Estimating the Effects of Rising International Corn Production and Trade on the US and Global Corn Market

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Abstract

Rising competition in the global corn market challenges the dominant role of the United States in the export market. We investigate how the rising competition in the global corn market has affected corn price dynamics in the US and the international market. Using monthly data from 2000 to 2021, we estimate Global Vector Autoregression models to determine how shocks to one country affect the corn market in another country. Results largely confirm our hypothesis that shocks to the demand and supply of corn in emerging countries (Brazil, Argentina, and Ukraine) have become more important in explaining export prices in the US and other regions. In particular, shocks to ending stocks, an indicator of market supply, negatively affect corn export prices. Depreciation of domestic currencies against the US dollar lowers corn export prices, and an increase in domestic CPI positively impacts export prices. Furthermore, market-specific shocks, proxied by a shock to the export price, increase export prices in other countries. However, the impact displays considerable heterogeneity depending on the origin of the shock.

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Dedication

I dedicate this work to two incredible women who always have been a source of inspiration and support: my beloved mother, Dilmaya, whose love and sacrifice have made me who I am today, and my esteemed advisor, Dr. Xiaoli, whose guidance and mentorship have been instrumental in shaping my academic journey.

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CHAPTER 1

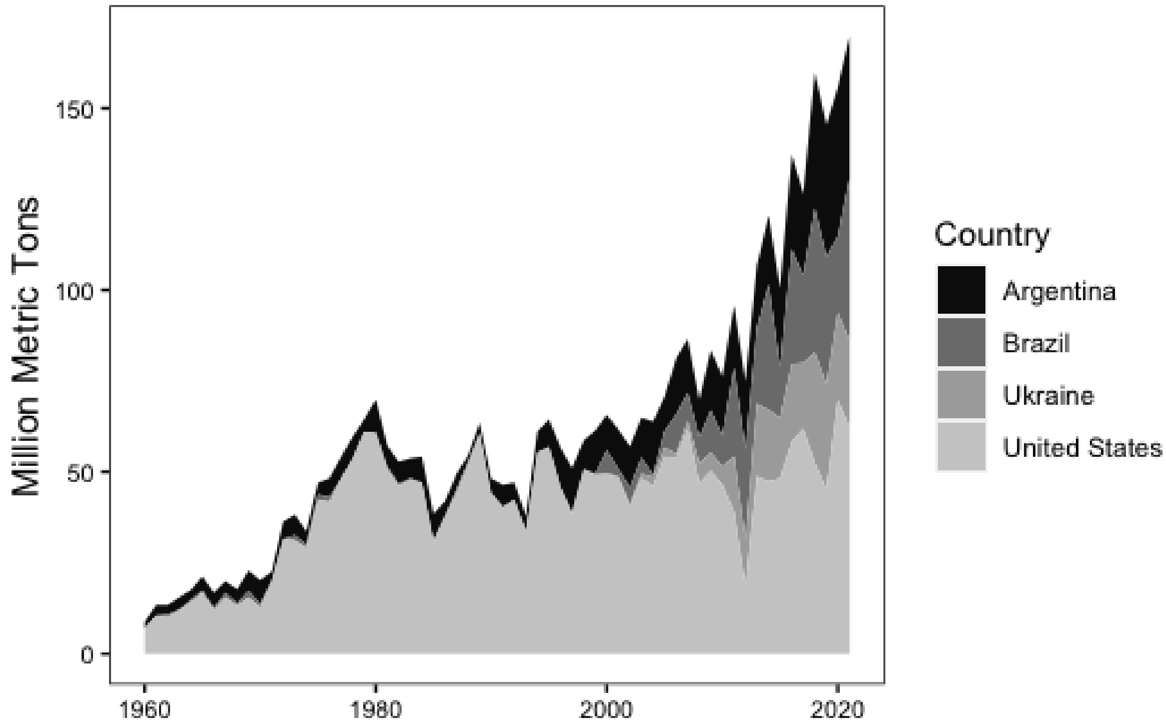
Introduction

One of the most notable recent developments in the global corn market is the rise of emerging countries like Brazil, Ukraine, and Argentina as international powerhouses for exports. At the beginning of the 2000s, the United States was the dominant player, accounting for about two-thirds of global corn exports. However, as shown in figure 1, the US's position has been challenged over the past two decades. Similar to the findings of Janzen and Adjemian (2017) and Avileis and Mallory (2022) for wheat and soybeans, the position of the U.S. as the price leader of grains has been fading. Since 2019/20, Brazil, Ukraine, and Argentina combined accounted for more than 55% of global corn exports, while the US share dropped to less than 30%, and by 2022/23 corn exports from Brazil will surpass those of the United States (Good, 2023).

In light of the increasingly important role of these emerging producers, concerns arise on how the US and global corn price dynamics have changed and whether the existing models can accurately document the impact of supply and demand shocks. The objective of this paper is to provide insights into how the rising competition in the global market has affected corn price dynamics. Specifically, we aim to understand 1) the impact of various domestic supply and demand shocks on corn price behavior in the US, 2) how shocks in a major emerging exporting country affect the corn price movement in the US and other countries, and 3) how the effects of various demand shocks have changed over time.

Figure 1.2 plots the US export prices for corn on the Gulf Coast since 2000. US export prices remained around 100 dollars per ton from 2000 to 2006. Fueled by increasing domestic demand for corn for ethanol production, corn prices increased significantly in subsequent years, as high as 280 dollars per ton in 2008. In late 2008 corn prices decreased significantly due to the financial crisis and weakening global

Figure 1.1: Corn Exports, 1960-2021

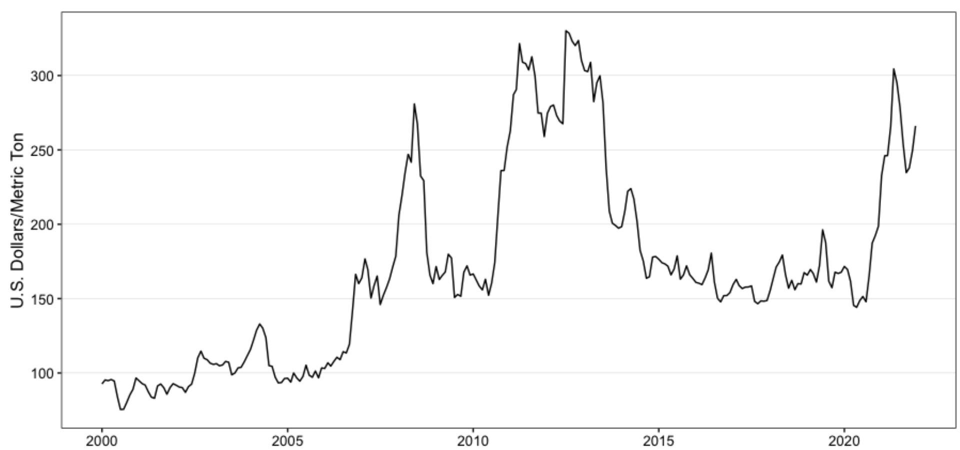


Source: USDA

demand. Following the 2012 drought, corn prices increased rapidly to a historic high of more than 300 dollars per ton. But the corn prices before 2012 were already high enough for competitor countries to increase their production. After 2012, US corn exports went down, leading the importers to seek alternative sources of corn exports, especially in South America (Allen and Valdes, 2016). After recovering from the drought, corn prices continued to go down and remained around 170 dollars per ton up to early 2020. However, prices rose again after the onset of Covid-19, reaching new highs.

A significant body of literature has analyzed market integration and price transmission between major corn producers (Balcombe, Bailey, and Brooks, 2007; Cruz Junior, Capitani, and Silveira, 2018; Mattos and Franco da Silveira, 2018). Overall, global price discovery has followed closely the export shares of the major producers. At the

Figure 1.2: U.S. corn export prices, 2000-2021



Source: FAO, food price and analysis tool beginning of the 2000s, the United States and Argentina were the largest players with up to 80% of export shares. The US was the price setter, with global markets following the price of corn in the Gulf of Mexico. Since 2010, Brazil and Ukraine have become new major exporters, which has been reflected in their increased participation in price determination (Arnade and Hoffman, 2019-10, 2019).

The growth in Brazilian corn exports is attributed to its rising winter crop production, which burst onto the scene in the mid-2000s after the development of new varieties of corn adapted to the country's central-west agricultural frontier. Those varieties allow farmers to double-crop corn after soybeans in the same year (Avileis and Mallory, 2022). It was only in 2001 that Brazil changed from being a net importer to a net exporter of corn, and even during the first decade of the 2000s, its export volumes were low, thus market integration between Brazil and the global market was low (Balcombe, Bailey, and Brooks, 2007). Several studies report that the Brazilian corn market became more integrated after 2010, and U.S. prices are increasingly responding to Brazilian prices (Cruz Junior, Capitani, and Silveira, 2018; Mattos and Franco da Silveira, 2018).

Up until the Russian invasion, Ukraine's production was rapidly expanding, driven by improvements in seed quality, infrastructure, and its comparative advantages in serving Asian, African, and European markets (Arnade and Hoffman, 2019-10, 2019). Meanwhile, Argentina has been a powerhouse for corn exports for decades, however, its growth stalled because of export taxes and quotas, that were recently eliminated (Meade et al., 2016). According to Arnade and Hoffman (2019-10, 2019) its contribution to global price discovery is significant.

The previous literature has revealed important insights into the price associations among the major corn producers. However, most of these studies focus on either market integration or price discovery, without examining how exogenous shocks in one country may affect prices in another. For instance, how does a supply disruption, potentially due to a severe drought in Brazil, affect corn prices in the United States? Would a sudden change in exchange rate impact the competitiveness of US corn and subsequently change US corn export prices? Does the rise in fertilizer prices have differential effects on corn prices in different countries? Understanding such questions is of importance to policymakers who wish to assess the relative competitiveness of their corn industry and design relevant policies to more efficiently respond to changes in the global market. For importing countries, knowledge of how corn prices interact and respond to exogenous shocks in each major corn producer can help them better prepare for potential disruptions of corn exports in the global market and stabilize domestic corn prices. In this paper, we aim to provide an in-depth analysis of the underlying demand and supply shocks of different origins that may affect corn price dynamics in each country, and how the impact of these shocks may propagate across the major corn players.

Previous studies identify that a complex interplay of supply and demand factors affects corn price dynamics. Bio-fuel programs in the United States and the European Union have directly increased the demand for corn and intensified corn price volatility (Baffes and Haniotis, 2010). These programs also created an indirect channel through which crude oil affects corn prices (Trujillo-Barrera, Mallory, and Garcia, 2012). Beyond that, crude oil also has a direct impact on corn prices due to its influence on fertilizer and transportation costs (Gilbert, 2010; Wang, Wu, and Yang, 2014). (Etienne, Trujillo-Barrera, and Wiggins, 2016) showed a short-term positive association between ammonia and corn prices. Macroeconomic factors such as the exchange rate have also been found to exert a significant impact on commodity prices (Harri, Nalley, and Hudson, 2009; Baffes and Haniotis, 2016). Other factors influencing commodity price fluctuations that have been examined in the literature include inventories, economic growth, production shocks, etc. (Abbott, Hurt, and Tyner, 2008; Piesse and Thirtle, 2009). However, in the context of global corn markets, these drivers have yet to be investigated in relation to price movements in major corn-exporting countries.

We use a global dynamic time series model, namely the global vector autoregression (GVAR) model of Pesaran, Schuermann, and Weiner (2004) and Dees et al. (2007) to estimate the inter-linkage among major corn exporting countries. The models allow us to evaluate how various shocks, both originating in the domestic and foreign markets, are transmitted across the countries and over time. The GVAR first estimates country-specific VARX (vector autoregression with exogenous variables) for each country, and then connects these VARX models using link matrices to build a global model. GVAR models have been used in the context of commodity markets such as Gutierrez, Piras, and Roggero (2015) that analyzed the global wheat price dynamics and recently by Considine, Hatipoglu, and Aldayel (2022) on oil prices.

We focus on five major corn exporting countries/regions: the US, Brazil, Argentina, Ukraine, and the European Union (EU), which combined account for over three-quarters of the global corn exports. A rest-of-world (ROW) aggregate is included in the model to account for the impact of other key players on the corn market. Data runs from 2000 to 2021 at a monthly frequency. Following Gutierrez, Piras, and Roggero (2015), we consider corn export prices, production, ending stocks, fertilizer prices, exchange rates, and the consumer price index for food for each country/region. Oil prices are considered an exogenous variable in the individual VARX models except for the US due to the latter's importance in oil price determination. The link matrix is constructed using corn export data for each country's relative export weight. Two separate models are estimated, one for 2000-2010 and another for 2011-2021, to compare how the effect of a shock to one country has affected another country differently before and after the rise of emerging exporting countries. Additional structural breaks are considered for robustness checks.

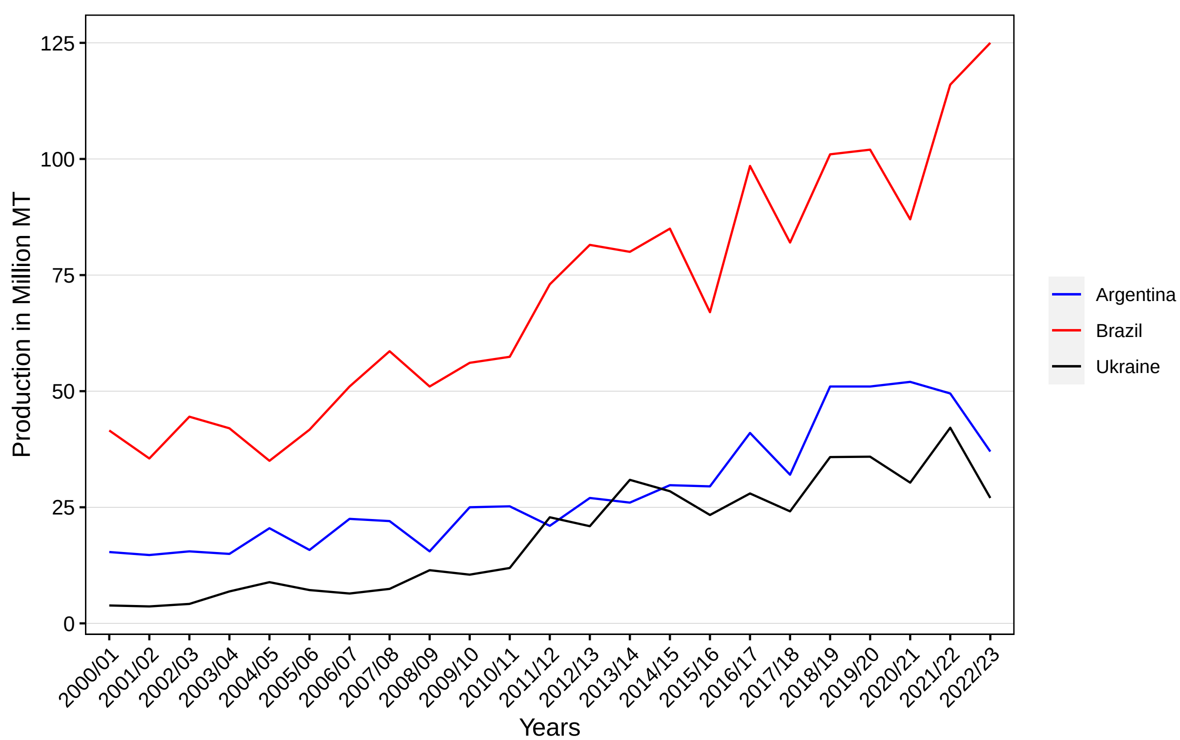
We find that different supply and demand shocks in emerging corn-producing countries have a significant impact on export prices in the EU and the US for the period 2011-2021, while most of the responses for 2000-2010 are insignificant, suggesting the increasing role of emerging corn-producing countries on corn price dynamics. In particular, corn production, exchange rate, and export prices in those countries play a major role in determining the export prices in the global corn market.

CHAPTER 2

Background

According to data from the United States Department of Agriculture's Foreign Agricultural Service (USDA FAS), global corn domestic consumption increased by nearly 89% between 2000/01 and 2022/23. This increase in consumption can be attributed to the world's fast-growing population, which has now surpassed 8 billion people, leading to increased demand. As a result, the corn market experienced the rise of new prospects, resulting in a more than 90% increase in global corn production.

