_t^{(j)}$ denote the j-th variable in X_t, and $X_t(c) = X_t \mathbf{1}\{Q_{t-1} \geq c\}$ correspondingly.

We employ a two-step estimation approach to model the effects of soil erosion on crop yields. In the first step, we estimate the parameter $\widehat{\boldsymbol{\alpha}}(c)$ for each $c \in \mathbb{C}$ using the following LASSO regression:

$$\widehat{\boldsymbol{\alpha}}(c) := \operatorname{argmin}_{\boldsymbol{\alpha}} \left\{ \frac{1}{T} \sum_{t=1}^{T} \left(\Delta(p_t^j - p_t^k) - [X_t', X_t'(c)]' \boldsymbol{\alpha} \right)^2 + \lambda \left\| \boldsymbol{D}(c) \boldsymbol{\alpha} \right\|_1 \right\}, \tag{2.5}$$

In this formulation, the ℓ_1 penalty can be rewritten as

$$\lambda \left\| \boldsymbol{D}(c)\boldsymbol{\alpha} \right\|_1 = \lambda \sum_{j=1}^{2+pL} \left[\left\| X^{(j)} \right\|_n \left| \boldsymbol{\alpha}^{(j)} \right| + \left\| X^{(j)}(C) \right\|_n \left| \boldsymbol{\alpha}^{(2+pL+j)} \right| \right].$$

$$\left\| X^{(j)} \right\|_n := \left(\frac{1}{T} \sum_{t=1}^{T} [X_t^{(j)}]^2 \right)^{1/2} \tag{2.6}$$

This adjustment ensures that the penalty is applied consistently across all coefficients, affecting variables uniformly.

The tuning parameter λ can be selected using criteria such as the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SBC), or the plug-in procedure (PI). Since AIC tends to produce less sparse solutions, while SBC imposes a stronger penalty on the degrees of freedom and is more conservative in variable selection, we choose AIC for tuning parameter selection in (2.5).

We define $\hat{c}$ as the estimate of c_0 that minimizes the following expression:

$$\hat{c} := \mathrm{argmin}_{c \in \mathbb{C} \subset \mathbb{R}} \left\{ \frac{1}{T} \sum_{t=1}^{T} \left(\Delta(p_t^j - p_t^k) - [X_t', X_t'(c)]' \, \widehat{\boldsymbol{\alpha}}(c) \right)^2 + \lambda \left\| \boldsymbol{D}(c) \widehat{\boldsymbol{\alpha}}(c) \right\|_1 \right\}. \tag{2.7}$$

The bias introduced by the shrinkage in the LASSO loss function poses a challenge in deriving the limiting distribution of the LASSO estimator. To enable valid statistical inference, we must employ an estimation strategy to eliminate this bias. However, modeling threshold regression with a rich set of variables introduces a unique challenge. Threshold models involve splitting the sample based on a continuously-distributed variable, and with a large number of regressors, there's a risk that the number of observations in any split sample may be smaller than the number of variables. This can lead to a reduced-rank sample covariance matrix, rendering standard approaches inadequate.

To debias our LASSO estimator, we require an approximate inverse of a certain singular sample covariance matrix, as discussed by Li and Yan (2024). Their approach builds on the work of van de Geer et al. (2014), expanding a 2-by-2 block matrix to construct an approximate inverse matrix in cases where a threshold effect may exist. For a more detailed exploration of LASSO applied to high-dimensional threshold regression models and related extensions, readers can refer to Li and Yan (2024). However, we do not delve into these extensions further here.

Once $\hat{c}$ is obtained, we compute the debiased LASSO estimates for the threshold model as follows:

$$\widehat{\boldsymbol{a}}(\hat{c}) \quad = \quad \widehat{\boldsymbol{\alpha}}(\hat{c}) + \frac{1}{T}\widehat{\boldsymbol{\Theta}}(\hat{c}) \sum_{t=1}^{T} \left(\Delta(p_t^1 - p_t^2) - [X_t', X_t'(\hat{c})]' \, \widehat{\boldsymbol{\alpha}}(\hat{c})\right)^2,$$

where

$$\widehat{\boldsymbol{\Theta}}(\hat{c}) = \begin{bmatrix} \widehat{\boldsymbol{B}}(\hat{c}) & -\widehat{\boldsymbol{B}}(\hat{c}) \\ -\widehat{\boldsymbol{B}}(\hat{c}) & \widehat{\boldsymbol{A}}(\hat{c}) + \widehat{\boldsymbol{B}}(\hat{c}) \end{bmatrix},$$

and $\widehat{\boldsymbol{B}}(\hat{c})$ and $\widehat{\boldsymbol{A}}(\hat{c})$ are the inverse or approximate inverse of the split sample covariance matrices. Specifically, $\widehat{\boldsymbol{B}}(\hat{c})$ corresponds to $\frac{1}{T}\sum_{t=1}^{T}\left[X_t' - X_t'(\hat{c})\right]'\left[X_t' - X_t'(\hat{c})\right]$, and $\widehat{\boldsymbol{A}}(\hat{c})$ corresponds to $\frac{1}{T}\sum_{t=1}^{T} X_t'(\hat{c})X_t(\hat{c})$.

As Li and Yan (2024) derived the asymptotic distribution of tests involving an increasing number of parameters for the debiased Lasso estimator for threshold models, it is convenient to conduct a test to guarantee that a threshold effect indeed exists. Although the debiased Lasso estimates are valid for inference irrespective of whether the threshold effect is assumed a priori, we first conduct a test for linearity to check whether at least one variable exhibits a threshold effect before presenting the debiased Lasso estimates.