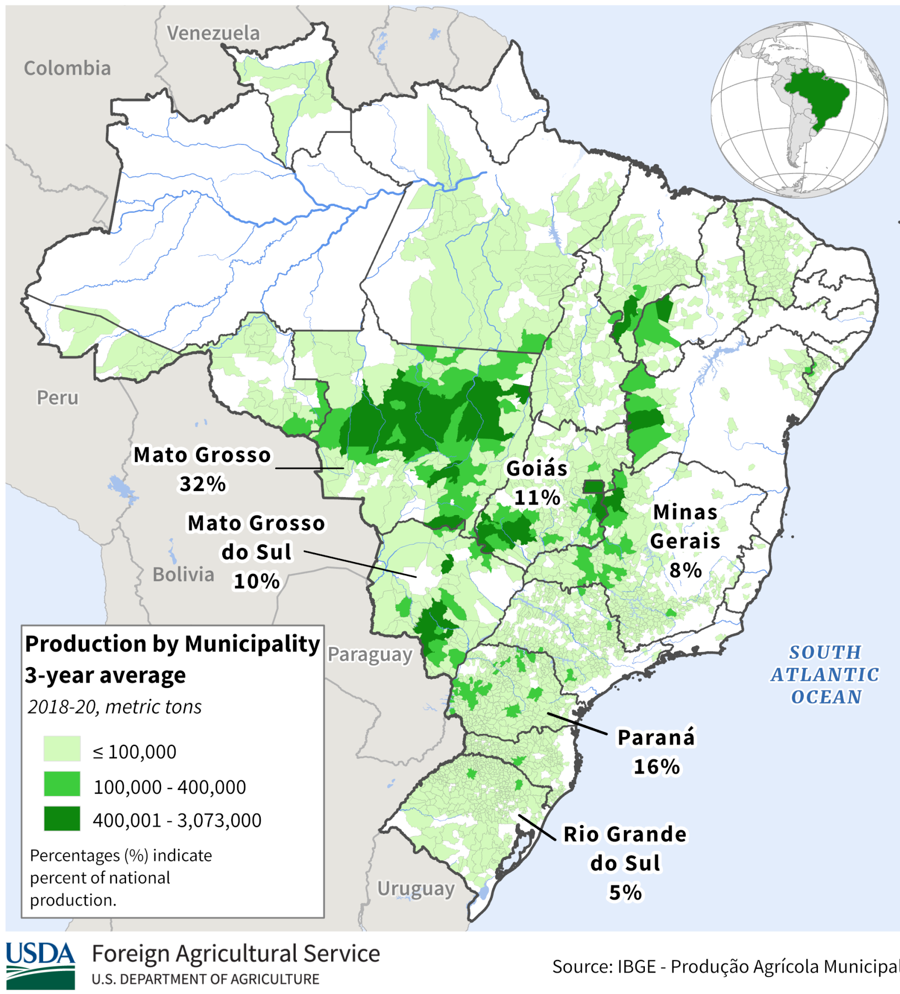
Figure 2.1: Corn Production in Argentina, Brazil, and Ukraine



2.0.1 *Brazilian corn production*

Corn is one of Brazil's most essential agricultural commodities, significantly impacting both the domestic economy and global trade. Brazil is the world's thirdlargest corn producer, after the United States and China. As shown in figure 2, the country's corn production has seen substantial growth over the past two decades, driven by factors such as technological advancements, favorable government policies, and increasing domestic and international demand.

Figure 2.2: Map of Brazil Showing Corn Producing Area

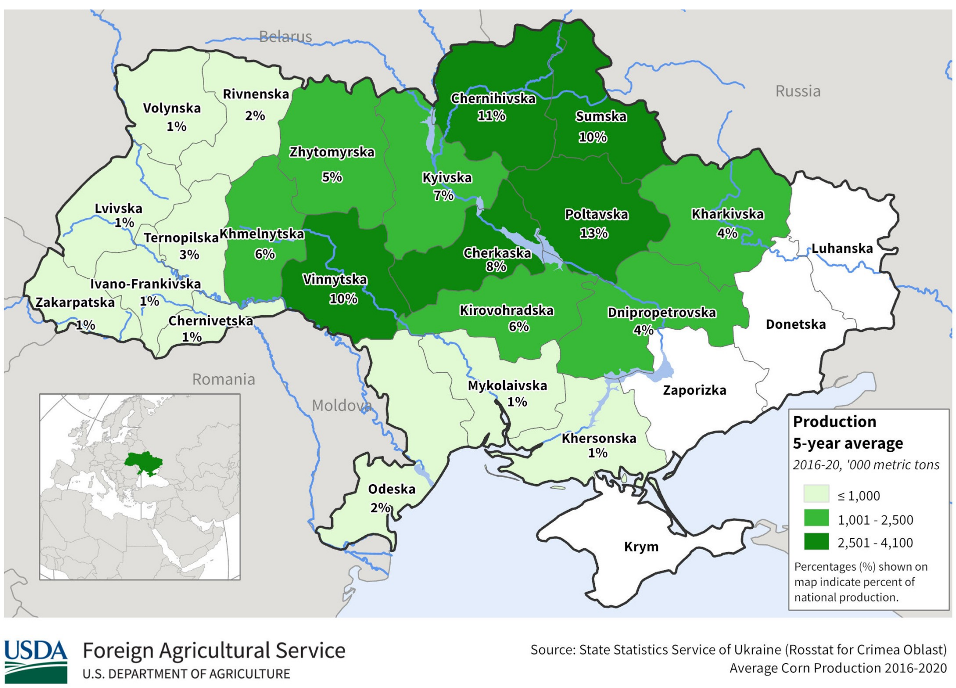


Source :- USDA, Foreign Agricultural Services

Figure 2.2 shows the major corn-producing regions in Brazil. Brazil's corn production is divided into two major growing seasons: the first crop (or "summer corn") and the second crop (or "winter corn" or "safrinha"). The first crop is grown mainly in north-eastern Brazil from September to December, while the second crop is grown from January to March in a large area of the center-west frontier. Winter corn accounts for around 73% of total Brazilian corn production. It is mainly grown in corn-producing regions such as the states of Mato Grosso, Paraná, and Mato Grosso do Sul. These regions have diverse climatic conditions, especially allowing for the cultivation of winter corn varieties.

The adoption of agricultural practices, such as no-till farming and precision agriculture, has enhanced corn yields in Brazil. Moreover, the utilization of genetically modified (GM) corn varieties has contributed to the growth in corn production. The Brazilian government has implemented various policies supporting the agricultural sector, including credit facilities, research investments, and infrastructure development to reduce transportation costs and enhance exports. These strategies eventually help in increasing corn production.

Figure 2.3: Map of Ukraine Showing Corn Producing Area



Source :- USDA, Foreign Agricultural Services

2.0.2 *Ukraine corn production*

Ukraine is a significant player in the global corn market, ranking among the top ten corn-producing countries. Its strategic location and fertile lands have facilitated the growth of its corn production over the past two decades as can be seen in figure 2. Between 2000/01 and 2021/22, corn production in Ukraine increased from 3.8 million metric tons (MMT) to more than 42 MMT which decreased to 27 MMT due to the Russia-Ukraine war. The growth in corn production can be attributed to several factors, including increased yields, the expansion of corn acreage, and technological advancements.

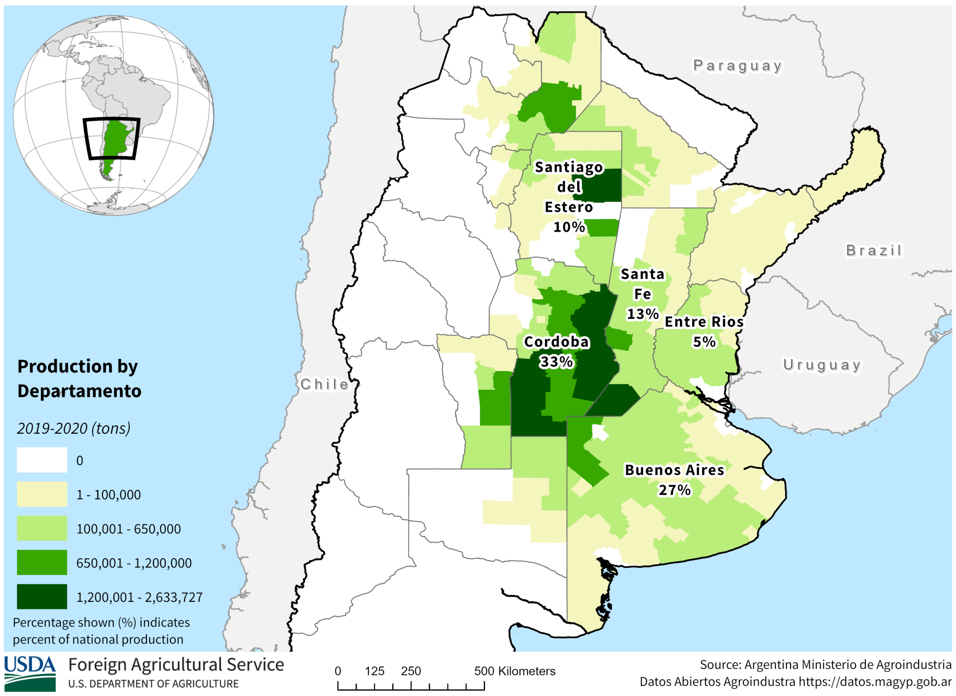
Improved farming practices and better access to modern technology have contributed to increased corn yields in Ukraine. The average corn yield increased from 3.01 metric tons per hectare (MT/HA) in 2000/01 to an estimated 6.75 MT/hectare in 2022/23. As can be seen in figure 2.3, corn is planted in a large area in Ukraine. The expansion of corn acreage has been a significant factor in the increase in corn production. Between 2000/01 and 2022/23, corn acreage in Ukraine expanded from 1.2 million hectares to 4 million hectares. The ongoing conflict with Russia has negatively impacted the country's agricultural sector, leading to disruptions in production and trade. However, Ukraine is one of the major players for corn in the international market for the past decade.

2.0.3 *Argentina corn production*

The tremendous increase in corn production in Argentina over the past 20 years has further strengthened the country's position as a major player in the world corn market. As shown in figure 2, between 2000/01 and 2021/22, corn production in Argentina increased from 15.3 million metric tons (MMT) to an estimated 49.5 MMT. The estimates have however reduced to 37 MMT due to unfavorable weather events.

This overall growth in the past decades can be attributed to various factors, including technological advancements, increased yields, and the expansion of corn acreage.

Figure 2.4: Map of Argentina Showing Corn Producing Area



Source :- USDA, Foreign Agricultural Services

As can be seen in figure 2.4, the expansion of corn acreage has been a significant factor in the increase in corn production. Between 2000/01 and 2022/23, corn acreage in Argentina expanded from 2.8 million hectares to 6.7 million hectares. This growth has also been driven by the removal of export tax from the beginning of 2016. The increase in corn production in Argentina has important implications for the global corn market. As a major producer, Argentina has the potential to influence global corn prices and supply.

CHAPTER 3

Empirical Methods

We use the global vector autoregression (GVAR) model of Pesaran, Schuermann, and Weiner (2004) to estimate the inter-linkage among major corn exporting countries. The GVAR method is useful for analyzing shock transmission mechanisms involving many countries/regions and a long sample period. The basic idea of GVAR is to first estimate country-specific vector autoregression with exogenous variables (VARX) models, and then connect these VARX models using link matrices to build a global model.

More specifically, we estimate the following reduced-form VARX model for each country i:

$$y_{it} = \phi_{i0} + \phi_{i1}t + \sum_{k=1}^{K} A_{ki}y_{it-k} + \sum_{l=1}^{L} B_{li}y^*_{it-l} + \sum_{q=1}^{Q} C_{qi}d_{t-q} + u_{it} \tag{3.1}$$

where $t = 1, ...T$ refers to the time period; ϕ_{i0} is a vector of deterministic intercepts; ϕ_{i1} is a vector of deterministic trends, y_{it} is a vector of country-specific variables, y^*_{it} is a vector of foreign variables; d_t is a vector of global exogenous variables. A, B, and C are the matrices of lagged polynomial coefficients associated with y_{it}, y^*_{it}, and d_t respectively. K,L and Q are the lag orders and u_{it} is a vector of error terms that are assumed to be uncorrelated. We use the Akaike information criteria (AIC) to determine the lag order of variables.

For instance, assume the lag structure for the endogenous and the exogenous variables are (2,2), and no lag terms are included for global variables. The individual VARX (2,2) model for a country can be written as:

$$y_{it} = \phi_{i0} + \phi_{i1}t + A_{i1}y_{it-1} + A_{i2}y_{it-2} + B_{i0}y^*_{it} + B_{i1}y^*_{it-1} + B_{i2}y^*_{it-2} + u_{it} \tag{3.2}$$

Rewriting the domestic and foreign variables for each country as x_{it} such that, $x_{it} = \begin{pmatrix} y_{it} \\ y^*_{it} \end{pmatrix}$ Hence, each country's VARX model can be written as,

$$a_{i0}x_{it} = \phi_{i0} + \phi_{i1}t + a_{i1}x_{it-1} + a_{i2}x_{it-2} + u_{it} \tag{3.3}$$

where, $a_{i0} = (I, -B_{i0}), a_{i1} = (A_{i1}, B_{i1}), a_{i2} = (A_{i2}, B_{i2})$.

The next step in the analysis is the construction of the foreign-specific variables, y^*_{it}. In the GVAR setting, y^*_{it} is constructed using a link matrix W_i. In our analysis, we follow Gutierrez, Piras, and Roggero (2015) and use the export weight of each country relative to the exports of all competitor countries to compute the link matrix. Given W_i, we have $x_{it} = W_i y_t$. Plugging this relationship in equation (3.3), we obtain the following VARX model for each country:

$$a_{i0}W_i y_t = \phi_{i0} + \phi_{i1}t + a_{i1}W_i y_{it-1} + a_{i2}W_i y_{it-2} + u_{it} \tag{3.4}$$

Now, combining each country-specific model in equation (3.4), the GVAR model can be written as:

$$G_0 y_{it} = \alpha_0 + \alpha_1 t + G_1 y_{it-1} + G_2 y_{it-2} + \epsilon_t \tag{3.5}$$

where, $G_0 = \begin{pmatrix} a_{00}W_0 \\ a_{10}W_1 \\ \dots \\ a_{N0}W_N \end{pmatrix}, G_1 = \begin{pmatrix} a_{01}W_0 \\ a_{11}W_1 \\ \dots \\ a_{N1}W_N \end{pmatrix}, G_2 = \begin{pmatrix} a_{02}W_0 \\ a_{12}W_2 \\ \dots \\ a_{N2}W_N \end{pmatrix},$

$$\alpha_0 = \begin{pmatrix} \phi_{00} \\ \phi_{10} \\ \dots \\ \phi_{N0} \end{pmatrix}, \alpha_1 = \begin{pmatrix} \phi_{01} \\ \phi_{11} \\ \dots \\ \phi_{N1} \end{pmatrix}, \epsilon_t = \begin{pmatrix} u_{0t} \\ u_{1t} \\ \dots \\ u_{Nt} \end{pmatrix}$$

If G_0 is an invertible matrix, we can rewrite the GVAR model in the reduced form:

$$y_t = b_0 + b_1 t + F_1 y_{t-1} + F_2 y_{t-2} + v_t \tag{3.6}$$

where $F_1 = G_0^{-1} G_1, F_2 = G_0^{-1} G_2, b_0 = G_0^{-1} \alpha_0, b_1 = G_0^{-1} \alpha_1, v_t = G_0^{-1} \epsilon_t$.

One concern with time series analysis is the possibility of nonstationary variables and the presence of cointegrating relationships. In the event such a long-run relationship exists, cointegration must be considered in the analysis. In the context of VAR models, cointegration is typically considered under the Vector Error-Correction (VECMX) framework. Specifically, equation (3.2) can be rewritten as,

$$\Delta y_{it} = c_{i0} - \alpha_i \beta_i' [x_{i,t-1} - \gamma_i (t-1)] + B_{i0} \Delta \tilde{y}^*_{i,t} + \Gamma_i \Delta x_{i,t-1} + \epsilon_{it} \tag{3.7}$$

where y_{it} and y^*_{it} are the same as defined in equation (3.1), $x_{it} = (y'_{it}, \tilde{y}^{*'}_{it})'$, α_i is $k_i \times r_i$ is a matrix of rank r_i and β_i is a $(k_i + k_i^*) \times r_i$ matrix of rank r_i.

Similar to conventional VAR and VECM models, we use impulse response functions and forecast error variance decomposition at various horizons to account for inferences. Without a clear priori economic theory, the generalized impulse response function (GIRF) which is invariant to the ordering of the variables can be used to interpret the GVAR results. We use generalized impulse response functions (GIRFs) by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1996) to assess

GVAR results. From equation 3.5, the GIRFs can be given as,

$$GIRF(y_t; u_{ilt,}, n) = E(y_{t+1}|\epsilon_{ilt} = \sqrt{\sigma_{ii,ll}}, \tau_{t-1}) - E(y_{t+n}|\tau_{t-1}); n = 0, 1, 2... \tag{3.8}$$

where τ_{t-1} is the information set at time t-1, $\sqrt{\sigma_{ii,ll}}$ is the diagonal element of the variance-covariance Σ_ϵ. Hence, the GIRF with one standard error shock is defined as,

$$GIRF(y_t; u_{ilt,}, n) = \frac{e_j' A_n G_o^{-1} \Sigma_\epsilon e_l}{\sqrt{e_l' \Sigma_\epsilon e_l}} \tag{3.9}$$

where $e_l = (0, 0, ..., 0, 1, 0..., 0)'$ is a selection vector for country-specific shocks with unity as the lth element. Similarly, foreign-specific shocks can also be estimated by defining the selection vector as $e_l = (0, w_{i0}, ...0, w_{i1}, 0...0)'$ where $\sum_{j \neq i} w_{ij} = 1$.

CHAPTER 4

Data

Monthly data from 2000 to 2021 is considered in our analysis. Based on the global production and export patterns, we consider five major exporting countries/regions: the US, Brazil, Argentina, Ukraine, and the European Union (EU). A rest-of-world (ROW) model is included to account for the effect of other players. While China is a big corn producer, it does not export a significant amount of corn to the world market. We hence do not consider China separately in the analysis but include it in the ROW aggregate. For each country/region, we estimate either a five- or four-variable VARX model.

The selection of variables follows previous studies such as Etienne, Irwin, and Garcia (2018) and Gutierrez, Piras, and Roggero (2015). The endogenous variables used in the model include export prices (p^e_{it}), domestic ending stocks (e_{it}), corn production (pd_{it}), fertilizer price converted into local currency (p^f_{it}), the exchange rate per unit of U.S. dollar (r_{it}), and the consumer food price index (cp_{it}). The exchange rate is excluded from the US model due to collinearity with other exchange rates. We use corn production data instead of ending stocks as an endogenous variable for emerging corn-producing countries (Argentina, Brazil, and Ukraine) as the exports from these countries are largely dependent upon production. Similarly, export price is not included in the ROW model variables because corn price is determined in the international market outside of the effects of ROW. We use crude oil price (o_{it}) as the global variable for all other countries/regions models except the US model where it is treated endogenously. The main assumption is that the US economy plays an important role in oil price determination.

Corn export price data were obtained from various sources, including the FAO food price and analysis tool, the European Union Commission, International Grain

Council, and the USDA.[1] The corn production and ending stocks were computed based on the USDA World Agricultural Supply and Demand Estimates (WASDE), reflecting the production and ending stocks in the current or upcoming marketing year. We use the consumer price index for food and non-alcoholic beverages to reflect the demand for food products. These data were obtained from the OECD database and national statistics. The fertilizer price and oil price data were obtained from the World Bank pink sheet and were converted to the local currency for each country. The exchange rates were collected from the Federal Reserve Bank and national banks, expressed in local currency per unit U.S. dollar. To reduce skewness and the impact of extreme variables, all variables were expressed in logarithms in the analysis.

The GVAR model uses both country-specific and foreign-specific variables to account for the effect of various supply and demand factors. For foreign-specific variables, the weighted average of export prices, exchange rate, ending stock, corn production, and food price indices are used. For instance, in a foreign-specific variable, the average of export prices is calculated as, $p_{it}^{e*} = \sum_{j \neq i} w_j p_{jt}^{e}$. All the variables we use in the country model are shown in table 4.1. As noted earlier, we follow Gutierrez, Piras, and Roggero (2015) and use the relative trade share of each country to construct the weight matrix. The assumption is that all the exogenous shocks could pass on to export prices via the trade channel.

Table 4.2 shows the specific trade weights used in the analysis, computed based on the average shares of exports in total world exports. The weight matrix for the sample period 2000-2010 is constructed using the export data from 2007/8-2009/10. Similarly, export data from 2018/19-2020/21 is used for the sample period 2011-2021. For instance, in the period 2000-2010, Argentina exported 13,875.667 (in 1,000 MT) of corn on average from 2007/8 to 2009/10 out of the world's total average of 93,085.333 (in 1,000 MT), making Argentina's share of world's export to be 0.149 (13875.667

[1]We thank Carlos Arnade and Linwood Hoffman for sharing their price data used in Arnade and Hoffman (2019-10, 2019).

Table 4.1: Variables Used in the Model

Variables	Argentina	Brazil	EU	Ukraine	US	ROW
Export price	1	1	1	1	1	
Production	1	1		1		
Exchange rate	1	1	1	1		1
Food CPI	1	1	1	1	1	1
Fertilizer price	1	1	1	1	1	1
Ending stock			1		1	1
Global variable						
Oil price	1	1	1	1	2	1

Note: 1- used in the country model. 2- oil treated as endogenous in the US model. We do not include fertilizer price variable in foreign-specific variables for possible multicollinearity problems.

/93085.333). So, excluding Argentina, the share of exports from other countries is 0.851 (1-0.149). Meanwhile, Brazil's share on average for the same period is 0.095 (8,842/93,085.333). In the trade weight matrix, Brazil's trade weight for Argentina is computed as 0.112 (0.095/0.851). In other words, the number in the weight matrix represents the weight of the column country in the total global export share, and the numbers in each row add up to one.

Table 4.2: Trade Weights Based on Corn Export Statistics

Countries	Argentina	Brazil	EU	Ukraine	US	ROW
			2000-2010			
Argentina	0	0.112	0.017	0.053	0.670	0.149
Brazil	0.165	0	0.016	0.05	0.630	0.140
EU	0.151	0.096	0	0.046	0.578	0.128
Ukraine	0.156	0.099	0.015	0	0.597	0.133
US	0.347	0.221	0.033	0.105	0	0.294
ROW	0.171	0.109	0.016	0.052	0.653	0
			2011-2021			
Argentina	0	0.227	0.032	0.197	0.397	0.148
Brazil	0.259	0	0.030	0.189	0.38	0.142
EU	0.218	0.183	0	0.159	0.32	0.120
Ukraine	0.252	0.211	0.030	0	0.37	0.138
US	0.309	0.260	0.036	0.225	0	0.170
ROW	0.241	0.202	0.028	0.175	0.354	0

Source: USDA, PSD database. Note: Trade weights are computed as the average of exports in total world exports from 2007-2010 for the 2000-2010 period and from 2018-2021 for the 2011-2021 period.

CHAPTER 5

Results

The Augmented Dickey-Fuller (ADF) test shows that the majority of the series are nonstationary. As seen in tables 5.1 and 5.2, we fail to reject the null hypothesis of non-stationarity for most of the variables. Exceptions include the fertilizer variable (p^f_{it}) which is stationary for all the countries/regions except Brazil and Ukraine, the exchange rate variable (r_{it}) for ROW in the 2000-2010 period, and the production variable (pd_{it}) for Brazil and Ukraine

Table 5.1: Augmented Dickey-Fuller Test Statistics for Endogenous and Exogenous Variables for 2000-2010

Variables	Argentina	Brazil	EU	Ukraine	U.S.A.	ROW
p^e_{it}	-2.668	-3.392	-2.627	-3.046	-2.809	-
pd_{it}	-3.071	-2.492	-	-1.890	-	-
p^f_{it}	-3.464^Y	-3.303	-3.635^Y	-2.93	-3.645^Y	-3.702^Y
r_{it}	-2.71	-2.515	-2.189	-1.616	-	-3.539^Y
cp_{it}	-2.126	-2.05	-2.916	-2.258	-3.313	-2.595
s_{it}	-	-	-2.697	-	-3.157	-1.974
p^{e*}_{it}	-2.975	-2.775	-2.723	-2.856	-3.078	-2.856
pd^*_{it}	-2.071	-2.408	-2.518	-2.914	-2.518	-2.518
r^*_{it}	-2.703	-2.837	-2.225	-2.329	-2.399	-2.375
cp^*_{it}	-2.562	-1.829	-1.957	-1.877	-1.859	-1.804
s^*_{it}	-2.802	-2.802	-3.106	-2.802	-3.380	-2.740
o^*_{it}	-2.531	-2.531	-2.531	-2.531	-2.531	-2.531

Notes: The regressions include a trend and the 95% critical value of the test is -3.45.

As noted earlier, the optimal lag order for each country's VARX model is determined based on AIC criteria. Table 5.3 shows the lag orders we use in our model, where k and l denote the number of lags for country-specific and foreign-specific variables used in the model, respectively. As can be seen, up to three lags are included for country-specific variables. For foreign variables, either one or two lags are selected for the models selected. We then conduct cointegration analysis, which

Table 5.2: Augmented Dickey-Fuller Test Statistics for Endogenous and Exogenous Variables for 2011-2021

Variables	Argentina	Brazil	EU	Ukraine	U.S.A.	ROW
p^e_{it}	-1.0626	-1.410	0.253	-1.818	-0.378	
pd_{it}	-2.137	-4.114^Y	-	-3.791^Y	-	-
p^f_{it}	-1.159	-1.959	-2.192	-2.342	-0.914	-2.054
r_{it}	-2.483	-3.202	-2.829	-0.718	-	-2.088
cp_{it}	-0.519	-1.678	-0.99	-2.234	-0.756	-3.228
s_{it}	-	-	-2.976	-	-0.982	-3.138
p^{e*}_{it}	-1.0473	-0.965	-1.062	-0.889	-1.071	-0.999
pd^*_{it}	-4.30299^Y	-3.246	-3.338	-2.543	-3.338	-3.338
r^*_{it}	-1.424	-2.178	-2.393	-2.584	-2.306	-2.326
cp^*_{it}	-2.06	-2.043	-2.172	-0.650	-2.710	-2.214
s^*_{it}	-3.132	-3.132	-3.236	-3.131	-3.134	-3.038
o^*_{it}	-1.851	-1.851	-1.851	-1.851	-1.851	-1.851

Notes: The regressions include a trend and the 95% critical value of the test is -3.45. Y *denotes statistical significance at 5 %.*

is estimated using the reduced rank restriction. We allow unrestricted intercept and trend restricted to lie in the cointegration space in the country-specific model (in equation 3.7) and rank orders are computed using Johansen's trace statistics at 95% significance level. The number of cointegrating relationships for each country model is shown in table 5.3. For the 2000-2010 period, we find two cointegrating vectors for all individual countries/regions. In the second subsample, with the exception of the US and Argentina, there exists one cointegrating vector.

Table 5.3: VARX Order and Number of Cointegrating Relationship

Countries	2000-2010			2011-2021		
	k_i	l_i	Coint	k_i	l_i	Coint
Argentina	3	2	2	2	1	0
Brazil	2	2	2	1	1	1
EU	3	1	2	2	1	1
Ukraine	3	2	2	2	1	1
USA	2	1	2	2	1	2
ROW	3	1	2	2	2	1

Note: Cointegration relationships are computed using Johansen's trace statistics at 95% critical value level.

The main assumption behind the estimation strategy in the GVAR model is the weak exogeneity of foreign variables (y^*_{it}) with respect to the long-run parameters of the conditional model as defined in equation (3.7). The hypothesis for weak exogeneity can be tested as described in Johansen (1992) and Harbo et al. (1998). Specifically, the following regression is carried out for each n^{th} element of (y^*_{it}),

$$\Delta y^*_{it,n} = \mu_{in} + \sum_{j=1}^{r_i} \gamma_{ij,t} E\hat{C}M^j_{i,t-1} + \sum_{k=1}^{k_i} A_{ik,t} \Delta y_{i,t-k} + \sum_{l=1}^{l_i} \nu_{il,t} \Delta y^{*\tilde{}}_{i,t-l} + \epsilon_{it,n} \tag{5.1}$$

Here, $E\hat{C}M^j_{i,t-1}$ is the estimated error correction terms, where $j = 1, 2, \ldots, r_i$ and r_i refers to the cointegrating relations for the ith country model, $\Delta y_{i,t-k}$ is the set of endogenous variables with $k = 1, \ldots, k_i$ and k_i is the lag order. Similarly, $\Delta y^{*\tilde{}}_{i,t-l}$ is the set of foreign exogenous variables where, $l = 1, ...l_i$ and l_i is the lag order. We run F-test to carry out a weak exogeneity test in which the joint hypothesis,$\gamma_{ij,n} = 0; j = 1, 2, \ldots r_i$.

Table 5.4 shows the results of the weak exogeneity test for the 2000-2010 and 2011-2021 periods. In the context of the global corn market, this hypothesis suggests the model doesn't consider the existence of a dominant country and hence suggests the joint determination of export prices in the long run. As can be seen, the weak exogeneity assumption is satisfied for most of the variables and country-specific models. Several exceptions stand out. First, the hypothesis is rejected for exchange rate and ending stocks in Ukraine for the 2000-2010 period. Ukraine started becoming more relevant in the global corn market after 2010. So this issue is less concerning in the case of Ukraine for the 2000-2010 period. Second, for the 2011-2021 period, the hypothesis is rejected for production in the ROW region which is also not a major issue since the influence of ROW production is likely small in global corn exports.

Before proceeding to the detailed results, we inspect the stability of the GVAR model using the eigenvalues. We have 29 endogenous variables for each sub-period

Table 5.4: F Statistics for the Test of Weak Exogeneity of Exogenous and Global Variables

Countries	p_{it}^{e*}	pd_{it}^{*}	r_{it}^{*}	p_{it}^{c*}	s_{it}^{*}	o_{it}	critical values
				2000-2010			
Argentina	2.386	2.255	0.268	0.844	1.439	0.507	3.076
Brazil	0.529	0.949	1.536	2.473	0.103	0.475	3.076
EU	2.885	0.260	1.645	0.649	1.403	1.003	3.076
Ukraine	0.411	0.047	5.588^{Y}	0.053	3.263^{Y}	0.024	3.076
U.S.A.	0.401	0.080	0.383	0.021	0.461	-	3.075
ROW	0.434	0.232	2.902	2.279	1.371	2.471	3.075
				2011-2021			
Argentina	-	-	-	-	-	-	-
Brazil	0.275	2.069	1.021	2.547	0.288	0.345	3.924
EU	0.122	0.012	0.357	0.001	2.033	2.226	3.924
Ukraine	0.471	2.460	0.030	0.0001	2.523	3.371	3.924
U.S.A.	0.048	0.505	0.903	0.900	0.208	-	3.075
ROW	0.249	4.260^{Y}	1.019	1.883	1.003	2.016	3.923

Note: The critical values are at the 5% significance level. Y *denotes statistical significance at the 5 % level.*

with a maximum lag of 3 for the 2000-2010 period and 2 for the 2011-2021 period. Hence, the companion VAR(1) model has 87 eigenvalues (out of which 48 are complex) for the 2000-2010 period and 58 eigenvalues for the 2011-2021 period (out of which 26 are complex). Following previous literature Pesaran, Schuermann, and Weiner (2004), we do not expect the rank of the global model to exceed the total number of co-integrating relationships in the individual country model, i.e 12 for 2000-2010 and 6 for 2011-2021 in our case. Therefore, the global model should have at least 17 (i.e., 29-12) and 23 (i.e., 29-6) eigenvalues falling on the unit circle for the periods 2000-2010 and 2011-2021 respectively. Our model satisfies these properties, hence the model is dynamically stable.