For this testing problem, where the true threshold parameter c is unknown, the null hypothesis is given by:

$$H_0 : \boldsymbol{\delta} = [\delta_1, \delta_2, \boldsymbol{\delta'_{31}} \cdots, \boldsymbol{\delta'_{3L}}]' = 0 \quad \text{versus}$$
$$H_a : \text{at least one of } \boldsymbol{\delta} = [\delta_1, \delta_2, \boldsymbol{\delta'_{31}} \cdots, \boldsymbol{\delta'_{3L}}]' \neq 0$$

Under the null hypothesis, the model is linear, so this is known as a test for linearity. Typically, a Wald-type test is employed for this purpose. Specifically, we use the estimator $\widehat{\boldsymbol{a}}(\widehat{\boldsymbol{c}})$ and test whether the second half of this vector (corresponding to $\boldsymbol{\delta}$) is zero using the Wald test statistic. The Wald statistic is defined as:

$$W_n = \frac{\sqrt{n}\, \boldsymbol{g}'\widehat{\boldsymbol{a}}(\widehat{c})}{\sqrt{\boldsymbol{g}'\widehat{\boldsymbol{\Psi}}\left(\widehat{c}\right)\boldsymbol{g}}}, \tag{2.8}$$

where $\widehat{\boldsymbol{\Psi}}$ is the heteroskedasticity- and autocorrelation-consistent (HAC) covariance matrix estimate. The vector $\boldsymbol{g}$ must be a $4 + 2pL$ vector that satisfies $\|g\|_2 = 1$.

To conduct this test, we debias the nonzero estimates among δ obtained from the LASSO estimation and calculate their nonsparsity as $\widehat{s}_{th}$. We then set the elements of $\boldsymbol{g}$ corresponding to these nonzero estimated δ values to $1/\sqrt{\widehat{s}_{th}}$.The Wald test statistic is then asymptotically distributed as

$$W_n \xrightarrow{d} N(0, 1).$$

The theoretical restriction requires that the number of parameters involved in the test can increase to infinity, but the rate of this growth must be slower than the total number of parameters. To satisfy this condition, we focus only on the non-zero coefficients estimated by LASSO.

Next, we aim to construct a uniformly valid Granger causality test within the high-dimensional threshold model to examine whether an exogenous shock series Granger-causes the price differential series $\Delta(p_t^j - p_t^k)$. The Granger causality test is nested within the framework proposed by Li and Yan (2024), which is similar to the Granger Causality Tests shown in Babii et al. (2022) and Adamek et al. (2023).

As denoted in (2.4), $\boldsymbol{z_{t-l}^{jk}}$ represents the vector for all different series at the same lag l period. We now introduce a new notation, $\boldsymbol{z_t^{jk}(q)}$, which captures all $\{1, \cdots, L\}$ lagged period values for the q-th shock, where $q = \{1, \cdots, p\}$. Correspondingly, $\boldsymbol{\gamma_3(q)}$ is the vector of parameters for the q-th exogenous shock. Thus, we have $\sum_{q=1}^{p} \boldsymbol{\gamma_3(q) z_t^{jk}(q)} = \sum_{l=1}^{L} \boldsymbol{\gamma_{3l} z_{t-l}^{jk}}$. The same notation applies to $\boldsymbol{\delta_3(q)}$.

The null hypothesis that $\boldsymbol{z_t^{jk}(q)}$ does not Granger-cause $\Delta(p_t^j - p_t^k)$ and the corresponding alternative hypothesis are:

$$H_0 : \boldsymbol{\gamma_3(q)} = \boldsymbol{\delta_3(q)} = 0 \quad \text{versus}$$

$$H_a : \text{at least one of the } 2L \text{ parameters among } \boldsymbol{\gamma_3(q)} \text{ or } \boldsymbol{\delta_3(q)} \neq 0$$

The specified Wald statistic for Granger causality tests is very similar to the Wald statistic used for testing linearity. In this case, we conduct the test across all periods for each exogenous shock. We set the elements of $\boldsymbol{g}$ corresponding to each shock to $1/\sqrt{2L}$.

3 Empirical Application

The empirical analyses in our study focus on international corn markets, specifically three of the top four major exporting markets: the US, Argentina, and Ukraine.*[1] Despite its widespread consumption and spatial dispersion, corn production is typically concentrated in specific regions. These three markets collectively accounted for approximately 60% of the world's corn exports by volume before the 2021/2022 marketing year. During the 2022/2023 trade year, these three exporters still maintained around 50% of world maize export volume.[2]

Given the intricate spatial dynamics of the corn market, analyzing spatial linkages is crucial for an understanding of the underlying market dynamics and overall performance and behavior.

We collected monthly maize prices and other relevant variables from multiple sources, which are listed in the appendix. As noted above, the main dependent variable of interest in this study is the maize price in international markets, all measured in USD. We gathered yellow corn export prices for the US, Ukraine, and Argentina. Additionally, we collected exchange rates for USD/UAH (US/Ukraine), USD/ARS (US/Argentina) and UAH/ARS (Ukraine/Argentina). For exogenous shocks, we collected the Baltic Exchange Dry Index, measuring the cost of shipping dry goods like maize worldwide.To capture US market factors, we collect unemployment rates, the consumer price index, the industrial production index, interest rates, gasoline

[1]Although Brazil is also a major exporter, it is not included in our analysis due to the lack of early data, such as data prior to 2008, within our selected time span. The rankings of these four exporting markets have changed over time.

[2]This decline is partly due to the challenges faced by Ukraine in exporting corn since the Russian invasion in February 2022, as Ukraine's shipments by sea, which traditionally accounted for the bulk of its exports, have been severely limited.(U.S. Department of Agriculture, Foreign Agricultural Service (2024))

prices and corn stocks. Market factors for Ukraine, such as unemployment rates, the consumer price index, and the industrial production index, along with those for Argentina, such as unemployment rates, consumer price index, and inflation rate.[3][4]

For the U.S./Argentina estimation, our dataset includes 241 observations from January 2004 to January 2024. For the U.S./Ukraine, we have 233 observations from September 2002 to January 2022. For Ukraine/Argentina, there are 217 observations from January 2004 to January 2022.[5]

As mentioned previously, all exogenous shocks are measured as percentage changes from the previous time period[6], allowing a focus on immediate changes in the variables. The basic unit of analysis used throughout is the natural logarithm of the price ratio, denoted as $p_t^j - p_t^k (= \ln(P_t^j/P_t^k))$, where j and k indicate locations (i.e., $j, k = 1, 2, 3$ denote the US, Ukraine, and Argentina respectively), and t is a time index such that $t = 1, \cdots, T$. The international price data are shown in logarithmic form in Figure 1b.