The contemporaneous effects of foreign variables on their domestic counterparts for the 2000-2010 and 2011-2021 time periods are shown in table 5.5. These estimates can be interpreted as impact elasticities between domestic and foreign

Table 5.5: Contemporaneous Effects of Foreign Variables on Domestic Counterparts

Countries	p^{e*}_{it}	pd^{*}_{it}	r^{*}_{it}	cp^{*}_{it}	s^{*}_{it}
			2000-2010		
Argentina	1.104(9.950)	-0.284(-1.272)	0.650(3.375)	0.537(2.091)	-
Brazil	0.507(4.891)	-0.068(-0.914)	1.174(2.604)	0.229(1.564)	-
EU	0.479(4.708)	-	0.171(1.382)	0.295(3.734)	-0.279(-1.490)
Ukraine	0.407(2.356)	-0.236(-1.335)	-0.210(-2.196)	1.041(2.880)	-
US	0.911(7.673)	-	-	0.020(0.482)	-0.186(-1.490)
ROW	-	-	0.065(2.292)	0.785(3.564)	-0.092(-0.713)
			2010-2021		
Argentina	1.000(14.510)	0.492(2.167)	0.370(1.434)	0.172(0.999)	-
Brazil	1.076(7.633)	0.097(1.476)	0.471(3.155)	0.248(2.679)	-
EU	0.346(5.944)	-	0.007(0.093)	0.134(1.772)	0.108(1.237)
Ukraine	0.712(8.270)	0.483(1.472)	0.286(0.853)	0.043(0.88)	-
US	0.874(9.532)	-	-	0.194(3.414)	0.134(0.428)
ROW	-	-	0.311(6.302)	-0.220(-0.736)	-0.004(-0.076)

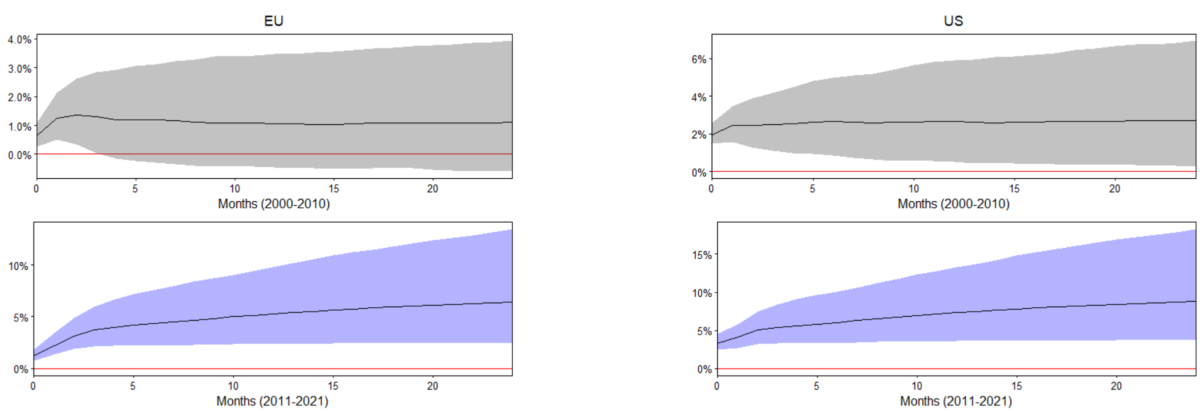
Note: The numbers in parenthesis represent white heteroscedastic corrected t-statistics

variables. Results show that the short-run associations between prices and foreign variables are positively significant, suggesting a strong impact from demand and supply shocks in foreign countries on prices. These results are consistent with the findings of Gutierrez, Piras, and Roggero (2015) for wheat export prices for the EU and US. The large magnitude of impact elasticities for foreign prices p^{c*}_{it}, in particular in Argentina, Brazil, and the US, suggests that the export prices in these countries/regions strongly respond to changes to prices in foreign markets. However, comparing the results for the two sub-periods, we note that the impact elasticity has increased for Brazil and Ukraine in the later period, while slightly decreasing for Argentina and the US. In general, the t-statistics for other variables are not significant indicating no verification of short-run co-movements.

5.1 Generalized Impulse Response Functions (GIRFs)

Direct interpretation of the results from VAR-type models is generally complicated due to the lag structures and the dynamics involved. As noted before, the generalized impulse response functions (GIRFs) can be used to interpret the GVAR results (Koop, Pesaran, and Potter, 1996; Pesaran and Shin, 1996). The impulse response functions evaluate the short-run dynamics between the variables, i.e., how one variable responds to a shock originating from another variable over time. Unlike conventional IRFs, the GIRFs are invariant to the ordering of variables.

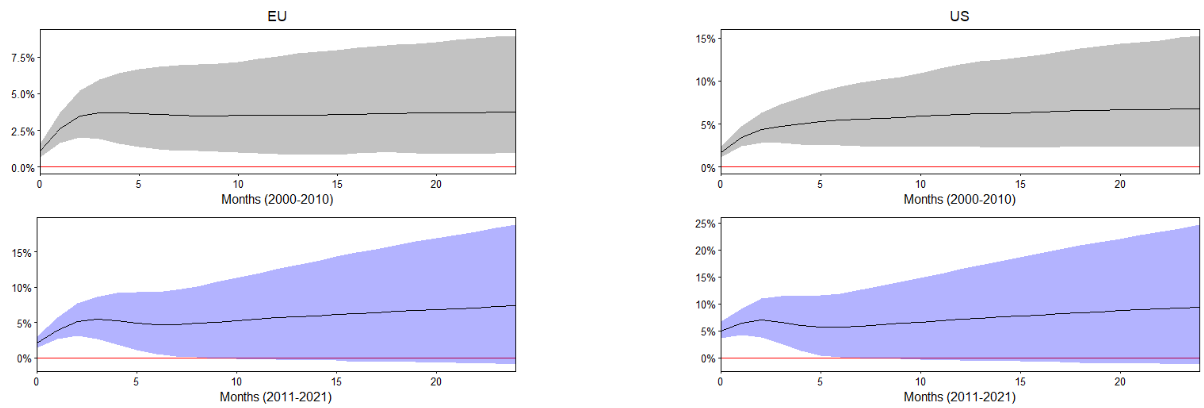
Figure 5.1: Response of a shock to Argentine export price on EU and the US export price



(a) **(b)**

Figures 5.1 to 5.19 show the general impulse response functions of export price to various shocks. The GIRFs contain bootstrap median estimates bounded by their 90% confidence intervals. Each simulation consists of one positive standard error shock to the variable. The GIRFs for two different sample period, 2000-2010, and 2011-2021 is discussed below.

Figure 5.2: Response of a shock to Brazilian export price on EU and the US export price

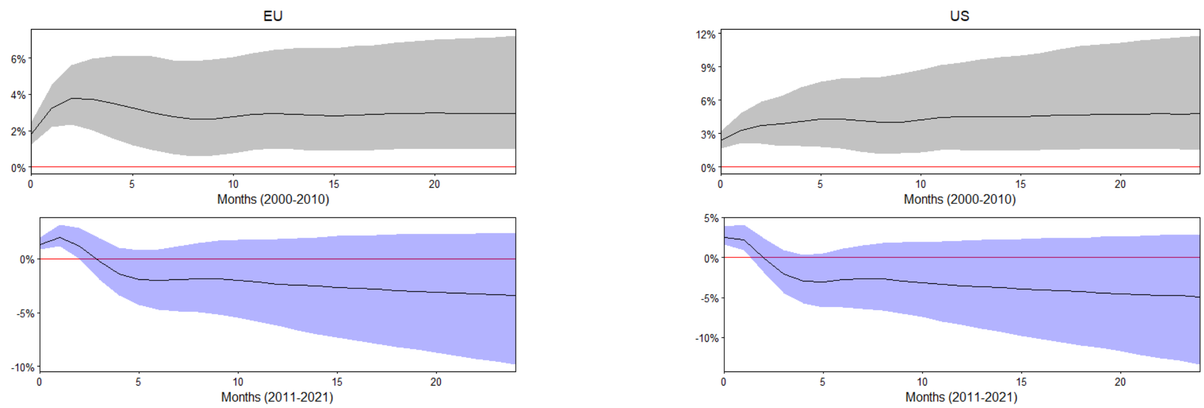


(a) **(b)**

5.1.1 *Shock to Export Prices*

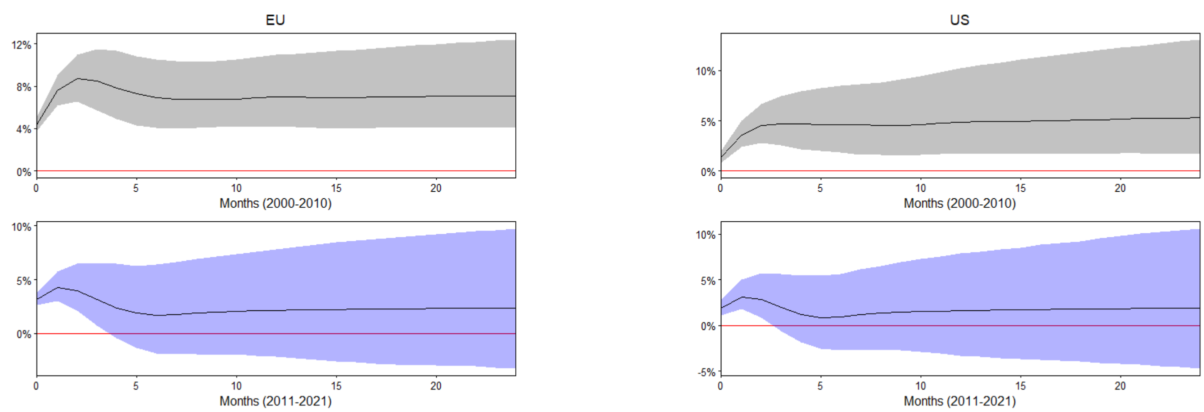
Based on the specification of the model, a shock to export price may be interpreted as a corn market-specific shock. For instance, this shock may be a result of weather disturbances, or changes in domestic bio-fuel policies. Export prices in the EU and US rise for both periods in response to a positive shock to export prices in Argentina and Brazil (figures 5.1 and 5.2). In our case, a one standard deviation shock refers to an increase in Argentine export price by 3.1% for 2000-2010 and 3.3% for 2011-2021. For 2000-2010, the initial response of the shock to Argentine export prices in the EU and the US export prices is around 0% and 2% respectively, and it declines after the first few months. The response, however, is of a larger magnitude of shows more statistical significance during the second period (2011–2021). The EU export prices initially responded with a 1.2% increase in a one-standard-deviation shock to Argentina export prices, which subsequently increased to 4.3% after six months. Similar to this, US export prices initially responded with a 3.3% increase and then jumped to 6 % after six months.

Figure 5.3: Response of a shock to Ukrainian export price on EU and the US export price



(a) **(b)**

Figure 5.4: Response of a shock to to EU export price on export price

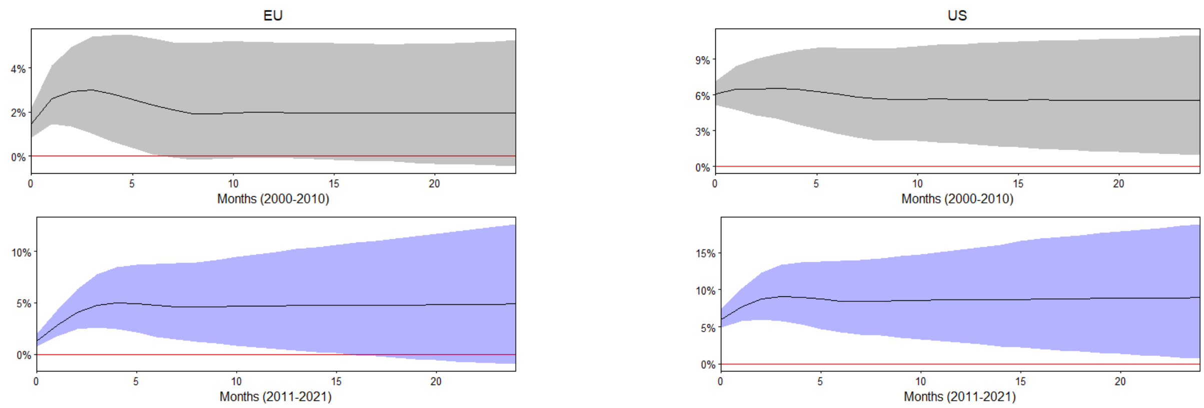


(a) EU **(b)** US

Similarly, a shock to Brazilian export prices leads to an initial response of around a +2% increase in EU and US export prices for the 2000-2010 period. For the latter sub-period, the magnitude of an initial response to the same shock in the EU is 2% which rises to 4.7% after six months in the EU. In the case of US, the initial response is 5% which increases to 5.7% after six months. Here, one standard deviation shock refers to an increase in Brazilian export price by 6.4%.

The results of a shock to Ukraine export prices are slightly different from those of Argentina and Brazil (figure 5.3). A shock to export prices in Ukraine generates

Figure 5.5: Response of a shock to U.S. export price on export price



(a) EU **(b)** US

positive significant responses in the EU in both subperiods. However, US export prices only respond to the shock significantly in the first few months after the shock occurs.

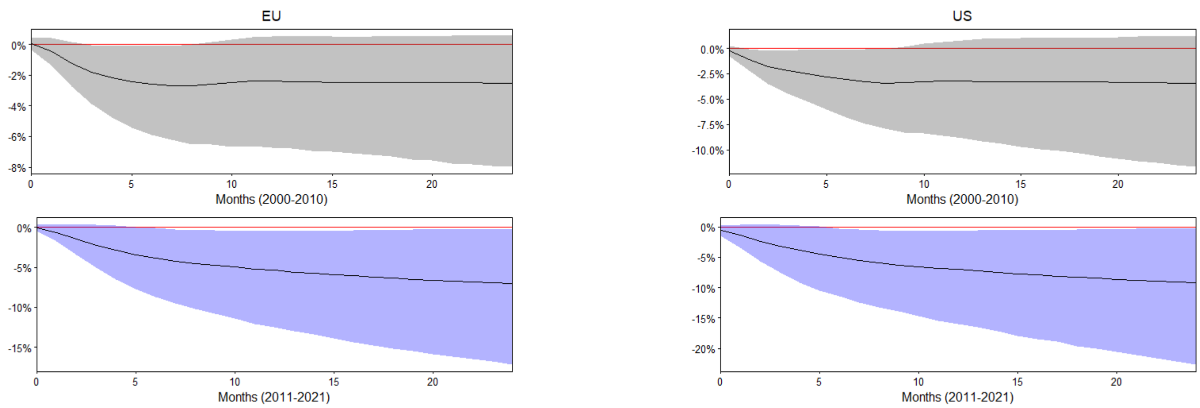
In case of a shock to EU export price (figure 5.4), it produces an initial response of +3.16% for the 2011-2021 period compared to +4.4% for the 2000-2010 period on its own export price. To the shame shock, the US export price responds with an initial mean magnitude of +1.34% for the 2000-2010 period and +1.86% for a later period.

A shock to US export price (figure 5.5) shows that export price in the EU responds initially by +1.44% for 2000-2010 and +1.27% for the 2011-2021 period. Similarly, the US responds initially by +6.07% and +5.93% for the 2000-2010 and 2011-2021 periods respectively. The response from the EU and the US to its own shock can be interpreted as the EU and the US reacting less for a later period to its own domestic shock which might be due to the increasing influence of countries like Argentina, Brazil, and Ukraine.

5.1.2 *Shock to Exchange Rates*

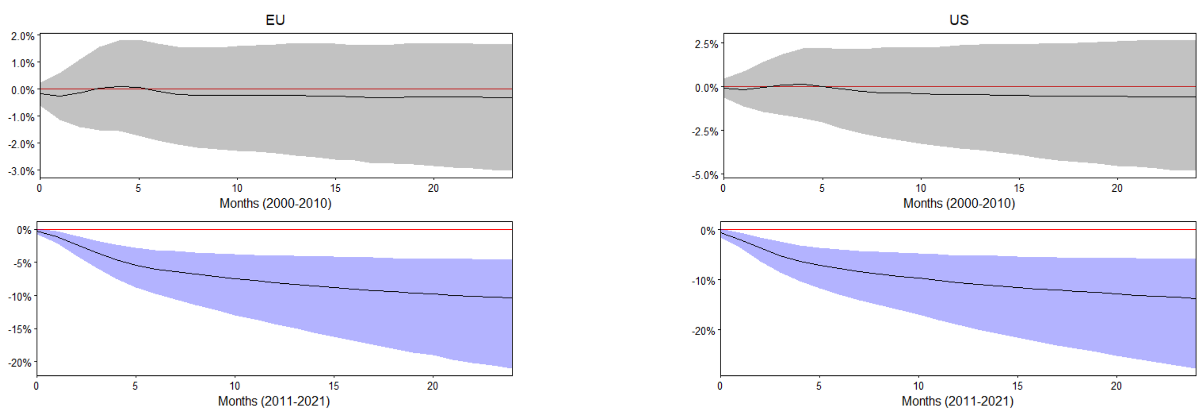
Figures 5.6 to 5.9 show that a positive shock to the national currencies of Argentina, Brazil, the EU, and Ukraine has a negative effect on export prices in the EU and the

Figure 5.6: Response of a shock to the Argentine exchange rate on EU and the US export price



(a) **(b)**

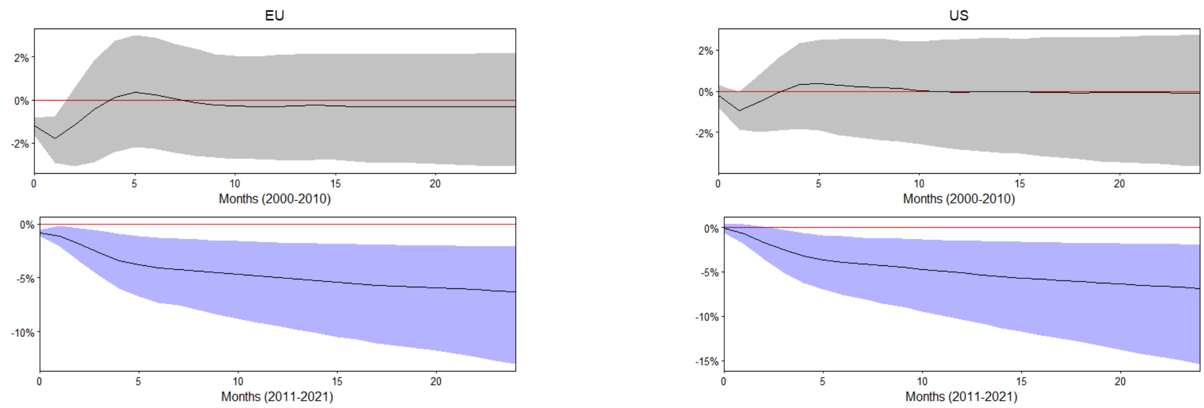
Figure 5.7: Response of a shock to the Brazilian exchange rate on EU and the US export price



(a) **(b)**

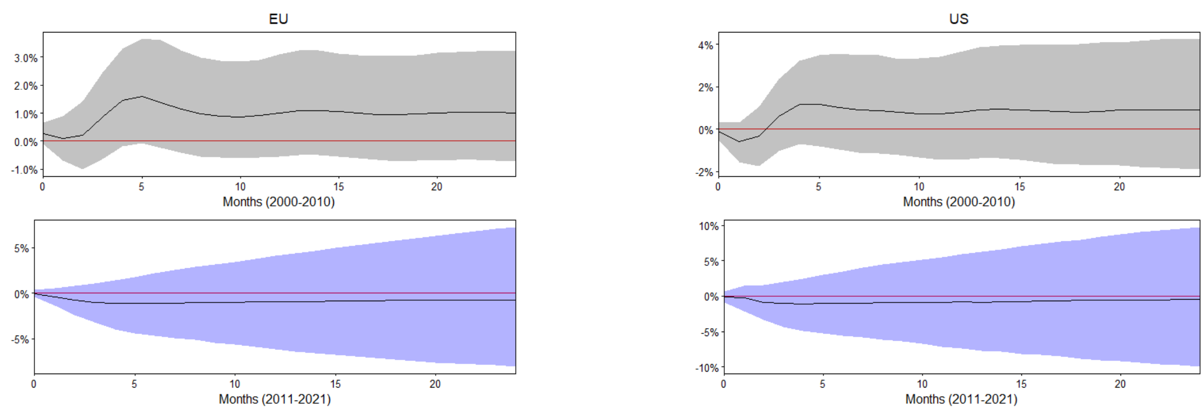
US for the period 2011-2021. A depreciation in the value of the domestic currency against the US dollar makes the exports less competitive in the global market, hence lowering export prices. These results align with the findings of Gutierrez, Piras, and Roggero (2015) that appreciation of domestic currencies against US dollars resulted in higher wheat export prices. A positive standard deviation shock in the Argentine exchange rate (figure 5.6) which equals an increase in currency by 3.85% (decrease in value per unit USD) leads to a decline of export prices by 3.9% in EU and 5% in the US after six months.

Figure 5.8: Response of a shock to EU exchange rate on EU and the US export price



(a) **(b)**

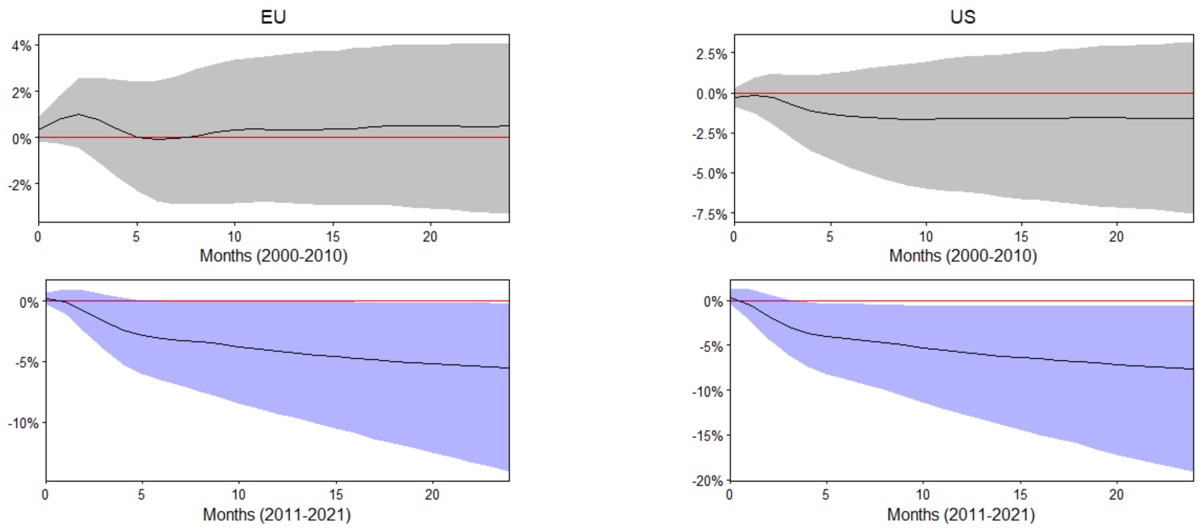
Figure 5.9: Response of a shock to the Ukrainian exchange rate on EU and the US export price



(a) **(b)**

For Brazil (figure 5.7), a positive standard deviation shock refers to an increase in the Brazilian exchange rate by 3.07%. The EU and the US export price responds to this shock with a decrease of corn export prices by 5.97% and 7.7%, respectively, after six months. In the case of the EU, a positive shock resembles to increase in the Euro exchange rate by 1.54% which is responded to by a decrease in EU and the US export prices by 4% and 3.89% respectively. Hence, An increase in the Argentine, Brazilian, and EU currencies positively significantly affects US corn export prices, suggesting that the depreciation of Argentine and Brazilian currencies would decrease US export

Figure 5.10: Response of shock to corn production in Argentina on EU and the US export price



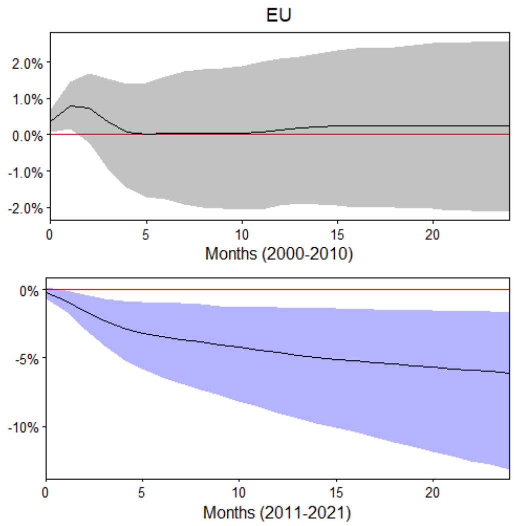
(a) **(b)**

prices. We found negative but statistically insignificant results for the Ukrainian exchange rate for the 2011-2021 period.

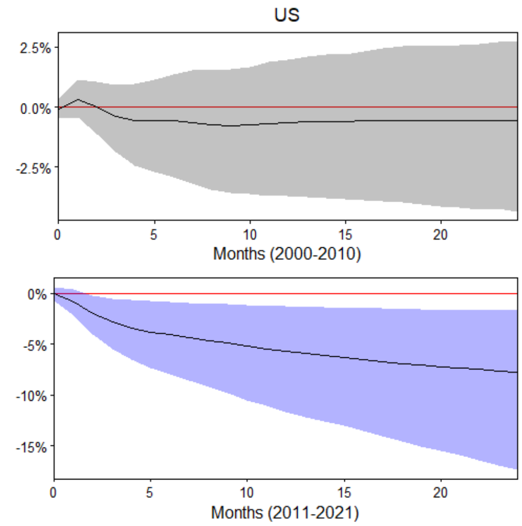
5.1.3 *Shock to Corn Production*

Next, we evaluate how a positive one standard deviation shock to corn production in emerging corn-producing countries, Argentina, Brazil, and Ukraine (figures 5.10, 5.11 and 5.12), affects export prices. A positive standard deviation shock is equivalent to an increase in corn production by 4.27%, 1.69%, and 5.27% in Argentina, Brazil, and Ukraine respectively for the 2011-2021 period. Unsurprisingly, an increase in production in these countries leads to a significant reduction in export prices in the EU and the US after 2011. The GIRFs suggest that a shock to corn production in Argentina and Brazil significantly decreases corn export prices by 3-5% in the EU and the US after six months.

Figure 5.11: Response of shock to corn production in Brazil on EU and the US export price

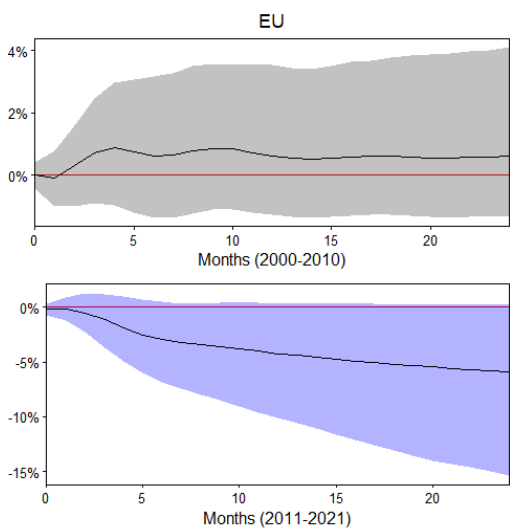


(a)

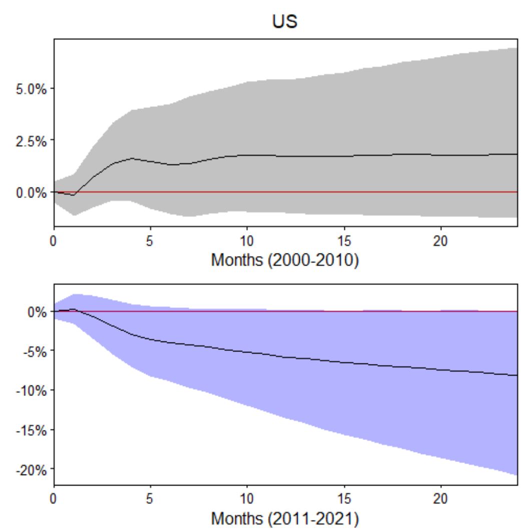


(b)

Figure 5.12: Response of shock to corn production in Ukraine on EU and the US export price



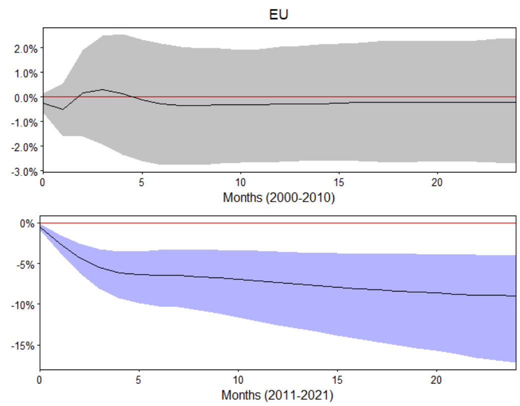
(a)



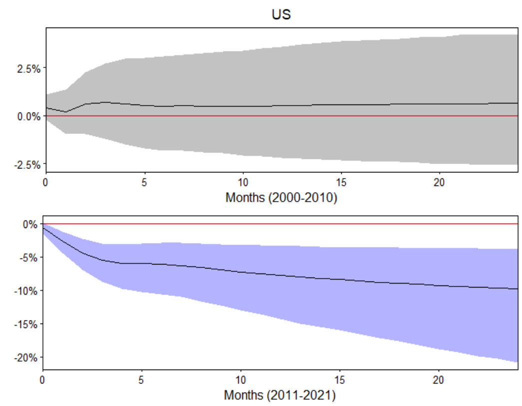
(b)

For Ukraine, results suggest that a shock to its production does not generate any statistical significance response for either the US or EU export prices. These results appear to be overall consistent with the findings of Arnade and Hoffman (2019-10, 2019) that although Ukraine has become an increasingly important player

Figure 5.13: Response of a shock to EU ending stock on EU and the US export price

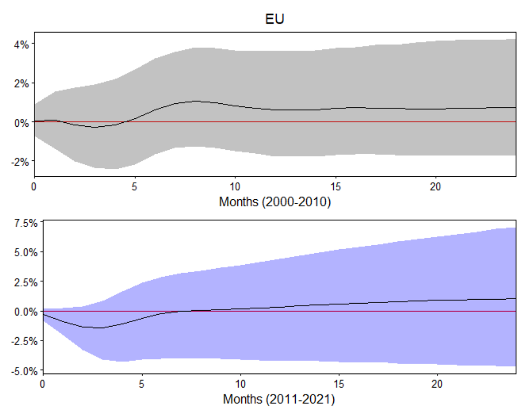


(a)

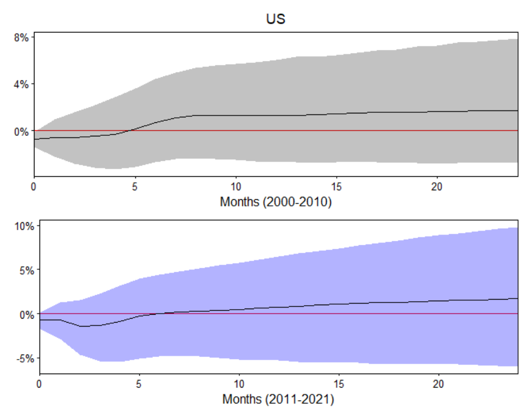


(b)

Figure 5.14: Response of a shock to US ending stock on EU and the US export price



(a)



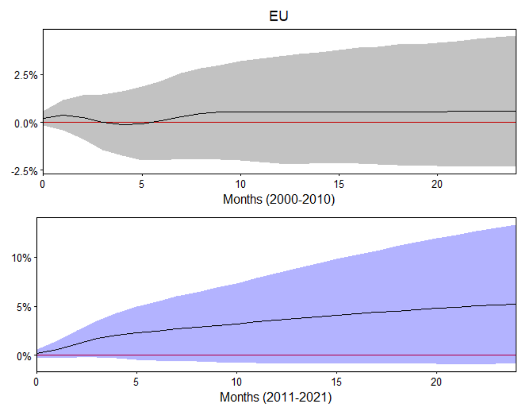
(b)

in the global market, its role in affecting prices remains limited, at least during our sample period.