[3]Cubic spline interpolation was employed to estimate the missing data. The Ukraine price data has 19 missing observations from September 2002 to January 2022. Additionally, due to changes in the units of measurement reported by the data source for the consumer price index and industrial production index, each variable has two gaps, including the Ukraine consumer price index, industrial production index, and the Argentinian industrial production index.

[4]To align the data frequencies for our econometric analysis, cubic spline interpolation was applied to convert the quarterly US corn stock, Argentina unemployment rate and Ukraine employment rate into the same frequency as all other monthly variables.The data for US corn beginning stocks spans from 2002 Q3 to 2024 Q1 (we use standard calendar quarters; however, the data source uses the market year, which refers to the start of the main harvest), resulting in 87 observations corresponding to 256 monthly observations. The data for Ukrainian unemployment ranges from 2002 Q3 to 2021 Q4, totaling 78 observations, which have been converted to 233-month observations. The data for Argentinian unemployment spans from 2003 Q4 to 2024 Q1, comprising 82 observations, which have been converted to 240-month observations. Note that these variables are typically not volatile on a month-to-month basis, making spline interpolation a reasonable approach to converting the data to a monthly basis.

[5]The shorter time span for Ukraine-related cases is due to the availability of unemployment data only until 2021 Q4. Data release delays have occurred due to the ongoing military conflict, as outlined in Ukraine's law on reporting during martial law.

[6]The differential of the natural logarithm of the value serves as an approximation of this percentage.

Figure 2 presents a graphical representation of logarithmic pairs of prices plotted against each other, offering insights into the relationship between price levels and price differentials. Deviations from the 45-degree line in each plot reveal distinct basis patterns, where one price tends to be higher or lower than the other. These patterns likely reveal the influence of transaction costs associated with regionally distinct market trades. While these countries are exporters only, in the market integration framework, maize flows between the three markets can occur in any direction, depending on potentially profitable arbitrage opportunities. Our observations from the figures indicate that situations where the price of Ukrainian maize surpasses the prices of US maize and Argentina maize occur more frequently.

To examine the characteristics of time series prices and identify the most appropriate model for evaluating spatial price linkages, we conducted augmented Dickey-Fuller tests for each pair of price differentials. The results of the Augmented Dickey-Fuller (ADF) tests for the stationarity of the price differentials are presented in Table 1 in the appendix, which indicates that the null hypothesis of nonstationarity of the price differentials is strongly rejected in every case. This is as expected since a nonstationary differential would imply that prices can drift arbitrarily far apart.

Transmission elasticities($\frac{\partial P_t^j}{\partial P_t^k}$) close to one provide support for market integration, with 1.0 corresponding to perfect market integration.

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

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

where c is a threshold parameter, and $\gamma_1 + \delta_1$ is the parameter for 'trade' regime. Each of the linearity tests was applied to the collection of prices. Tests on pairs of prices were conducted on the differential between logarithmic prices. The nonlinearity testing results are presented in Table 2.

We implemented a set of nonlinearity tests using the R package 'nonlinearTseries' Garcia (2024) including Teraesvirta's neural network test, White's neural network test, Keenan's one-degree test, Tsay's test for quadratic nonlinearity, the likelihood ratio test for threshold nonlinearity, and the test of linearity against threshold (SETAR)[7] Hansen (1999). At the 85% confidence level, both theUSA/Ukraine and Ukraine/Argentina price differentials show evidence of rejecting linearity across multiple tests, suggesting the potential presence of threshold nonlinearity. TheUSA/Ukraine price differential exhibits some evidence of threshold nonlinearity, particularly in the Likelihood Ratio Test, but does not pass other nonlinearity tests. The Ukraine/Argentina time series demonstrates stronger evidence of nonlinearity in several tests, especially in the SETAR 2 vs 3 and 1vs3 tests, indicating that this time series may align more closely with a complex nonlinear model. In contrast, theUSA/Argentina time series does not show significant nonlinearity across any of the tests.Threshold models are a likely candidate for a nonlinear representation of the price relationships.

The question remains as to the most appropriate specification of the alternative models of price parity. We have suggested that, despite the fact that prices are all

[7] Hansen's test of linearity against threshold, using 1000 bootstrap replications, was applied in this analysis.

quoted in US dollar terms, exchange rates may nevertheless play a role in international price linkages. Specifically, if import prices pertain to an intermediary step in trade between internal markets, where different currencies may exist, and international markets, exchange rates may still be relevant to the price linkages. If exchange rates are found to exert a statistically significant effect on price linkages, exchange rate over- or under-shooting may exist. Further, it is unclear as to whether additional variables may be relevant to price linkages. Markets are separated by unobservable transactions costs, which may in turn be influenced by other economic variables. Hence, we utilize LASSO methods to select an optimal specification.

We estimate five versions of an 'error correction' model of spatial price linkages, each progressively more detailed. The first model is a simple linear 'error correction' model based solely on price differentials. The second model introduces exchange rates into the analysis. A third model explores nonlinear relationships by applying a threshold autoregressive model that considers price differentials alone. The fourth model extends the threshold model to include both price differentials and exchange rates. Finally, we estimate a model that incorporates additional covariates, as estimated by the debiased LASSO method of Li and Yan Li and Yan (2024). These additional covariates are intended to capture residual factors that may cause simple price linkages to deviate from equilibrium parity conditions.

We initially estimate price relationships for the three pairs of market prices using a standard autoregressive model of the form:

$$\Delta(p_t^j - p_t^k) = \gamma_1(p_{t-1}^j - p_{t-1}^k), \tag{3.2}$$

where $(j, k) = \{(1, 2), (1, 3), (2, 3)\}$, with the indices representing the US, Ukraine, and Argentina as $1, 2, 3$ respectively. γ_0 and γ_1 are parameters reflecting the degree of market integration. In particular, we expect a small but negative value of γ_1, so the price differential $p_t^j - p_t^k$ converges to 0 at the rate of $1 + \gamma_1 < 1$. A value of γ_1 closer to zero implies a slower adjustment to shocks. This model has been used extensively to evaluate price transmission and parity conditions.