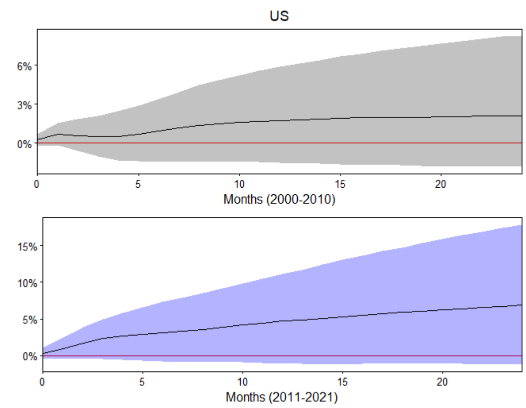
5.1.4 *Shock to Ending Stocks*

The theory of storage suggests an inverse relationship between export prices and inventory levels. As can be seen in figures 5.13 and 5.14, this negative relationship is found for the EU shock for 2011-2021 where a positive standard deviation shock, equivalent to an increase in ending stocks by 7.07%, leads to a reduction of both EU and the US export price by around 6% after six months. As can be seen, the response

Figure 5.15: Response of shock to Argentina food price on EU and the US export price

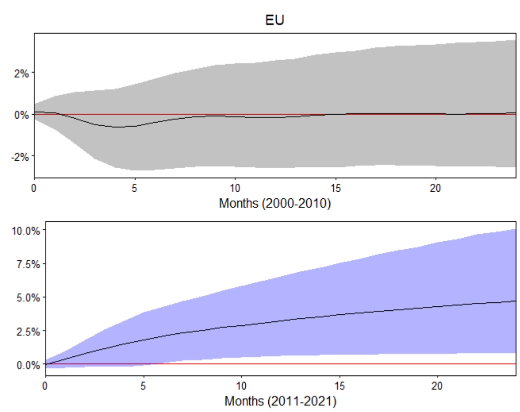


(a)

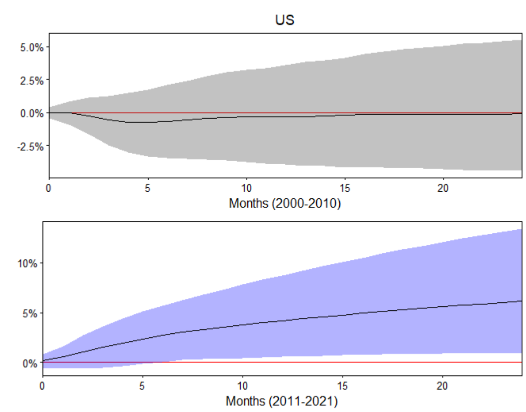


(b)

Figure 5.16: Response of shock to Brazil food price on EU and the US export price



(a)



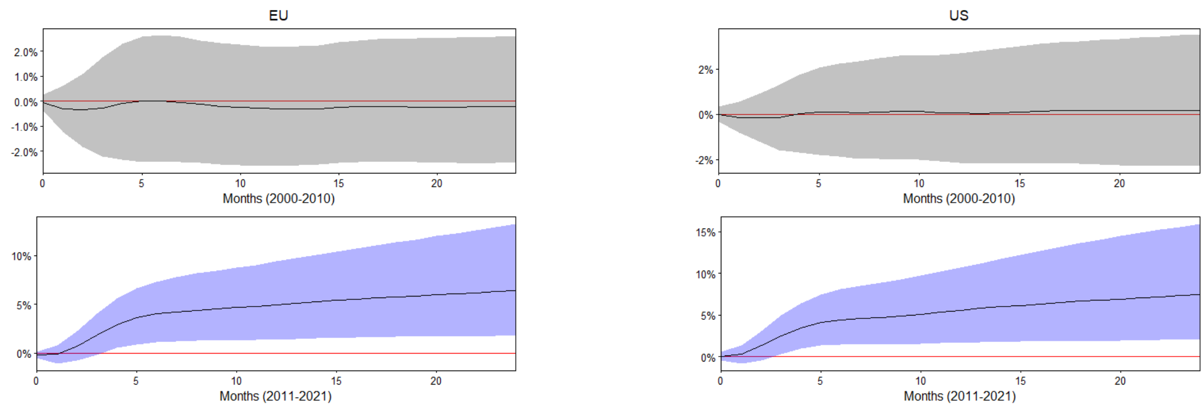
(b)

is non-significant for an earlier period. The impulse response graph for the US is not significant for either sub-period. However, it is interesting to note that for the entire sample period, the shock generated negatively significant responses for export prices (the GIRFs for the whole sample period is included in an appendix).

5.1.5 *Shock to Food CPI*

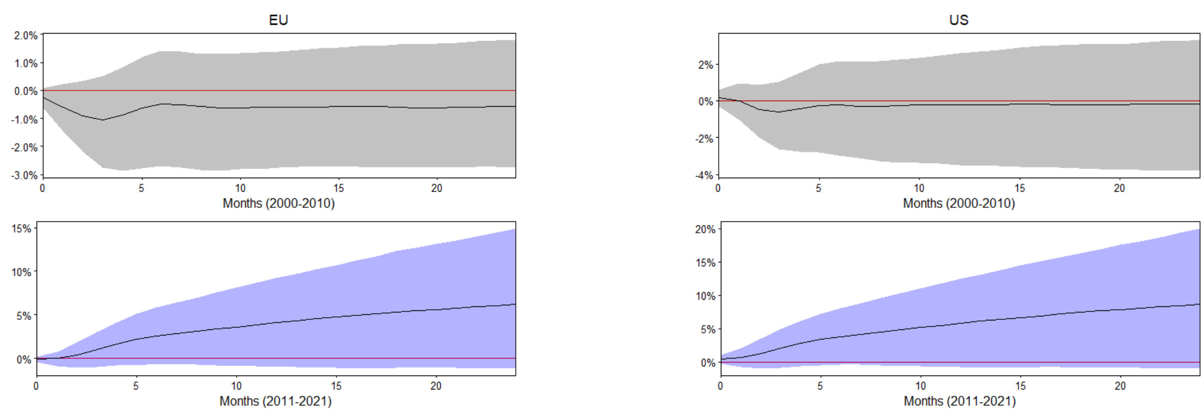
Demand shocks overall generate a positive impact on export prices for the 2011-2021 period, as illustrated by figures 5.15-5.19. An increase in the demand for food

Figure 5.17: Response of shock to EU food price on EU and the US export price



(a) **(b)**

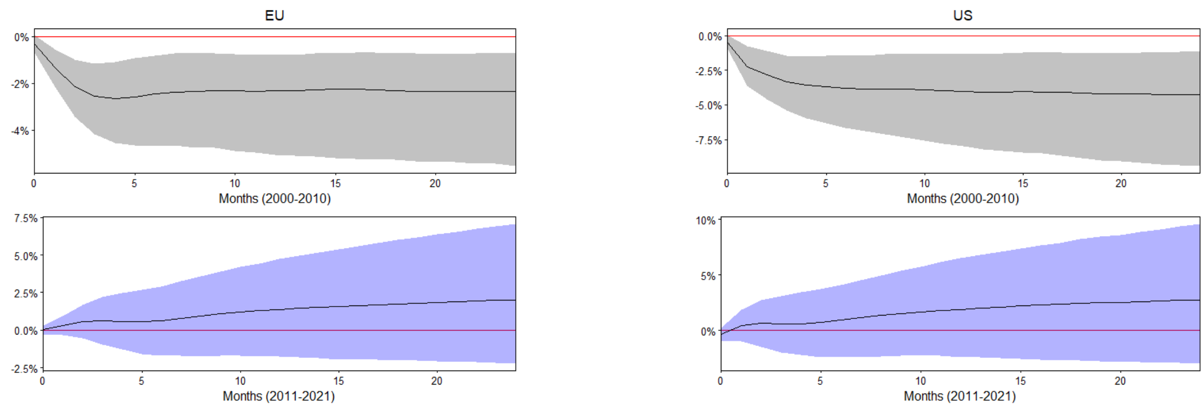
Figure 5.18: Response of shock to Ukraine food price on EU and the US export price



(a) **(b)**

products, all else equal, pushes the demand curve for corn outward, raising corn prices. This result is consistent with a number of previous studies that found demand shocks exert a positive impact on commodity prices (Kilian, 2009; Baffes and Etienne, 2016; Etienne, Irwin, and Garcia, 2018). However, the response varies depending on the origination of the shock. A positive shock to Brazil and EU food CPI increases export prices by 2-3% in the EU and US for the 2011-2021 period and this response is statistically significant. Even though the impulse response pattern is not significant for other countries, the impulse response pattern is similar.

Figure 5.19: Response of shock to US food price on EU and the US export price



(a) **(b)**

Table 5.6: Summary of Generalized Impulse Response Functions

Shocked Country	Response in EU and US Export Price	
	2000-2010	2011-2021
Shocks to export price		
Argentina, Brazil	Positive response	Increased positive response
Ukraine, EU and US	Positive response	Dreased positive response
Shocks to exchange rate		
Argentina, EU	Negative response	Increased negative response
Brazil	Insignificant	Negative response
Ukraine	Insignificant	Insignificant
Shocks to corn production		
Argentina, Brazil	Insignificant	Negative response
Ukraine	Insignificant	Insignificant
Shocks to ending stock		
EU	Insignificant	Negative response
US	Insignificant	Insignificant
Shocks to food price		
Argentina, Ukraine	Insignificant	Insignificant
Brazil, EU	Insignificant	Positive response
US	Negative response	Insignificant

Note:- A positive standard deviation shock is given to every variable

The GIRFs for 2000-2010 are not significant for most countries/regions. Perhaps a bit surprisingly, corn export prices in the US negatively respond to a shock to the US food CPI (figure 5.19). One possible explanation is that an increase in food

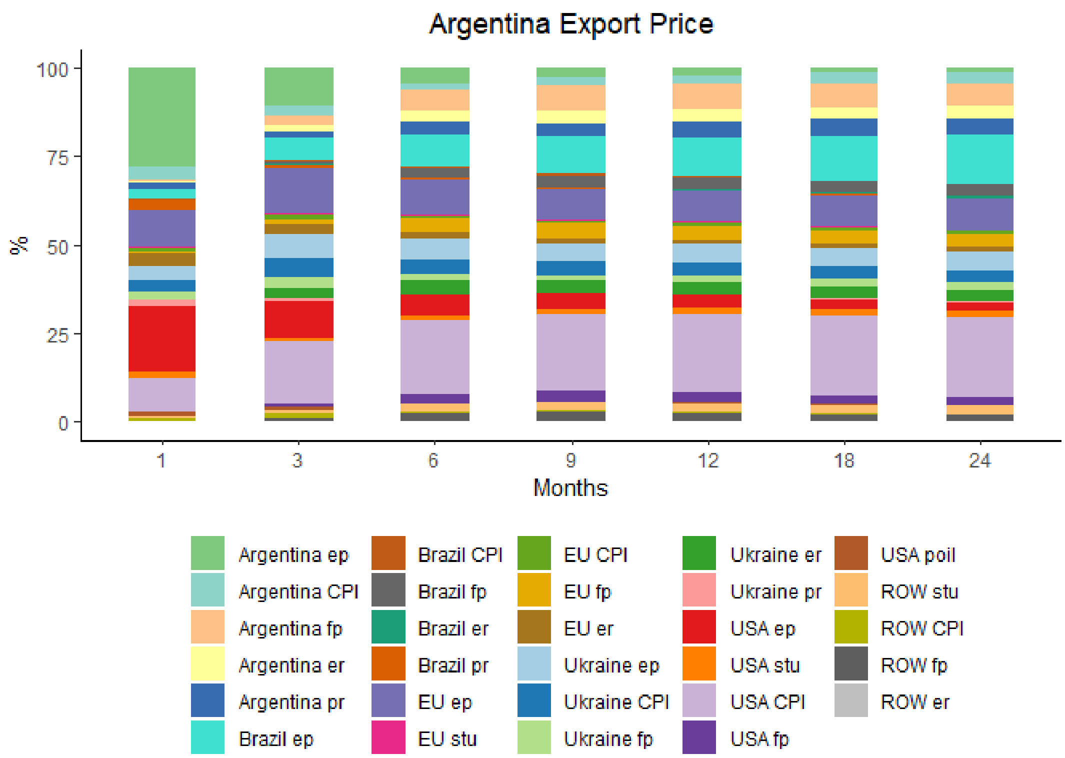
CPI in the US might have lowered the demand for corn for ethanol production as corn becomes less cost-competitive compared to gasoline. Since the demand for corn for feed in the US is relatively inelastic, the lower demand for corn for ethanol might have pushed the export supply curve outward, lowering export prices. The results from the generalized impulse response function are summarized in table 5.6.

5.2 GENERALIZED FORECAST ERROR VARIANCE DECOMPOSITION (GFEVD)

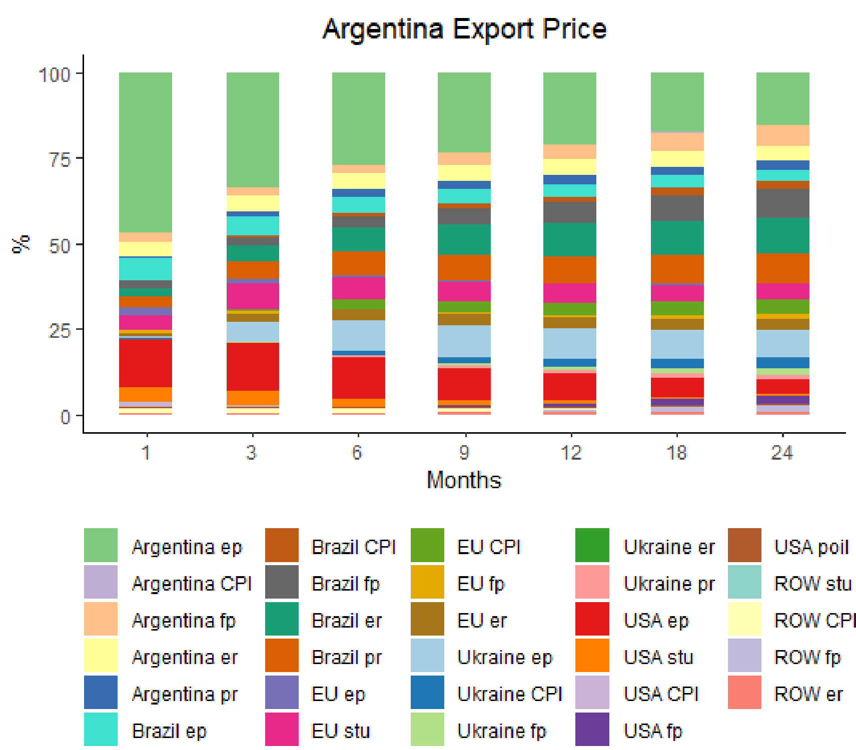
FEVD allows us to evaluate the relative importance of various shocks in explaining the variance of another variable at different time horizons. Figures 5.20a and 5.20b show the GFEVDs Argentina corn export prices for the 2000-2010 and 2011-2021 periods, respectively. Argentina's own export prices, EU export prices, and US export prices account for the majority of the fluctuation in export prices for the first three months of the 2000–2010 time frame. For later stages, major contributors include US CPI, export prices from Brazil, and food prices in Argentina. Similarly, for the period 2011-2021, the Argentine export price, followed by the US export price, is the largest contributor to the forecast error variance decomposition of the shock. The production of Brazil, the exchange rate, the cost of fertilizer, and the cost of exports from Ukraine all eventually assume similar importance in explaining the shock's variance over time.

The majority of the variation in Brazil's export prices between 2000 and 2010 can be attributed to its own export prices, followed over a longer time period by fertilizer prices and US CPI. In contrast, over the period of 2011–2021, the export price initially accounts for the majority of variation, but with time, its significance diminishes as the contributions of variables such as fertilizer costs, exchange rates and corn production of Brazil, and the export price of Ukraine rise over time. When

Figure 5.20: GFEVD for Argentina

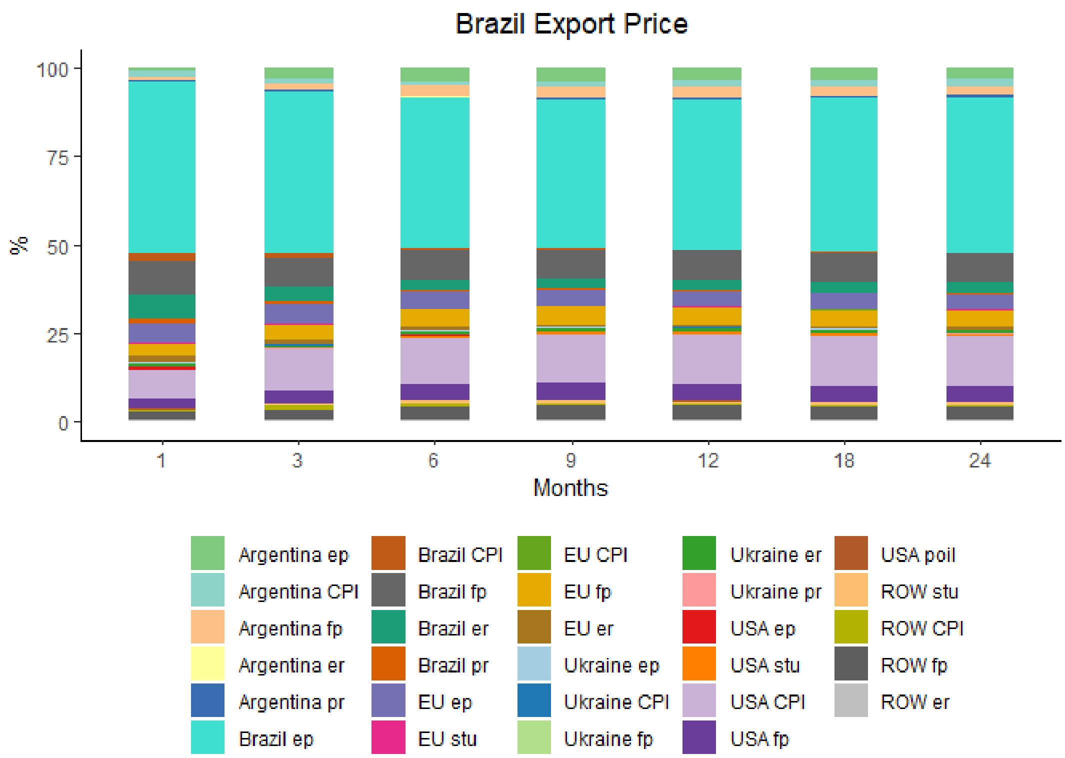


(a) 2000-2010

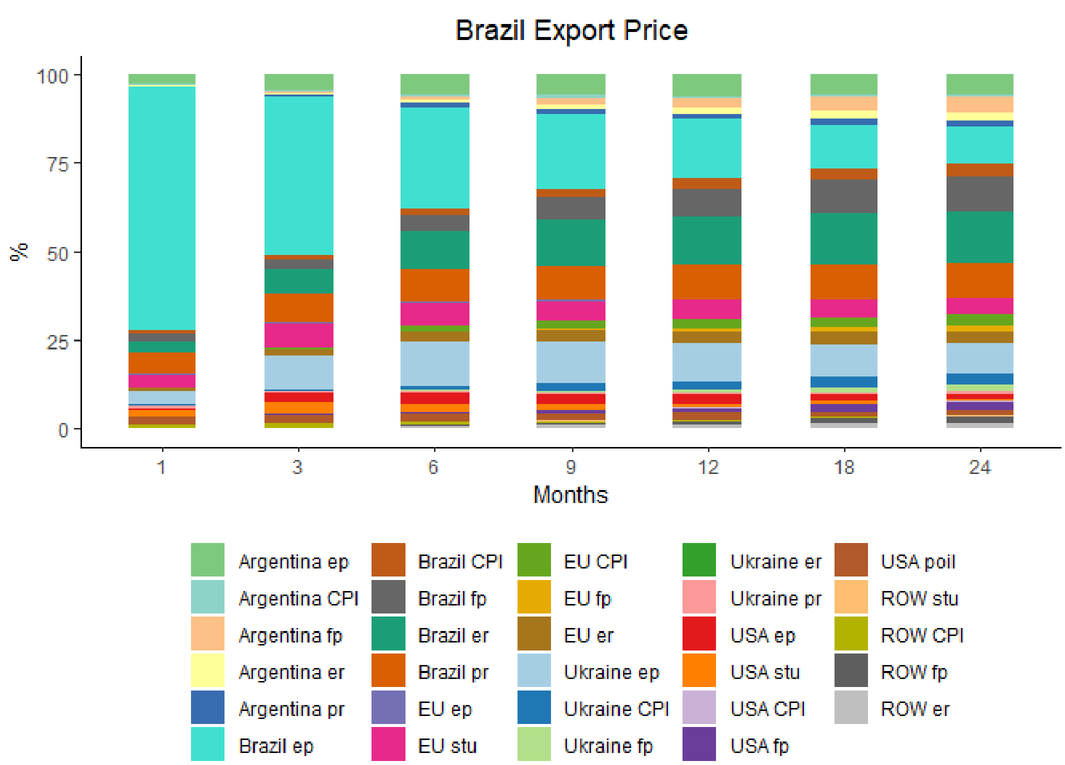


(b) 2011-2021

Figure 5.21: GFEVD for Brazil



(a) 2000-2010



(b) 2011-2021

compared to the prior period, US variables have a reduced contribution for later time periods.

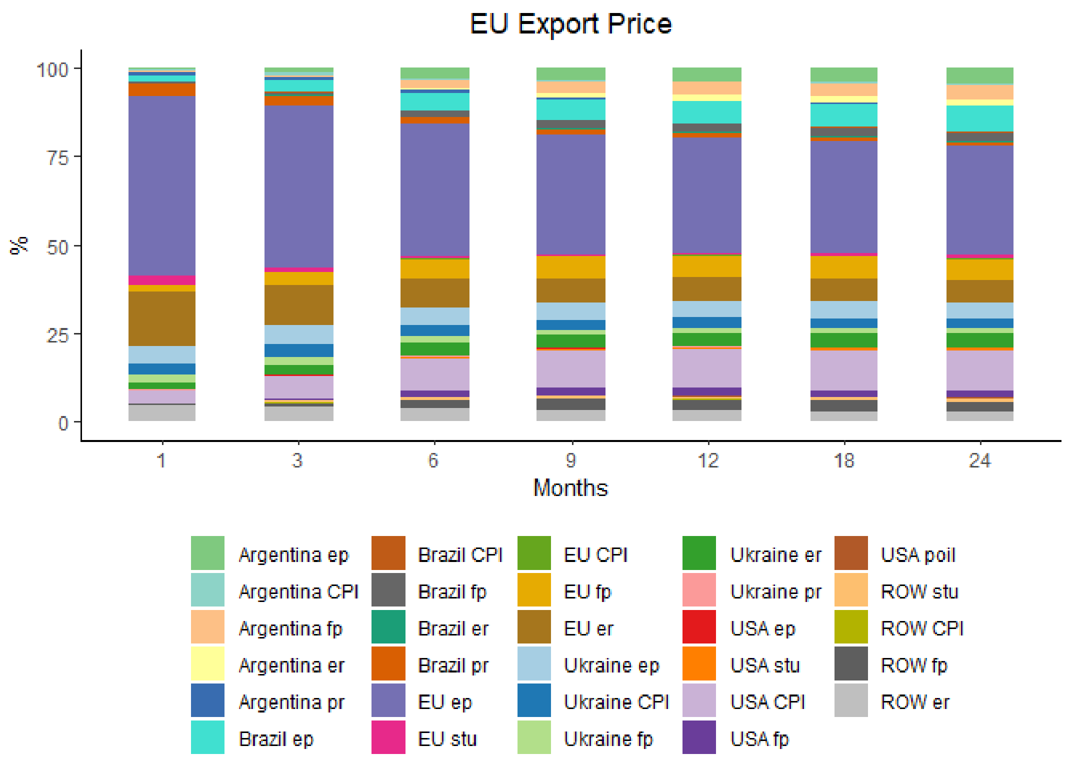
The GFVED of EU export prices (figure 5.22a) for the 2000–2010 time frame demonstrates that the EU's own export prices and exchange rate account for the majority of the variation during the initial phases. Later, the US CPI and export prices from Brazil also contribute. On the other hand, the EU's own export prices, the currency rate, and ending stocks account for the majority of variation in the first phases during the 2011 and 2021 period (figure 5.22b). The contribution of corn production, fertilizer prices, the exchange rate from Brazil, and export prices from Argentina, Brazil, and Ukraine rises with time in explaining the variation to the shock.

For the GFVED of Ukraine export prices in 2000–2010, figure 5.23a demonstrates that a shock to its own export price accounts for the majority of the early fluctuation, with export prices from Argentina, the EU, and Ukraine's fertilizer prices gradually adding to the explanation during the later stages. However, figure 5.23b), shows that for 2011-2021, a variety of factors, including export prices from all areas, the currency rate of Brazil, and ending stocks in the EU, contributed to the variability of the shock.

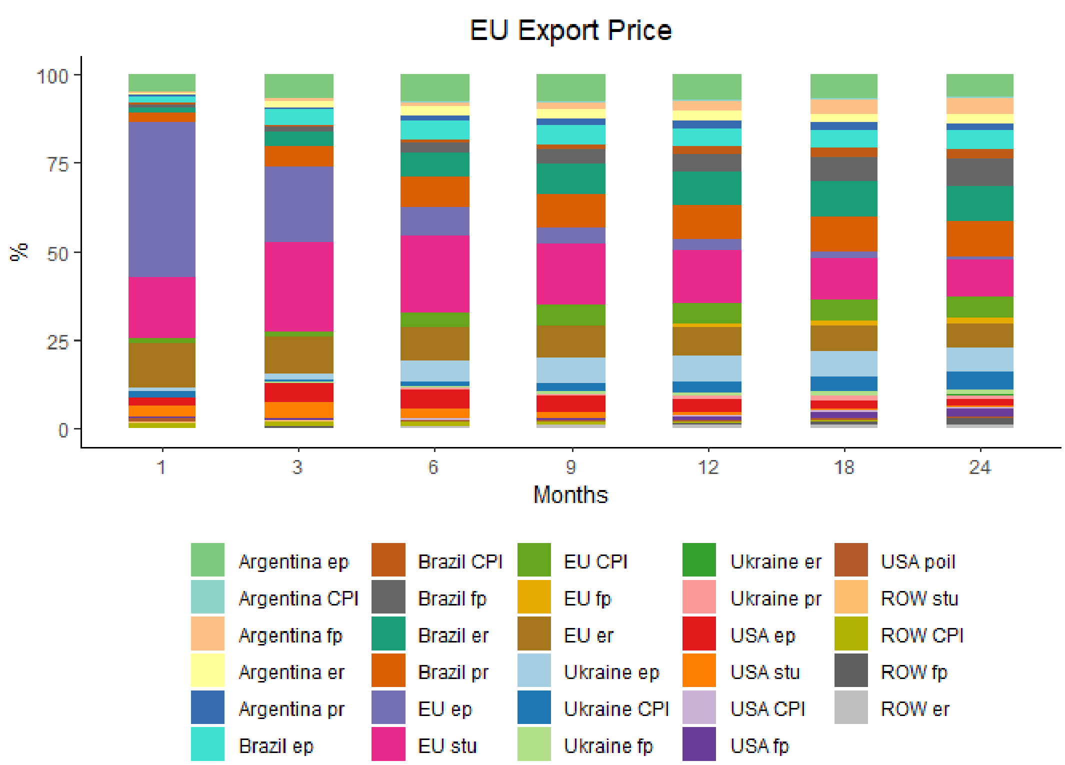
The GFEVD for US export prices for the period 2000–2010 (figure 5.24a) shows that the majority of the initial fluctuation comes from shocks to its export prices, CPI, and ending stocks. These results suggest that at least in the short term, corn export prices in the US are driven by demand and supply fluctuations occur ed domestically. Later, export prices in Brazil and the EU play a significant role in explaining the variation. In the 2011–2021 period (figure 5.24b), US and Argentina export prices initially are responsible for the majority of variation; however, as time passes on, a variety of other variables become more significant, including export prices from Argentina, Brazil, and Ukraine, Brazilian fertilizer prices, Brazilian corn production, and exchange rate. These results suggest that US corn prices have been increasingly affected by supply and demand shocks in emerging countries as their export share drops.

In summary, the GFEVDs provide important insights into explaining the significance of different variables on export prices. Results show that own export prices, followed by other factors like the US food CPI, currency rates, fertilizer costs, and corn production, are the main explanations for the changes in the export prices of Argentina, Brazil, the EU, and Ukraine between 2000 and 2010. In the beginning, the US makes a considerable contribution to the explanation of a shock to the export price, but its importance wanes over time. The export prices of the nations/regions are first explained by their export prices in the 2011–2021 period, but over time, a larger variety of factors, such as fertilizer costs, currency rates, corn production, and export prices of other nations, become increasingly important. Compared to before, the US's importance in explaining the export price has diminished.