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

$$\Delta(p_t^j - p_t^k) = \gamma_1(p_{t-1}^j - p_{t-1}^k) + \gamma_2 \pi_t^{jk}, \tag{3.3}$$

where π_t^{jk} is the exchange rate between countries one and two. If γ_2 is significantly different from zero, imperfect exchange rate pass-through is implied. It may seem odd to evaluate exchange rate effects when prices are quoted in a single currency, but price distortions caused by exchange rate shocks are possible, even in such cases.

Besides model (3.2) and (3.3), we then try the threshold tyape model. the third model is as shown in (3.1). In addition, we use exchange rates as covariates and estimate threshold models of the form:

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

In the threshold context, the symmetric lagged price differential $Q_{t-1} = |p_{t-1}^j - p_{t-1}^k|$ transforms into $\tilde{Q}_t$, representing the quantile of Q_{t-1} in selected samples. The estimation of thresholds is conducted using a grid search. An assumption is made that all Q_{t-1} values are distinct. This is a convenient condition, ensuring that the transformation into quantiles is a one-to-one function without any loss of generality.

This assumption holds under the assumption of continuous distribution for Q_{t-1}.

Tables 3, 4, and 5 present the estimates for the models described above. All eror correction estimates are negative and significant with model (3.2) and (3.3). In the threshold models (3.1) and (3.4), we expect $\gamma_1 + \delta_1 < \gamma_1 < 0$ based on our conceptual framework. With only price differentials, the estimates show that the speed of adjustment in the 'trade' regime is much faster than the speed of adjustment in the 'no-trade' regime, except in the model (3.1) for Ukraine/Argentina. For the 'no-trade' regime, the degree of 'error correction' is positive but insignificant in the USA/Ukraine and USA/Argentina models of (3.1). This finding is consistent with expectations, as our conceptual framework suggests that markets are not linked in the 'no-trade' regime. The threshold models imply much faster adjustment to deviations from equilibrium conditions than when thresholds are ignored.

When exchange rates are considered, models (3.3) consistently suggest that the degree of 'error correction' in response to deviations from equilibrium is at least as fast as in models that omit exchange rates.

It's interesting to note that when considering the exchange rate effect in the models, undershooting is observed in all cases except for the (3.4) 'no-trade' regime in the USA/Argentina case. Significant imperfect exchange rate pass-through is evident in every case under the (3.4) 'trade' regime. In the linear model (3.3), significant imperfect pass-through is only observed in the USA/Ukraine markets.

As previously mentioned, the model (2.4) and estimation procedures for threshold regression we use provide the advantage of variable selection and threshold detection, thereby eliminating the need for conventional nonlinear tests typically required in threshold models. In our study, the covariates included across all market pairs are the exchange rate, the Baltic Exchange Dry Index, unemployment rates, and industrial production indexes for each market. Additionally, for pairs involving the US, we incorporate US interest rates, US corn stock, and US gas prices as control variables. Due to data availability, consumer price indexes are used for the US and Ukraine, while inflation rates are applied for Argentina. Besides, we take posible maximal lag order $L = 6$ for the monthly dataset.

To ensure comparability with our baseline model (the linear model that includes price differentials and exchange rates), we set the first and second elements in the scaling diagonal matrix $\boldsymbol{D}(c)$ in (2.5) to 0. This guarantees that the LASSO estimation will always select the parameters γ_1 and γ_2 in (2.4). We report the estimates of γ_1, γ_2, δ_1, and δ_2 in Tables 3, 4, and 5. If the first-step LASSO does not select the variables, their debiased LASSO estimates are always insignificant. The AIC values reported are based on the LASSO estimations of (2.5) and (2.7). Since the debiasing procedure is conducted for inference, it desparsifies all estimators, making them nonzero. If we calculate the AIC based on the debiased results, we cannot directly compare all five models at the same stage. Although the AIC for (2.4) is not always the smallest in all cases, this occurs because the objective functions of the fixed-dimension models (i.e., (3.2), (3.3), (3.1), and (3.4)) do not include the penalty term that is always considered in LASSO.

To further validate the presence of a threshold effect, we conduct a test for linearity, as shown in Section 2. This test checks whether at least one parameter among the subset of threshold effect parameters (i.e., those that LASSO selects as non-zero) has a threshold effect before illustrating the debiased LASSO estimates. As shown in Table 6, we statistically reject the null hypothesis that the model is linear for every market pair.

These findings provide a basis for examining the two-regime adjustments in the markets. In all three cases, the estimates of adjustment in response to deviations from equilibrium (γ_1) are negative and close to zero, indicating a consistent correction mechanism. The nonlinear impact of the degree of 'error correction' aligns with our conceptual framework, as all γ_2 estimates are also negative and close to zero. Notably, all these results are statistically significant. Regarding exchange rate pass-through, significant imperfect pass-through is observed in the 'trade' regime between the USA and Argentina, as well as in both regimes between Ukraine and Argentina.

To further understand the underlying dynamics, we conducted Granger causality tests on the price differentials, as summarized in Table 7. The p-values highlight the key drivers of these market adjustments. Notably, the unemployment rates and consumer price index (or inflation) for all countries are significant at least at the 1% significance level. Additionally, the US Industrial Production Index is significant in the case involving the USA/Argentina.

4 Summary and Concluding Remarks

In this study, we develop a comprehensive model of market integration in spatially distinct international maize export markets, focusing on the degree of 'error correction,' exchange rate pass-through, and the influence of other market factors. By situating these models within high-dimensional threshold frameworks and incorporating an expanding set of covariates relevant to spatial market integration, we extend the current literature on international maize markets. The use of debiased LASSO estimation, along with linearity tests and Granger causality tests, allows for a comprehensive exploration of the underlying nonlinear dynamics driving maize market integration.

Our findings are consistent with the existing literature (Goodwin and Piggott

(2001), Goodwin et al. (2021) et al.), demonstrating a faster adjustment to deviations from market equilibrium during periods of profitable trade and arbitrage compared to 'no-trade' scenarios. This suggests that spatially distinct maize markets are more responsive to price signals when trading opportunities are present, indicating the efficiency of market integration in the presence of potential arbitrage. Furthermore, our results reveal strong linkages across the examined markets, highlighting the importance of nonlinear adjustments in understanding international maize market dynamics.

While our results support the hypothesis of perfect exchange rate pass-through in most cases, we identify significant instances of imperfect pass-through, particularly in 'trade' regimes. This observation points to the important role of exchange rates in influencing cross-border maize price integration. Additionally, the Granger causality tests highlight the significance of macroeconomic factors, such as unemployment rates and consumer prices, in shaping market integration.These factors lead to periods of disequilibrium, creating greater arbitrage opportunities and illustrating the complexity of international maize market integration.

Overall, our study demonstrates the effectiveness of high-dimensional threshold models and debiased LASSO estimation in capturing the complex and nonlinear characteristics of international maize markets. The inclusion of a broad set of covariates and the identification of key drivers of market adjustments contribute to a more thorough understanding of the interactions among spatially distinct markets. Future research could further explore the dynamic relationships between macroeconomic variables, trade policies, and market integration, especially in the context of evolving global trade dynamics and emerging market disruptions.

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5 Appendix

5.1 Tables and Figures

Table 1: Augmented Dickey-Fuller Test Results

Price Pair	**Dickey-Fuller Statistic**	**Lag Order**	**p-value**
Ukraine/Argentina	-4.6972	6	< 0.01
USA/Argentina	-4.5451	6	< 0.01
USA/Ukraine	-4.7320	6	< 0.01

Table 2: Summary of Nonlinearity and SETAR Test Results

Test / Time Series	**USA/UKR**	**USA/Argentina**	**Ukraine/Ar**
Teraesvirta's Neural Network Test			
χ^2	1.521	2.168	1.865
p-value	0.467	0.338	0.394
White Neural Network Test			
χ^2	0.714	1.497	2.326
p-value	0.700	0.473	0.313
Keenan's One-Degree Test			
F-statistic	1.391	1.558	0.799
p-value	0.239	0.213	0.372
Tsay's Test for Nonlinearity			
F-statistic	1.169	0.668	1.496
p-value	0.251	0.572	0.181
Likelihood Ratio Test for Threshold Nonlinearity			
χ^2	22.724	5.846	6.644
p-value	0.078*	0.335	0.340
SETAR 2 vs 3 Test			
Test Statistic	8.284	7.207	15.14
p-value	0.300	0.409	0.021
SETAR Linearity Test (1vs2 and 1vs3)			
1vs2 Test Statistic	5.808	7.120	4.220
1vs2 p-value	0.531	0.367	0.781
1vs3 Test Statistic	14.299	14.541	19.66
1vs3 p-value	0.406	0.379	0.113

Note: *p<0.15

	(3.2)	(3.3)	(3.1)	(3.4)	(2.4)
Degree of Error Correction	-0.107***	-0.129***	0.041	-0.131***	-0.123**
γ_1	(0.029)	(0.032)	(0.067)	(0.041)	(0.056)
Exchange Rate		-0.003*		-0.003	-0.008
γ_2		(0.002)		(0.002)	(0.011)
Threshold Degree of Error Correction			-0.182**	-0.070	-0.006***
δ_1			(0.075)	(0.072)	(0.000)
Threshold Exchange Rate				-0.033**	0.005
δ_2				(0.014)	(0.006)
Threshold Estimate			0.134	0.309	0.038
Observations	233	233	233	233	233
AIC	-1279.182	1280.067	-1283.083	-1283.359	-1283.162
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 3: Model Estimates of Error-Correction Model: USA/Ukraine

	(3.2)	(3.3)	(3.1)	(3.4)	(2.4)
Degree of Error Correction	-0.145***	-0.145***	0.217	-0.096**	-0.162***
γ_1	(0.034)	(0.034)	(0.171)	(0.047)	(0.030)
Exchange Rate		-0.000		0.001	0.000
γ_2		(0.001)		(0.001)	(0.001)
Threshold Degree of Error Correction			-0.377**	-0.087	-0.147***
δ_1			(0.174)	(0.067)	(0.041)
Threshold Exchange Rate				-0.005*	0.007 ***
δ_2				(0.003)	(0.002)
Threshold Estimate			0.040	0.115	0.069
Observations	241	241	241	241	
AIC	-1576.927	-1574.946	-1579.599	-1578.509	-1577.607
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 4: Model Estimates of Error-Correction Model: USA/Argentina

	(3.2)	(3.3)	(3.1)	(3.4)	(2.4)
Degree of Error Correction	-0.112***	-0.114***	-0.190***	-0.156***	-0.061*
γ_1	(0.031)	(0.031)	(0.045)	(0.049)	(0.033)
Exchange Rate		-0.004		-0.000	-0.015***
γ_2		(0.007)		(0.007)	(0.005)
Threshold Degree of Error Correction			0.147**	-0.038	-0.138 **
δ_1			(0.061)	(0.075)	(0.070)
Threshold Exchange Rate				-0.098***	0.016
δ_2				(0.038)	(0.011)
Threshold Estimate			0.309	0.252	0.097
Observations	217	217	217	217	217
AIC	-1193.209	-1191.638	-1197.017	-1197.580	-1224.215