Figure 5.22: GFEVD for EU

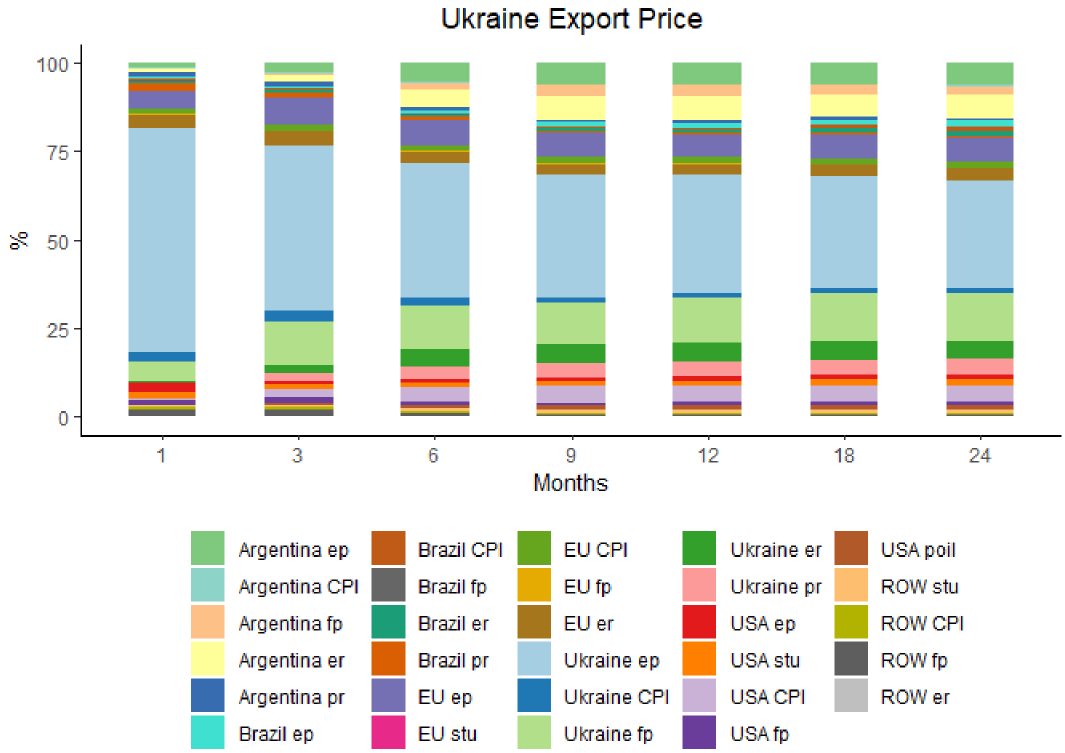


(a) 2000-2010

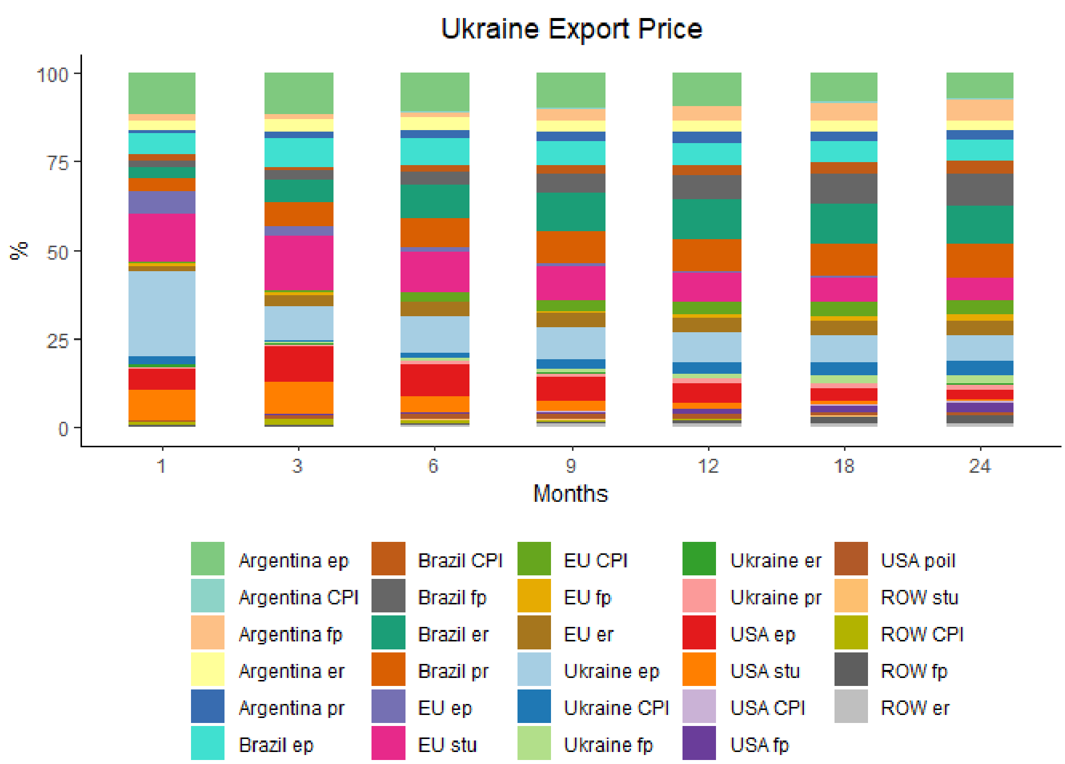


(b) 2011-2021

Figure 5.23: GFEVD for Ukraine

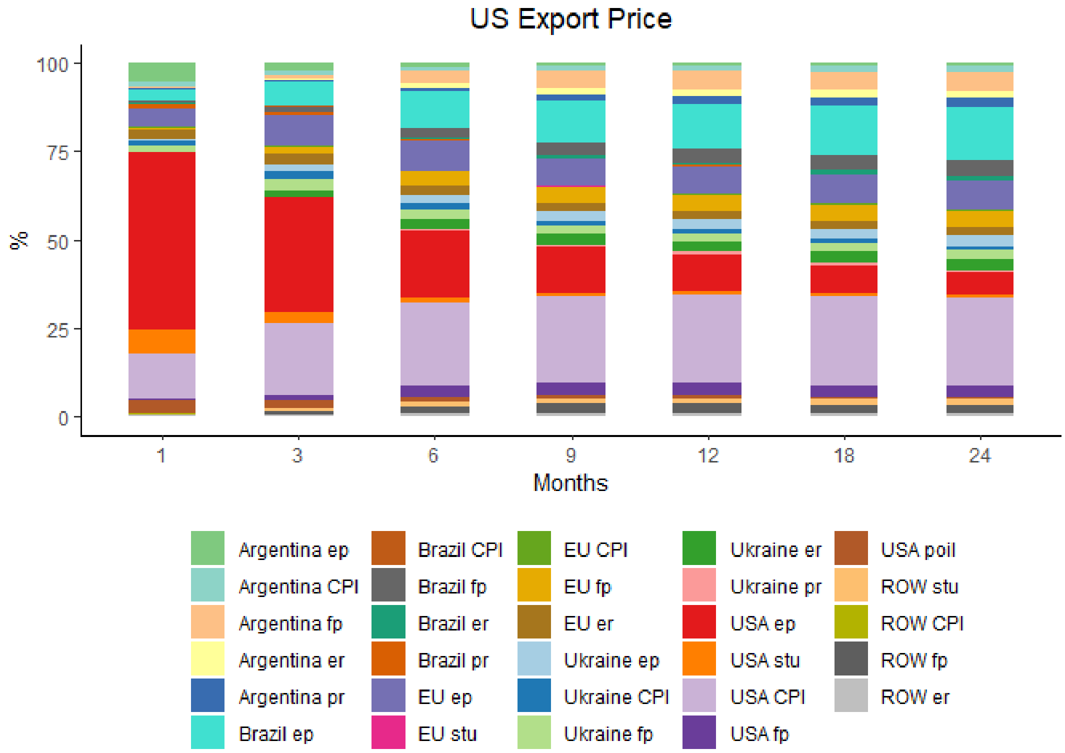


(a) 2000-2010

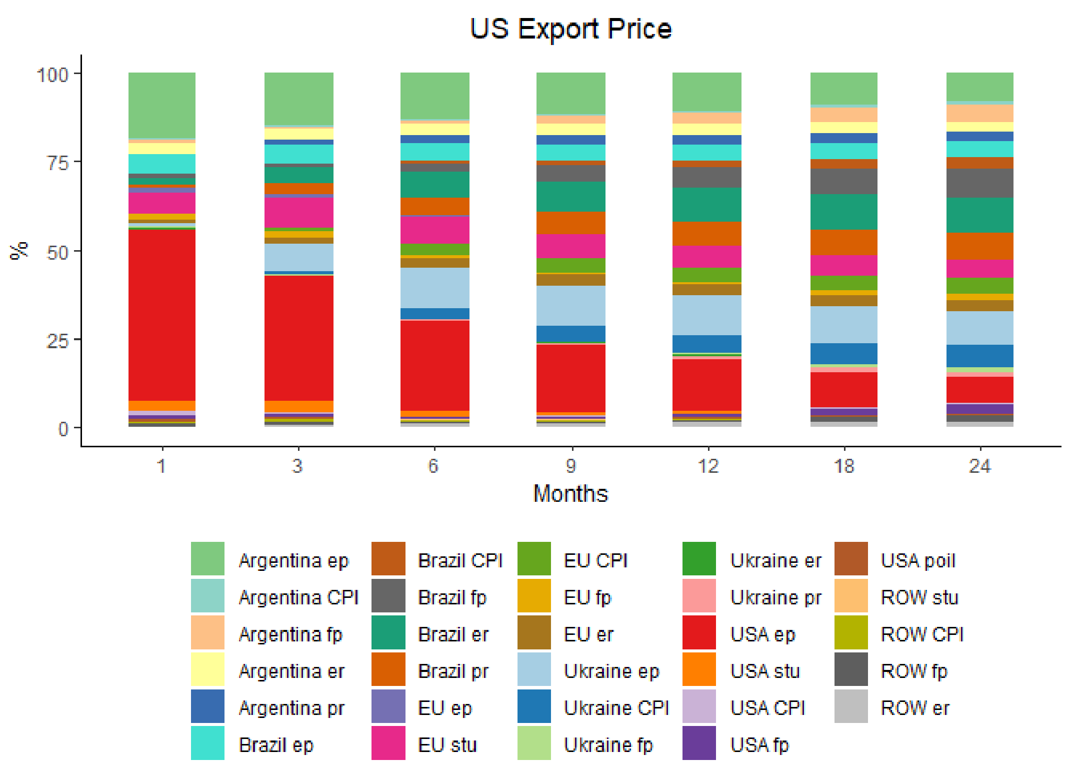


(b) 2011-2021

Figure 5.24: GFEVD for US



(a) 2000-2010



(b) 2011-2021

CHAPTER 6

Conclusions

The rising competition in the global corn market challenges the US' dominant role in the export market. We investigate how the increasing competition in the global corn market has affected the corn price dynamics in the US and the international market. Using monthly data from 2000 to 2021, we estimate Global Vector Autoregression models to determine how shocks to one country affect the corn market in another country. We consider five countries/regions: the US, Brazil, Argentina, Ukraine, and the EU. A rest-of-world aggregate is also included in the analysis. Endogenous variables considered in the analysis include export prices, corn production, ending stocks, exchange rates, fertilizer prices, and consumer price index.

Estimation results largely confirm our hypothesis that shocks to the demand and supply of corn in emerging countries (Argentina, Brazil, and Ukraine) affect export prices in the US and other countries/regions. While most of the generalized impulse response functions for 2000-2010 are insignificant, the response to various shocks for the 2011-2021 period is more significant. In particular, shocks to the ending stocks, an indicator of the supply status of corn in the market, negatively affect corn export prices after 2011. Appreciation of domestic currencies relative to the US dollar positively affects corn export prices, while increases in CPI positively impact export prices, especially for the period 2011-2021. Meanwhile, market-specific shocks, proxied by a shock to the export price, increase export prices in other countries/regions. In the case of emerging corn-producing countries except for Ukraine, a shock to export prices in these countries have a greater impact on EU and the US export prices for later sub-period. Similarly, corn production in Argentina, Brazil, and Ukraine impacts export prices negatively. The GFEVDs of a shock to export prices also show the decreasing role of the US in explaining a variation of the shock to export prices for the 2011-2021 period compared to the prior period.

Our study also helps in addressing changes in the global corn market brought on by outside shocks like COVID-19 and war. For instance, the Russian invasion of Ukraine has resulted in a decreased export of more than 20% of corn produced (Padilla et al., 2023). This has resulted in a short-term decline in worldwide corn supply and, as a result, an increase in global corn prices. Furthermore, the prolonged conflict has the potential to substantially hamper Ukraine's corn production due to access issues to agricultural inputs. According to our study, a shock to corn production in Ukraine will invariably affect corn export prices in the United States and the EU. It is anticipated that global shocks, as demonstrated by this war, will enhance market volatility in addition to driving up corn prices globally.

Combining these results, we conclude that new emerging corn-producing countries are challenging the dominant role played by the US in the global corn market. Given the different exogenous shocks in the international corn market such as the war in Ukraine, it is important for policymakers and market participants to take into account the various supply and demand factors, both domestically and in other major players, into consideration.

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Appendix

Table 6.1: Average pairwise cross-section correlations of all variables and VECMX* residuals for 2000-2010 period

Country	First Difference of Domestic Variables					
	p^e_{it}	pd_{it}	r_{it}	p^c_{it}	p^f_{it}	s_{it}
Argentina	0.53883706	0.03856966	0.11741982	-0.0347457	0.8206	
Brazil	0.4670941	-0.0207027	0.30254598	0.14696167	0.867	
EU	0.4721647		0.19794334	0.21211196	0.89962571	-0.0163
Ukraine	0.29417883	-0.1446106	0.10418671	0.2532554	0.8940	
USA	0.50926266			0.10727069	0.92506656	-0.1084
ROW			0.333402	0.14915261	0.93121857	-0.0030
Country	**VECMX* Residuals**					
	p^{e*}_{it}	pd^*_{it}	r^*_{it}	p^{c*}_{it}	s^*_{it}	
Argentina	-0.1032274	0.12368297	-0.0903835	-0.0317426		
Brazil	-0.1357437	0.04059012	-0.0194799	-0.0312146		
EU	-0.0879987		-0.0340819	-0.0398962	0.10586234	
Ukraine	-0.1954623	0.03779883	-0.0785838	0.00082355		
USA	-0.1469593			-0.0375981	0.01905928	
ROW			0.0087341	-0.1081674	0.07299035	

Table 6.2: Average pairwise cross-section correlations of all variables and VECMX* residuals for 2011-2021 period

Country	First Difference of Domestic Variables					
	p^e_{it}	pd_{it}	r_{it}	p^c_{it}	p^f_{it}	s_{it}
Argentina	0.58782623	0.30342894	0.14016853	0.09017277	0.7887	
Brazil	0.42966898	0.21632697	0.33240239	0.07557471	0.8306	
EU	0.40851762		0.18238	0.12604752	0.87559634	0.0645
Ukraine	0.52057259	0.17748538	0.09775094	0.04862092	0.7509	
USA	0.57266536			0.07256295	0.88587053	0.066
ROW			0.37361962	0.00264045	0.89968586	-0.0314

Country	VECMX* Residuals				
	p^{e*}_{it}	pd^*_{it}	r^*_{it}	p^{c*}_{it}	s^*_{it}
Argentina	-0.0650304	-0.0795979	-0.1022552	0.01757468	
Brazil	-0.2817912	-0.0668218	0.05964418	-0.015122	
EU	-0.0909185		0.00783355	0.04059379	-0.0048686
Ukraine	-0.1639	-0.247754	-0.1725548	0.02356836	
USA	-0.1357356			0.07683274	0.0204597
ROW			0.03482548	-0.02102	-0.0507742

Table 6.3: F Statistics for the Serial Correlation Test of Exogenous and Global Variables (VECMX* Residuals)

2000-2010								
Countries		p^{e*}_{it}	pd^{*}_{it}	r^{*}_{it}	p^{c*}_{it}	s^{*}_{it}	o_{it}	Critical values
Argentina	F(3,101)	1.907092	0.956228	3.683638^{Y}	4.872307^{Y}	-	-	2.694618
Brazil	F(3,106)	0.749997	0.202219	0.210333	5.041065^{Y}	-	-	2.690303
EU	F(3,107)	0.270878	-	0.215563	0.511064	1.122416	-	2.68949
Ukraine	F(3,101)	0.440424	0.071575	0.852474	0.890887	-	-	2.694618
USA	F(3,113)	1.072615	-	-	1.284996	0.477469	0.843771	2.684916
ROW	F(3,109)	-	-	0.305581	2.002354	0.580056	-	2.687908

2011-2021								
Countries		p^{e*}_{it}	pd^{*}_{it}	r^{*}_{it}	p^{c*}_{it}	s^{*}_{it}	o_{it}	Critical values
Argentina	F(3,114)	3.084434^{Y}	0.249811	1.648809	0.046768	-	-	2.684201
Brazil	F(3,118)	0.565754	0.187523	3.244957^{Y}	6.334073^{Y}	-	-	2.681466
EU	F(3,113)	0.80004	-	1.356176	1.45918	3.161816^{Y}	-	2.684916
Ukraine	F(3,113)	1.93246	0.141517	0.468612	1.324105	-	-	2.684916
USA	F(3,113)	1.363611	-	-	1.854863	0.21869	2.225966	2.684916
ROW	F(3,108)	-	-	1.913197	3.353133	0.105986	-	2.688691

Note: The critical values are at the 5% significance level. Y *denotes statistical significance at the 5 % level.*

Table 6.4: Structural Stability Tests Statistics for 2000-2010 period

Countries	p^e_{it}	pd_{it}	r_{it}	p^c_{it}	p^f_{it}	s_{it}	o_{it}
				PK sup			
Argentina	0.53299	0.711696	0.624309	1.544233^{Y}	0.517028	-	
Brazil	0.419153	0.604997	0.54608	0.50882	0.494409	-	
EU	0.568052	-	1.020045	0.742224	0.462594	0.46332	
Ukraine	0.922534	0.583045	1.117272	0.467832	0.939729	-	
USA	0.495562	-	-	0.524756	0.324376	0.569577	0.672
ROW	-	-	0.690766	0.716936	0.523325	0.589072	
				PK msq			
Argentina	0.03547	0.122407	0.063291	0.98004^{Y}	0.056835	-	
Brazil	0.046925	0.083688	0.04042	0.070864	0.026299	-	
EU	0.051509	-	0.303918	0.166147	0.03059	0.046269	
Ukraine	0.196267	0.021729	0.366545	0.042576	0.17599	-	
USA	0.053633	-	-	0.044318	0.016448	0.040889	0.109
ROW	-	-	0.144431	0.088152	0.075192	0.070933	
				Robust Nyblom			
Argentina	2.614595	4.169327	5.339349	5.276523	3.614282	-	
Brazil	3.688332	3.361405	4.297626	3.131264	2.915542	-	
EU	2.676476	-	3.515216	2.956532	4.218076	2.002407	
Ukraine	5.275144	4.64542	4.269934	3.812454	4.505964	-	
USA	2.419289	-	-	1.375037	1.683801	2.458404	3.628
ROW	-	-	3.090696	2.461711	2.262472	3.814862	
				Robust QLR			
Argentina	62.48619	39.62828	256.0067	70.19061	69.57194	-	
Brazil	39.35917	22.89473	40.32587	37.33916	27.6779	-	
EU	25.1042	-	28.83627	32.41599	26.99429	19.02829	
Ukraine	44.58929	37.22551	21.93919	145.5612	55.64935	-	
USA	25.94295	-	-	17.726	16.14119	19.2931	32.117
ROW	-	-	31.64991	23.57215	25.32665	26.35995	

Note: The critical values are at the 1% significance level. Y denotes statistical significance at the 1 % level.

Table 6.5: Structural Stability Tests Statistics for 2011-2021 Period

Countries	p^e_{it}	pd_{it}	r_{it}	p^c_{it}	p^f_{it}	s_{it}	o_{it}
			PK sup				
Argentina	0.345	0.803752	1.088146	1.74722^{Y}	0.824419	-	
Brazil	0.786	0.603398	0.715525	1.116112	1.263404	-	
EU	0.608	-	0.74185	0.624917	0.732314	0.382212	
Ukraine	0.557	0.840383	1.388277	0.985845	0.857811	-	
USA	0.493	-	-	0.519558	0.48083	0.491515	0.523
ROW	-	-	0.454729	0.633845	0.818245	0.772075	
			PK msq				
Argentina	0.019	0.104246	0.342669	0.703728^{Y}	0.217421	-	
Brazil	0.145	0.058368	0.127383	0.183942	0.313342	-	
EU	0.051	-	0.090163	0.087743	0.086819	0.032815	
Ukraine	0.067	0.194563	0.450457	0.239383	0.116279	-	
USA	0.029	-	-	0.080814	0.036607	0.057027	0.040
ROW	-	-	0.041953	0.029626	0.083921	0.057241	
			Robust Nyblom				
Argentina	1.835	2.058174	1.898369	2.664451	2.930973	-	
Brazil	1.190	1.289097	1.686997	1.754297	1.542031	-	
EU	1.838	-	1.523944	2.814431	2.762802	2.349785	
Ukraine	2.192	2.402419	2.982192	1.89181	1.788047	-	
USA	1.758	-	-	2.578897	2.383235	2.521597	2.083
ROW	-	-	3.324229	3.007194	3.396252	3.476075	
			Robust QLR				
Argentina	18.873	17.42003	14.62179	22.0946	26.32129	-	
Brazil	10.379	19.22075	22.92484	18.66729	16.50676	-	
EU	16.272	-	15.18438	26.73538	21.04622	21.9059	
Ukraine	22.696	16.16206	13.59468	23.03022	16.15046	-	
USA	18.336	-	-	20.70357	15.99853	15.36927	16.774
ROW	-	-	25.9819	31.61271	21.16267	17.25708	

Note: The critical values are at the 1% significance level. Y *denotes statistical significance at the 1 % level.*