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

Table 5: Model Estimates of Error-Correction Model: Ukraine/Argentina

Table 6: Test for Linearity

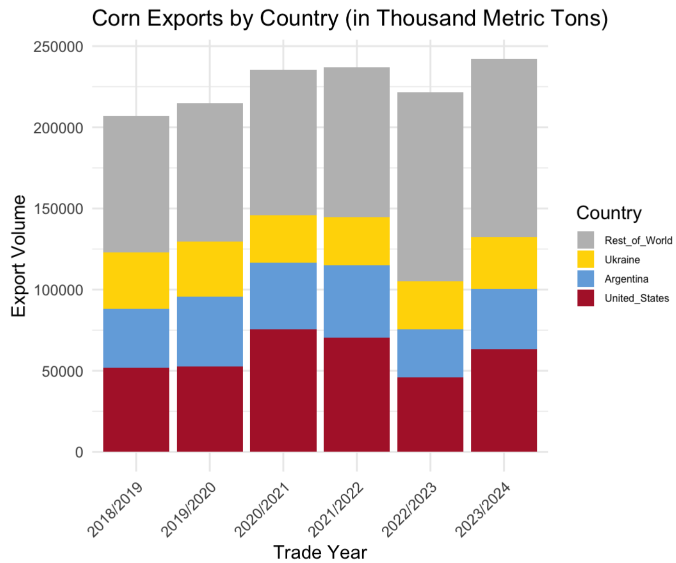
	Wald Test Statistic	p-value
USA/Ukraine	6.871	0.000***
USA/Argentina	3.615	0.000***
Ukraine/Argentina	8.433	0.000***

Note: ***$p<0.01$

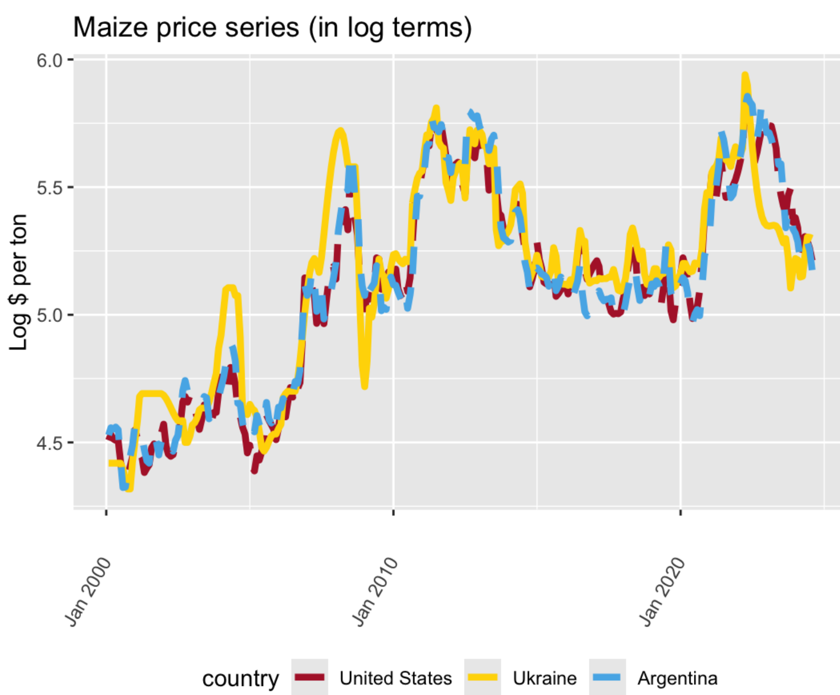
Table 7: Granger Causality Test Results

USA/Ukraine	Wald Test Statistic	p-value
Exchange Rate	0.749	0.454
Baltic Dry Index	0.105	0.916
US Consumer Price	13.094	0.000***
US Industrial Production	1.244	0.213
US Unemployment	7.885	0.000***
US Corn Stocks	0.059	0.953
US Gas	0.333	0.739
Ukraine Consumer Price	2.731	0.006***
Ukraine Industry Production	0.410	0.682
Ukraine Unemployment	48.434	0.000***
USA/Argentina	**Wald Test Statistic**	**p-value**
Exchange Rate	1.244	0.214
Baltic Dry Index Price	0.094	0.925
US Consumer Price	18.022	0.000***
US Industrial Production	3.469	0.001***
US Unemployment	8.104	0.000***
US Corn Stocks	0.085	0.932
US Gas	0.872	0.383
Argentina Inflation	3.331	0.001***
Argentina Industrial Production	0.831	0.406
Argentina Unemployment	89.417	0.000***
Ukraine/Argentina	**Wald Test Statistic**	**p-value**
Exchange Rate	0.658	0.511
Baltic Dry Index Price	0.154	0.878
Ukraine Consumer Price	5.184	0.000***
Ukraine Industry Production	0.932	0.351
Ukraine Unemployment	116.757	0.000***
Argentina Inflation	2.990	0.003***
Argentina Industrial Production	0.975	0.329
Argentina Unemployment	91.603	0.000***

Note: ***p<0.01



(a)



(b)

Figure 1: (a) Global Corn Exports by Country and Marketing Year, Source: U.S. Department of Agriculture, Foreign Agricultural Service (2024). (b) Maize Retail Price Series (in log terms) by Country

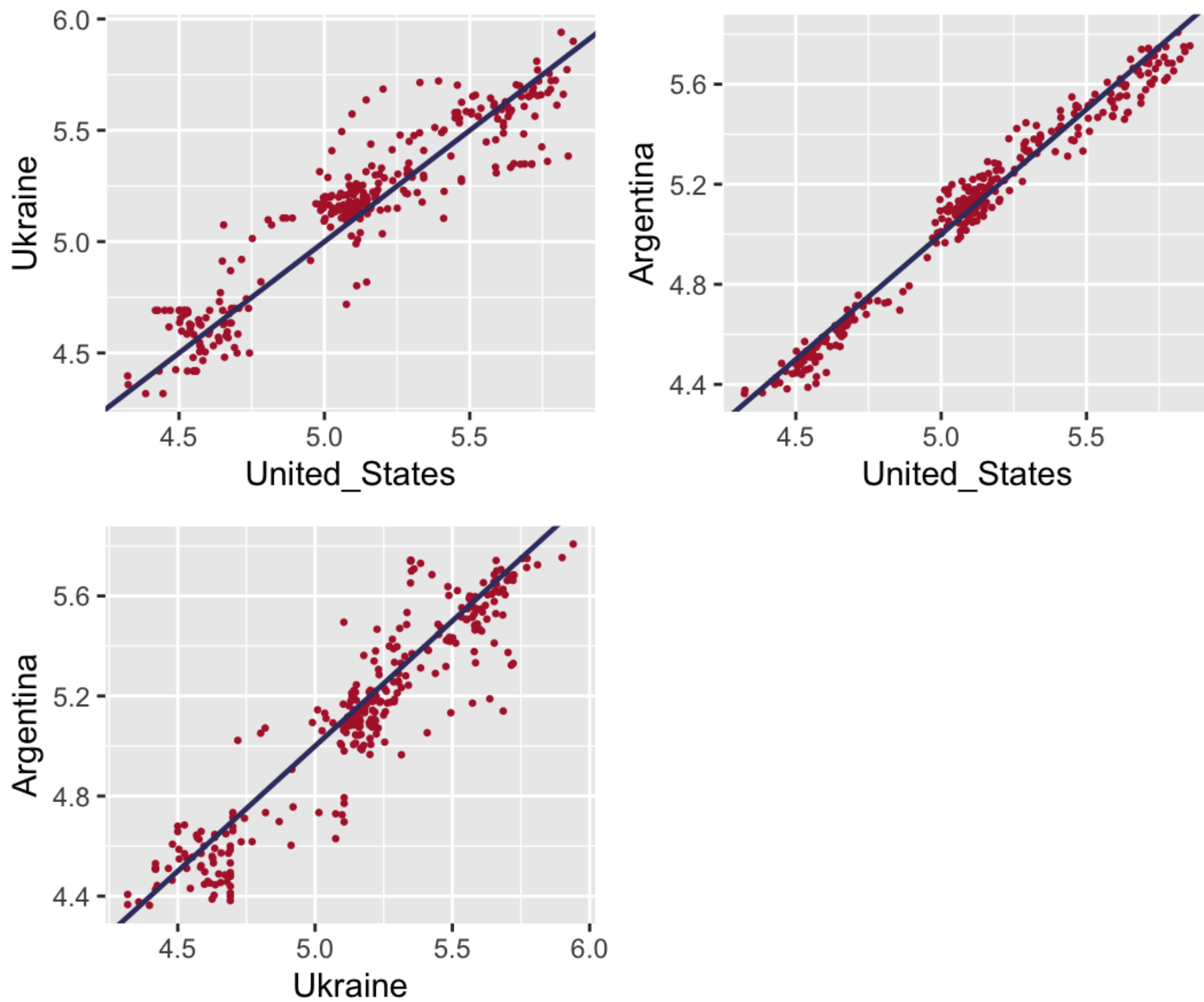


Figure 2: Maize Market Prices Pairs (in logarithms)

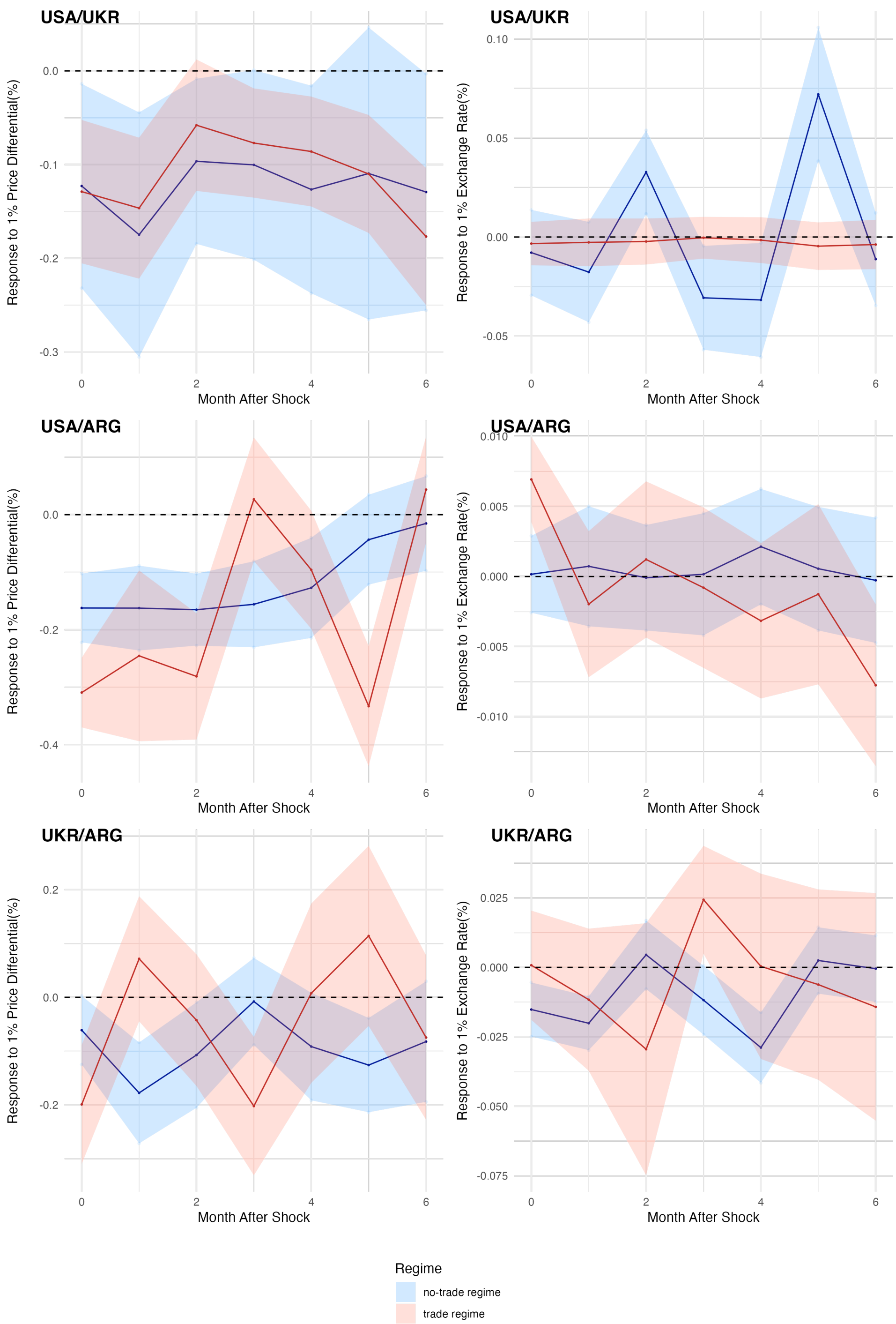


Figure 3: Impulse Response by Local Projection

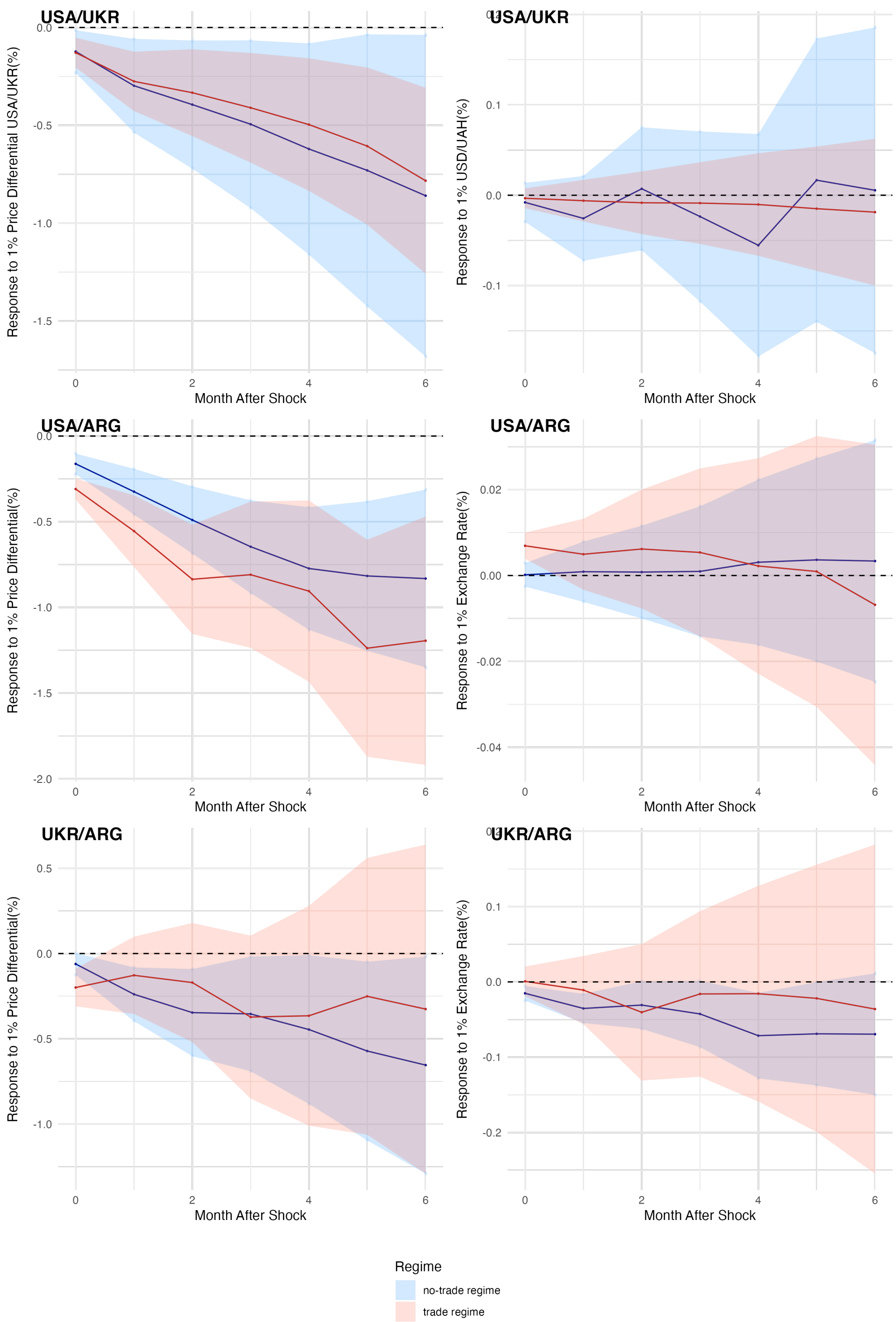


Figure 4: Cumulative Impulse Response by Local Projection

5.2 Data Source

- The international price series for the U.S., Ukraine, and Argentina is sourced from multiple databases. The U.S. data comes from the USDA Feed Grains Database (`https://www.ers.usda.gov/data-products/feed-grains-database/`), Argentina's data is sourced from the International Grains Council (`https://www.igc.int/en/Default.aspx`), and Ukraine's data is provided by the APK-Inform Agency (`https://www.apk-inform.com/ru/prices`). Additionally, the FPMA Tool was used to gather price series data.

- The exchange rate between Ukraine and the U.S. was calculated by downloading the wholesale, national average maize price series for Ukraine in both UAH and USD from the FPMA Tool. The U.S. Dollar exchange rate for Argentina was sourced from the Organization for Economic Co-operation and Development's Main Economic Indicators, retrieved from FRED, Federal Reserve Bank of St. Louis. Finally, the exchange rate between Ukraine and Argentina was determined by dividing these two series.

- The U.S. data for the Consumer Price Index, Industrial Production Index, US Regular All Formulations Gas Price, Federal Funds Effective Rate, and Unemployment Rate are all retrieved from FRED, Federal Reserve Bank of St. Louis. U.S. corn stock data is sourced from the USDA Feed Grains Database (`https://www.ers.usda.gov/data-products/feed-grains-database/`).

- Data for Ukraine, including the Unemployment Rate, Industrial Production Index, and Consumer Price Index (CPI), are obtained from the Economic and Financial Data for Ukraine (`https://www.ukrstat.gov.ua/imf/pokaze.html`).

- Argentina's Unemployment Rate and Industrial Production Index are sourced from https://www.indec.gob.ar/indec/web/Institucional-Indec-InformesTecnicos-14 and https://sdds.indec.gob.ar/nsdp.htm. Monthly inflation data for Argentina is obtained from the Banco Central de la República Argentina (https://www.bcra.gob.ar/PublicacionesEstadisticas/Principales_variables_i.asp).
- The Baltic Dry Index is sourced from https://www.investing.com/indices/baltic-dry-historical-data.